Second International Conference on Nexgen Technologies
Sengunthar Engineering College, Tiruchengode, Namakkal Dist. Tamilnadu (India)
8th - 9th March 2019 www.conferenceworld.in ISBN : 978-93-87793-75-0

NEW HEURISTIC APPROACH FOR SOLVING NON-CONVEX ECONOMIC LOAD DISPATCH

V.P. Sakthivel

Department of Electrical and Electronics Engineering,

Government College of Engineering, Dharmapuri (India)

ABSTRACT

Economic load dispatch (ELD) is one of the main optimization problem in power system planning and operation. Its objective is to allocate the power demand among the generators in the most economical way, while satisfying all physical and operational constraints. In this paper, anew heuristic algorithm, exchange market algorithm (EMA) for solving non-convex economic load dispatch (NCELD) problem is introduced. EMA mimics the behavior of share markets in normal and oscillatory market situation. The EMA is used to find solution for convex and non-convex ELD problems with smooth and non-smooth cost functions (with and without valve-point effect) with constraints such as generator capacity, transmission loss, ramp rate limits, and prohibited operating zones. In order to verify the effectiveness of the proposed EMA, it is implemented on two test systems, 13 and 15 generating units with non-convex and non-smooth cost functions. Furthermore, the numerical results are compared with those of GA and PSO techniques.

Keywords: *Power systems; exchange market algorithm; economic load dispatch; smooth function; valve-point loading*

Nomenclature

F_i	total fuel cost of the generators
a_i, b_i, c_i	cost coefficients of generator i.
P_D	power demand
P_L	transmission losses
B_{ij}	line loss coefficients
$P_{i,min}, P_{i,max}$	minimum and maximum generation of unit i.
P_i, P_i^0	current and previous power output of i^{th} unit respectively
UR_i, DR_i	up and down ramp limits of i^{th} unit respectively
k	index of prohibited zone
nz	number of prohibited zones of unit i

$P^L_{i,k}$, $P^U_{i,k}$	lower and upper limits of kth prohibited zone of generator i
n_i	n^{th} person of the first group
n_j	n^{th} person of the second group
r	random number within [0, 1]
$pop_j^{group(2)}$	j^{th} member of the second group
$pop_{1,i}^{group(1)}$	members of the first group
$pop_{2,i}^{group(1)}$	members of the second groupr_1 and r_2 random numbers
n_k	n^{th} member of the third group
$pop_k^{group(3)}$	k^{th} member of the third group and
S_k	share variation of the kth member of the third group
Δn_{t1}	share value added randomly to some shares
n_{t1}	total shares of member t
S_{ty}	shares of the t^{th} member
δ	information of exchange market
η_1	risk level for each member of the second group
t_{pop}	number of the t^{th} member in exchange market
n_{pop}	number of the last member in exchange market, l is a
μ	constant coefficient for each member
g_1	common market risk amount
$Iter_{max}$	maximum iteration number
$g_{1,max}$, $g_{2,max}$	maximum and minimum values of risk in market respectively
Δn_{t3}	share value added randomly to some shares
r_s	random number between -0.5 and 0.5
g_2	market variable risk in third group

I. INTRODUCTION

ELD is one of the most important issuesto be solved for smooth and economic operation of a power system. It is a process for sharing the total load on a powersystem among various generating plants to achieve greatest economyof operation.The conventional methods such as linear programming algorithm [1], quadratic

