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SEEKER OPTIMIZATION ALGORITHM FOR ECONOMIC DISPATCH PROBLEM

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Abstract: The Economic power dispatch problem is one of the most important problems to be solved in the operations of power system. It is basically a non-linear optimization problem having linear and non-linear equality and inequality constraints. This is a real time problem for properly allocating the real power output among the committed generators such that fuel cost is minimized while the demand requirement is met and the constraints imposed are satisfied. This paper presents a seeker optimisation algorithm (SOA) for the solution of the constrained economic load dispatch (ELD) problems in different power systems considering various non-linear characteristics of generators. In the SOA, the act of human searching capability and understanding are exploited for the purpose of optimisation. In this algorithm, the search direction is based on empirical gradient by evaluating the response to the position changes and the step length is based on uncertainty reasoning by using a simple fuzzy rule. ELD is solved for two typical test cases of 20 generator and 40-generator cases. A comparison of simulation results reveals the optimisation efficacy of the SOA over the prevailing optimisation techniques for the solution of ELD problems.

Keywords: *Economic Load Dispatch, heuristic algorithm, power system, seeker optimisation algorithm*

I INTRODUCTION

Today electrical power plays an exceedingly important role in all walks of life of an individual as well as the community. The Development of various sectors such as transportation, industrial, agriculture, entertainment, information and communication sectors etc. depends on electrical energy. In fact, the modern economy is totally dependent on electricity as a basic input. This in turn has led to the increase in the number of power generating stations and their capacities and the consequent increase in power transmission lines which connect the generating stations to the load centers, Interconnections between generating systems are also equally important for reliable and supply quality of power system which also provide flexibility in system operation.

Among different issues in power system operation Economic load dispatch (ELD) problem constitute a major part. Exhaustive literature survey is done for Economic load dispatch (ELD). Economic load dispatch (ELD) problem [1,2] is a constrained optimisation problem in power systems that have the objective of dividing the total power demand among the online participating generators economically while satisfying the various constraints.

Over the years, many efforts have been made to solve the problem, incorporating different kinds of constraints or multiple objectives, through various mathematical programming and optimisation techniques. The conventional methods [3] include lambda iteration method, base point and participation factors method [4], gradient method [5] etc. Among these methods, lambda iteration is a most common one and, owing to its ease of implementation, has been applied through various software packages to solve ELD problems. But for effective implementation of this method, the formulation needs to be continuous.

The basic ELD considers the power balance constraint apart from the generating capacity limits. However, a practical ELD must take ramp rate limits, prohibited operating zones, valve point loading effects and multi-fuel options into consideration to provide the completeness for the ELD problem formulation [6]. The resulting ELD is a non-convex optimisation problem, which is a challenging one and cannot be solved by the traditional methods.

ELD problem with valve point loading has also been solved by dynamic programming (DP) [7]. Although promising results are obtained in small-sized power systems while solving it with DP, it unnecessarily raises the length of solution procedure resulting in its vulnerability to solve large-size ELD problems in stipulated time frames [8].

Moreover, evolutionary and behavioural random search algorithms such as genetic algorithm (GA) [9–11], particle swarm optimisation (PSO) [12, 13] etc. have previously been implemented on the ELD problem at hand. In addition, integrated parallel GA incorporating ideas from simulated annealing (SA) and Tabu search (TS) techniques were also proposed [14]. Yalcinoz at al. [15] has used a real-coded representation technique along with arithmetic genetic operators and elitistic selection to yield a quality solution. GA has been deployed to solve ELD with various modifications over the years.

In a similar attempt, a unit independent encoding scheme has also been proposed based on equal incremental cost criterion [16]. In spite of its successful implementation, GA does possess some weaknesses leading to longer computation time and less guaranteed convergence, particularly in case of epistatic objective function containing highly correlated parameters [17, 18]. Moreover, premature convergence of GA is accompanied by a very high probability of entrapment into the local optimum [19].

Some other hybrid approaches such as GA combined with SA [20], evolutionary programming (EP) [21], improved TS [22], improved fast [23], evolutionary strategy optimisation [24] have been successfully applied to solve the ELD problem. Some other hybrid approaches such as GA combined with SA [20], evolutionary programming (EP) [21], improved TS [22], improved fast [23], evolutionary strategy optimisation [24] have been successfully applied to solve the ELD problem. Besides these soft computing methodologies, some other promising techniques such as Hopfield neural networks [25, 26] and two-phase neural network [27, 28] have been successfully applied to solve the constrained ELD.

This paper proposes a new optimisation approach, to solve the ELD using seeker optimisation algorithm (SOA) technique [1], In the SOA, optimum solution is regarded as one which is searched out by a seeker population. The underlying concept of the SOA is very easy to model and relatively easier than other optimization techniques prevailing in the literature.

II PROBLEM FORMULATION

The problem of ELD is multimodal, non-differentiable, and highly non-linear, mathematically, the problem can be stated as in (1)

$$\min F_T(P) = \sum_{i=1}^{NG} F_i(P_i)\ \$/hr\ , \quad i = 1, \ldots\ldots\ldots.., NG \qquad (1)$$

$$\min F_T(P) = \sum_{i=1}^{NG} F_i\left(a_i P_{gi}^2 + b_i P_{gi} + C_i\right)\ \$/hr\ , \quad i = 1, \ldots\ldots\ldots.., NG \qquad (2)$$

where,

Ft	total generation cost
Fi (P_{gi})	fuel cost of generator *i*.
a, b, c	cost coefficient of generator *i*
P_{gi}	output power of generator *i*
NG	total number of thermal generating units

Therefore, it can be considered as an optimization problem with an objective function subjected to some constraints. The constraints are represented as follows:

For normal system operations, the real power of each generating unit should be restricted by its upper limit and lower limits as follows:

$$P_i^{min} \leq P_i \leq P_i^{max} \quad ; \quad i = 1, \ldots\ldots\ldots.., NG \qquad (3)$$

where,

P_i^{min} *and* P_i^{max} minimum and maximum power generated by ith generator, respectively

The total power generation must cover the total demand and the real power loss in transmission lines. The relation can be described as follows:

$$\sum_{i=1}^{N} P_i - P_D - P_L = 0 \quad ; \quad i = 1, \ldots\ldots\ldots.., NG \qquad (4)$$

where,

P_D = Total system demand

P_L = Transmission Line Loss

III SEEKER OPTIMIZATION ALGORITHM

Seeker Optimization Algorithm is a population-based heuristic search algorithm. It regards the optimization process as an optimal solution obtained by a seeker population. Each individual of this population is called a seeker. The total population is randomly categorized into three subpopulations. These subpopulations search over several different domains of the search space.

All the seekers in the same subpopulation constitute a neighbourhood. This neighbourhood represents the social component for the social sharing of information.

In the SOA, a search direction and a step length are computed separately for each ith seeker on each jth variable at each time step t, i represents the population number and j represents the optimizing variable number.

Normally, there are two extreme types of cooperative behaviour prevailing in swarm dynamics. One, egotistic, is entirely pro-self and another, altruistic, is entirely pro-group. Every seeker, as a single sophisticated agent, is uniformly egotistic.

The attitude of ith seeker may be modelled by an empirical direction vector as shown below

$$\vec{d}_{j.ego}\ (t) = \text{sign}\ (\vec{p}_{i.best} - \vec{x}_{i.ego}\ (t))$$

Two optional altruistic directions may be modelled as

$$\vec{d}_{i,\ alt\ 1}\ (t) = \text{sign