ISBN : 978-93-87793-75-0

programming algorithm [2], non-linear programming algorithm [3], dynamic programming algorithm [4,5], Lagrangian relaxation algorithm [6,7] etc. were applied to the ELD problems.Due to highly nonlinear characteristics of the problem and a large number of constraints, the classical calculus-based methods cannot perform satisfactorilyfor solving ELD problems.Modern meta-heuristic algorithms such as particle swarm optimization (PSO) [8-12], adaptive PSO [13], chaotic PSO [14], differential evolution (DE) [15], evolutionary programming (EP) [16], genetic algorithm (GA) [17,18], real coded GA [19], bacterial foraging optimization (BFO) [20], biogeography based optimization (BBO) [21], gravitational search algorithm (GSA) [22], pattern search method (PSM) [23], clonal search algorithm [24] and artificial bee colony (ABC) [25, 26] are promising alternative for solving the complex ELD problems.Shaw et al. developed oppositional based learning conceptto accelerate the performance of the GSA [27]. Liao presented isolation Nicheimmune based GA algorithm for solving dynamic ELD (DELD) Problem [28]. Peng et al. proposed bi-population chaotic differentialevolution algorithm to solve DELD problem of apower system integrated with large scale wind farms [29]. In the proposedalgorithm, chaotic map update mechanism and metropolisrule are used to improve the performance of standard differentialevolution algorithm.Recently, Roy et al. proposed modified shuffled frog leaping algorithm with GA for the ELD problem [30]. Mohammadi-Ivatloo et al. presented a novel heuristic algorithm for solving ELD problems, by employing iteration based PSO with time varying acceleration coefficients method [31]. Saber presented a novel modified PSO, which includes advantages of BF andPSO for constrained DELD problem [32]. Vaisakh et al. implemented BF-PSO-DE algorithm by integratingBFO, PSO and DE for solving static and dynamic ELD problems ofvarious test systems [33].Exchange market algorithm (EMA) algorithm was first proposed by Ghorbani and Babaei [34]. It is inspired by the stock market in which the shareholders buy and sellany types of shares under balanced and oscillatory market conditions. Thisalgorithm uses two searcher operators and two absorbents These operators make EMA able to overcome the exploration and exploitation problems.In this paper, EMA has been presented in order to address the NCELD problem. In this algorithm, transmission losses, ramp rate limits and prohibited operating zones of generators have been considered. In order to study and demonstrate the effectiveness of the proposed algorithm, 13-units and 15-units are used. Theresults of the numerical studies along with comparisons of GA and PSO methods are showed the effectiveness of theproposed algorithm to solve the NCELD problem

II. ELD FORMULATION

The objective of ELD problem is to find an optimal power generation schedule while minimizing fuel cost and also satisfying various power system operating constraints.

2.1 Objective Function

The ELD problem is formulated as follows:

$$\text{Minimize}\, F = \sum_{i=1}^{ng} F_i(P_i) \quad (1)$$

The total fuel cost of the generators is defined by:

ISBN : 978-93-87793-75-0

$$F_i(P_i) = a_i P_i^2 + b_i P_i + C_i$$

Considering the valve-point effects, the fuel cost function of the i^{th} thermal generating unit is expressed as the sum of a quadratic and a sinusoidal function in the following form:

$$F_i(P_i) = a_i P_i^2 + b_i P_i + C_i + \left| e_i \times \sin(f_i \times (P_{i,min} - P_i)) \right|$$

2.2 Problem Constraints

2.2.1. Power Balance Constraints

The total power output of the generators must be equal to the sum of power demands and total transmission losses and is given by:

$$\sum_{i=1}^{ng} P_i = P_D + P_L$$

The transmission losses are expressed as

$$P_L = \sum_{i=1}^{ng} \sum_{j=1}^{ng} P_i B_{ij} P_j + \sum_{i=1}^{ng} B_{0i} P_i + B_{00}$$

2.2.2. Generator Capacity Constraints

The output power of each unit needs to be restricted with inequality constraints between lower and upper bounds. This constraint is represented by

$$P_{i,min} \le P_i \le P_{i,max}$$

2.2.3. Ramp Rate Constraints

The actual operating range of all the generating units is limitedby the ramp-rate constraint and is given as follows:

$$P_i - P_i^0 \le UR_i$$

$$P_i^0 - P_i \le DR_i$$

2.2.4.Prohibited Operating Zone

Prohibited operating zones in the input–output curve of generatorare due to steam valve operation or vibration in its shaft bearing. For units with prohibited operating zones, there are additionalconstraints on the unit operating range:

$$P_{i,min} \le P_i \le P_1$$

$$P_{i,k-1}^U \le P_i \le P_{i,k}^L \qquad k = 2, \ldots nz$$

$$P_{i,nz}^U \le P_i \le P_{i,max}$$

III. OVERVIEW OF EXCHANGE MARKET ALGORITHM

EMA, first introduced by Ghorbani and Babaei [34] is a flexible, robust, population based stochastic optimization algorithm with inherent parallelism. It is motivated by human behavior of stock market in which shareholders trade shares under balanced and oscillated market situations. This algorithm uses two searcher and absorbent operators in normal and oscillation modes respectively. In EMA, optimum solution is regarded as one that is searched out by a shareholder population. Each individual of this population is called a shareholder. The individuals of searcher group and absorbent group are responsible for improving the exploration and exploitation abilities of the algorithm.

3.1 Exchange Market in Normal Mode

In normal condition of the exchange market, the shareholders try to maximize their profit using elite shareholders experience. In the population, each shareholder is ranked according to the fitness function.

3.1.1 Shareholders with High Ranks

These shareholders do not change their shares without performing any risk and trade to maintain their ranks. This group of shareholders composes 10 – 30% of the population.

3.1.2 Shareholders with Average Ranks

This group of shareholders composes 20–50% of the population. The members of this group use the experiences of elite stockbrokers and take the least possible risk in changing their shares.

$$pop_j^{group(2)} = r \times pop_{1,i}^{group(1)} + (1-r) \times pop_{2,i}^{group(1)} \quad (2)$$

$i = 1, 2, 3, \ldots n_i$ and $j = 1, 2, 3, \ldots. n_j$

3.1.3 Shareholders with Weak Ranks

This group of shareholders composes 20–50% of the population. The members of this group utilize the differences of share values of elite and medium shareholders with their share values. The population of this group is given in the following equation.

$$S_k = 2 \times r_1 \times \left(pop_{i,1}^{group(1)} - pop_k^{group(3)}\right) + 2 \times r_2 \times \left(pop_{i,1}^{group(1)} - pop_k^{group(3)}\right) \quad (3)$$

$$pop_k^{group(3)\,new} = r \times pop_k^{group(3)} + 0.8 \times S_k$$

$$k = 1, 2, 3, \ldots n_k$$

3.2 Exchange Market in Oscillaion Mode

In this mode, the shareholders perform intelligent risks according to their own rank among other members to gain the maximum possible profit. The shareholders can be divided into three different groups based on their performances.

3.2.2 Shareholders with High Ranks

This group allocates 10-30% of the market population known as elite members, which do not participate in the market exchange.

ISBN : 978-93-87793-75-0

3.2.3 Shareholders with Medium Ranks

The market share of the second group is changed in such a way that the whole share values of the group is constant. The share values of the individuals can be updated as

$$\Delta n_{t1} = n_{t1} - \delta + (2 \times r \times \mu \times \eta_1) \quad (4)$$

$$\mu = \frac{t_{pop}}{n_{pop}}$$

$$n_{t1} = \sum_{y=1}^{n} (S_{ty}) \quad y = 1, 2, 3, \ldots, n$$

$$\eta_1 = \eta_{t1} \times g_1$$

$$g_1^k = g_{1,max} - \frac{g_{1,max} - g_{1,min}}{Iter_{max}} \times k$$

In order to maintain the shares, remain constant, each shareholder randomly sells some of the shares equal to the shares purchased. Hence, each shareholder reduces the share values which is given as follows.

$$\Delta n_{t,2} = n_{t,2} - \delta$$

where n_{t2} is the total share value of t^th^ member after employing share variations

3.2.4 Shareholders with Weak Ranks

The shareholders can either purchase or sell the shares. Hence, the total share value is variable. The share values of the individuals can be updated as

$$\Delta n_{t,3} = 4 \times r_s \times \mu \times \eta_2 \quad (5)$$

$$r_s = 0.5 - \text{rand}$$

$$\eta_1 = \eta_{t1} \times g_1$$

$$g_1^k = g_{1,max} - \frac{g_{1,max} - g_{1,min}}{Iter_{max}} \times k$$

IV. IMPLEMENTATION OF EMA TO NCELD PROBLEM

The detailed implementation of EMA is described as follows.

Step 1 Input data for market operation

The total shareholders in the market (m), shares (n), lower and upper limits of each shares (design variables), maximum iteration number, risk factors (g1 and g2) and EMA constants are initialized.

Step 2 Initialization of shareholders

Since the decision variables for ELD problems are values of generating unit, they are used to form the shares of shareholders. The i^{th} shareholder for n generating units is represented as

$$x_i = [x_{i1}, x_{i2}, \ldots, x_{im}]$$

Each share of the shareholder matrix is initialized using a uniform probability distribution function in the range (0 – 1) and located between the maximum and minimum limits of the design variables.

The shareholder can be represented below:

$$x_{ij} = x_{j\min} + \mathrm{rand} \times \left(x_{j\max} - x_{j\min} \right)$$

Step 3 Evaluation of shareholders' cost

The shareholders cost is evaluated by using Eq. (1)

Step 4 Ranking and allocation of shareholders

The shareholders are sorted in ascending order and are divided into three different groups. The 30%, 40% and 30% of population are allocated for elite, medium and weak shareholders respectively.

Step 5 Updating the shares of medium and weak shareholders in normal market condition

The share values of medium and weak ranking shareholders are updated using Eqs. (2) and (3) respectively.

Step 6 Reevaluation, ranking and allocation of shareholders

The medium and weak shareholders' costs are reevaluated using Eq. (1). Subsequently, the shareholders are repositioned and separated into three different groups.

Step 7 Updating the shares of medium and weak shareholders in oscillated market condition

The share values of medium and weak ranking shareholders in oscillated market situation are updated using Eqs. (4) and (5) respectively.

Step 8 Stopping Criteria

If the maximum iteration number is reached, then the EMA is terminated and the optimal generations schedule is obtained. Otherwise, the procedure is repeated from Step 3.

V. RESULTS AND DISCUSSION

In order to evaluate the effectiveness of the proposed EMA based NCELD problems, three different systems: a 6-unit system with equality and inequality constraints, prohibited operating zones, ramp-rate limits and transmission network losses; a 15-unit system with equality and inequality constraints, prohibited operating zones, ramp rate limits and transmission network losses; and a 13-unit system with equality and inequality constraints and a valve-point effect have been applied. For each of the test systems, 50 independent trials were carried out so as to compare the problem solving quality and convergence characteristics. The algorithm was implemented by MATLAB 7.1

5.1. Test system 1

In this case study, heuristic algorithm is applied on a larger test system consisting of the 15 generating units. The transmission losses and prohibited operating zone are considered. The total load demand of the system is 2630 MW. The generator coefficients, capacity limits ramp rate limits and prohibited zones are given in Table 1. The optimal generation schedule, cost and power loss obtained by the proposed EMA approach are compared with GA and PSO approaches in Table 2. Furthermore, thestatistical results of 50 independent trials for the 15-unit systemare tabulated in Table 3. The comparative results clearly show that the proposed EMAapproach is proficient of producing higher quality solutionthan the other evolutionary methods.The convergence characteristic of EMA is depicted in Fig. 1. It is seen from Fig. that EMA converges morequickly. It is observedfrom Tables2 and 3 that the cost obtained from EMA is the lowestamong the GA and PSO approaches.

ISBN : 978-93-87793-75-0

Table 1 System data for 15-units

Unit(i)	Pi^{min}	Pi^{max}	a_i	b_i	c_i	P^{UR}	P^{DR}	Pi^{prev}	POZs
1	150	455	671	10.1	0.000299	80	120	400	
2	150	455	574	10.2	0.000183	80	120	300	[185,225],[305,335],[420,450]
3	20	130	374	8.80	0.001126	130	130	105	
4	20	130	374	8.80	0.001126	130	130	100	
5	150	470	461	10.4	0.000205	80	120	90	[180,200],[305,335],[390,420]
6	135	460	630	10.1	0.000301	80	120	400	[230,255],[365,395],[430,455]
7	135	465	548	9.80	0.000364	80	120	350	
8	60	300	227	11.2	0.000338	65	100	95	
9	25	162	173	11.2	0.000807	60	100	105	
10	25	160	175	10.7	0.001203	60	100	110	
11	20	80	186	10.2	0.003586	80	80	60	
12	20	80	230	9.90	0.005513	80	80	40	[30,40],[55,65]
13	25	85	225	13.1	0.000371	80	80	30	
14	15	55	309	12.1	0.001929	55	55	20	
15	15	55	323	12.4	0.004447	55	55	20	

Table 2 Best solution for 15-unit system

Unit (MW)	GA	PSO	EMA
P_1	415.31	439.12	455
P_2	359.72	407.97	380
P_3	104.42	119.63	130
P_4	74.98	129.99	130
P_5	380.28	151.07	170
P_6	426.79	459.99	459.54
P_7	341.32	425.56	430
P_8	124.79	98.56	76.8065
P_9	133.14	113.49	50.647
P_{10}	89.26	101.11	159.926
P_{11}	60.06	33.91	79.96
P_{12}	50.0	79.96	80
P_{13}	38.77	25.0	25.32
P_{14}	41.94	41.41	17.64
P_{15}	22.64	35.61	15.324

ISBN : 978-93-87793-75-0

P_L	38.2782	32.4306	30.672
Minimum cost ($/hr)	33113	32858	32706.562

Table 3

Results obtained by various methods for 15-unit system

Compared items	**GA**	**PSO**	**EMA**
Max. cost	33337	33331	32986
Min. cost	33113	32858	32706.562
Mean cost	33228	33039	32760
CPU time (sec)	49.31	26.59	18.63

5.2. Test system 2

This case study system consists of 13 generating units with non-smooth cost function (with valve-point loading). Input data for this test system are given in Table 4. The total load demand of the system is 1800 MW. The obtained results using the proposed EMA approach are compared with those PSO in in Table 5. Table 6 shows the maximum, minimum and mean costs and computation time achieved by the heuristic algorithms. As indicated in Tables 5 and 6, the proposed EMA approach performs better than the PSO approach in terms of solution quality and computational efficiency.

Table 4 System data for 13-units

Unit(i)	Pi^{min}	Pi^{max}	a_i	b_i	c_i	e_i	f_i
1	0	680	550	8.1	0.00028	300	0.035
2	0	360	309	8.1	0.00056	200	0.042
3	0	360	307	8.1	0.00056	200	0.042
4	60	180	240	7.74	0.00324	150	0.063
5	60	180	240	7.74	0.00324	150	0.063
6	60	180	240	7.74	0.00324	150	0.063
7	60	180	240	7.74	0.00324	150	0.063
8	60	180	240	7.74	0.00324	150	0.063
9	60	180	240	7.74	0.00324	150	0.063
10	40	120	126	8.6	0.00284	100	0.084
11	40	120	126	8.6	0.00284	100	0.084
12	55	120	126	8.6	0.00284	100	0.084
13	55	120	126	8.6	0.00284	100	0.084

ISBN : 978-93-87793-75-0

Table 5 Best solution for 13-unit system

Unit (MW)	PSO	EMA
P_1	538.561	628.3185
P_2	299.355	149.5836
P_3	75.037	222.7934
P_4	159.734	109.8666
P_5	60.078	109.8665
P_6	109.864	109.8664
P_7	109.913	109.8664
P_8	109.87	109.8666
P_9	60.069	60.00
P_{10}	40.035	40.00
P_{11}	77.561	40.00
P_{12}	55.042	55.00
P_{13}	55	55.00
Minimum cost ($/hr)	18014.16	17963.784

Table 6 Results obtained by PSO and EMA methods for 13-unit system

Compared items	PSO	EMA
Max. cost	18249.89	18204.7452
Min. cost	18014.16	17963.784
Mean cost	18104.65	17965.48
CPU time (sec)	-	7.5

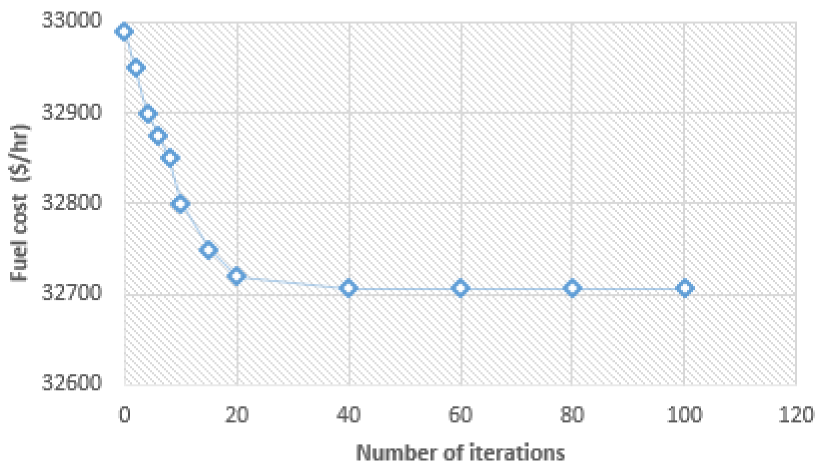

Fig. 1. Convergence Characteristic of EMA for 15-unit system

VI. CONCLUSIONS

A new heuristic algorithm based on exchange market algorithm (EMA) is introduced for solving the NCELD problem in this article. The EMA algorithm has been tested on two test systems (13 and 15 units) with convex and non-convex cost functions and compared with GA and PSO approaches. The proposed EMA based NCELD method provides better dispatch results within a shorter computational time than the other approaches. In this study, it is shown that the EMA approach could be easily applied to the solution of nonconvex economic dispatch problem

REFERENCES

[1] Jabr Rabih A, Coonick Alun H, Cory Brian J. A homogeneous linear programming algorithm for the security constrained economic dispatch problem. IEEE Transactions on Power Systems 2000;15(3):930–937.

[2] Fan JiYuan, Zhang Lan. Real-time economic dispatch with line flow and emission constraints using quadratic programming. IEEE Transactions on Power Systems 1998;13(2):320–326.

[3] Nanda J, Hari Lakshman, Kothari ML. Economic emission load dispatch with line flow constraints using a classical technique. IEE Proceedings on Generation, Transmissionand Distribution 1994;141(1):1–10.

[4] Liang Zi Xiong, Glover Duncan. A zoom feature for a dynamic programming solution to economic dispatch including transmission losses. IEEE Transactions Power Systems 1992;7(2):544–547.

[5] Barcelo Wayne R, Rastgoufard Parviz. Dynamic economic dispatch using the extended security constrained economic dispatch algorithm. IEEE Transactions on Power Systems 1997;12(2):961–967.

[6] Lee FN, Breipohl AM. Reserve constrained economic dispatch with prohibited operating zones. IEEE Transaction on Power Systems 1993;8(1):246–249.

[7] El-Keib AA, Ma H, Hart JL. Environmentally constrained economic dispatch using the Lagrangian relaxation method. IEEE Transaction on Power Systems 1994;9(4):1723–1727.

[8] Coelho LDS, Mariani VC. Particle swarm approach based on quantum mechanics and harmonic oscillator potential well for economic load dispatch with valve-point effects. Energy Conversion and Management 2008;49(11):3080–3085.

[9] Chaturvedi KT, Pandit M, Srivastava L. Self-organizing hierarchical particle swarm optimization for nonconvex economic dispatch. IEEE Transactions on Power Systems 2008;23(3):1079–1087.

[10] Selvakumar AI, Thanushkodi K. A new particle swarm optimization solution to nonconvex economic dispatch problems. IEEE Transactions on Power Systems 2007;22(1):42–51.

[11] Park JB, Lee KS, Shin JR, Lee KY. A particle swarm optimization for economic dispatch with non-smooth cost functions. IEEE Transactions on Power Systems 2005;20(1):34–42.

[12] Gaing ZL. Particle swarm optimization to solving the economic dispatch considering the generator constraints. IEEE Transactions on Power Systems 2003;18(3):1187–1195.

[13] Panigrahi BK, Pandi VR, Das S. Adaptive particle swarm optimization approach for static and dynamic economic load dispatch. Energy Conversion Management 2008;49(6):1407–1415.

[14] Coelho LDS, Lee CS. Solving economic load dispatch problems in power systems using chaotic and Gaussian particle swarm optimization approaches. Electric Power and Energy Systems 2008;30(4):297–307.

[15] Noman N, Iba H. Differential evolution for economic load dispatch problems. Electric Power System Research 2008;78(3):1322–1331.

[16] Sinha N, Chakrabarti R, Chattopadhyay PK. Evolutionary programming techniques for economic load dispatch. IEEE Transactions on Evolutionary Computation 2003;7(1):83–94.

[17] Chiang CL. Genetic-based algorithm for power economic load dispatch. IET Generation Transmission and Distribution 2007;1(2):261–269.

[18] Yasar C, Ozyon S. Solution to scalarized environmental economic power dispatch problem by using genetic algorithm. Electric Power and Energy Systems 2012;38(1):54–62.

[19] Damousis IG, Bakirtzis AG, Dokopoulos PS. Network-constrained economicdispatch using real-coded genetic algorithm. IEEE Transactions on Power Systems 2003;18(1):198–205.

[20] Panigrahi BK, Pandi VR. Bacterial foraging optimisation: Nelder–Mead hybridalgorithm for economic load dispatch. IET Generation Transmission and Distribution 2008;2(4):556–565.

[21] Roy PK, Ghoshal SP, Thakur SS. Biogeography based optimization for economicdispatch. Electric Power Components and Systems 2009;38(2):168–181.

[22] Roy PK, Mandal B, Bhattacharya K. Gravitational search algorithm based optimal reactive power dispatch for voltage stability enhancement. Electric Power Components and Systems 2012;40(9):956–976.

[23] Al-Sumait JS, AL-Othman AK, Sykulski JK. Application of pattern search method to power system valve-point economic load dispatch. Electric Power and Energy Systems 2007;29(1):720–730.

[24] Panigrahi BK, Yadav SR, Agrawal S, Tiwari MK. A clonal algorithm to solve economic load dispatch. Electric Power System Research 2007;77(10):1381–1389.

[25] Basu M. Artificial bee colony optimization for multi-area economic dispatch. Electric Power and Energy Systems2013; 49:181–187.

[26] Kumar R, Sadu A, Kumar R, Panda SK. A novel multi-objective directed bee colony optimization algorithm for multi-objective emission constrained economic power dispatch. Electric Power and Energy Systems 2012;43(1): 1241–1250

[27] Shaw B, Mukherjee V, Ghoshal SP. A novel opposition-based gravitationalsearch algorithm for combined economic and emission dispatch problems ofpower systems. Electric Power and Energy Systems 2012;35(1):21–33.

[28] Liao GC. Integrated isolation niche and immune genetic algorithm for solvingbid-based dynamic economic dispatch. Electric Power and Energy Systems2012;42(1):264–275.

[29] Peng C, Sun H, Guo J, Liu G. Dynamic economic dispatch for wind-thermalpower system using a novel bi-population chaotic differential evolution algorithm. Electric Power and Energy Systems 2012;42(1):119–126.

[30] Roy P, Roy P, Chakraborty A. Modified shuffled frog leaping algorithm withgenetic algorithm crossover for solving economic load dispatch problem withvalve-point effect. Applied Soft Computing 2013;13(11):4244–4252.

[31] Mohammadi-Ivatloo B, Rabiee A, Soroudi A, Ehsan M. Iteration PSO with timevarying acceleration coefficients for solving non-convex economic dispatchproblems. Electric Power and Energy Systems 2012;42(1):508–516.

[32] Saber AY. Economic dispatch using particle swarm optimization with bacterialforaging effect. Electric Power and Energy Systems 2012;34(1):38–46.

[33] Vaisakh K, Praveena P, Rao SRM, Meah K. Solving dynamic economic dispatchproblem with security constraints using bacterial foraging PSO-DE algorithm.Electric Power and Energy Systems 2012;39(1):56–67.

[34] Naser Ghorbani and Ebrahim Babaei, “Exchange market algorithm,” Applied Soft Computing, Vol.19, pp.177-187, 2014.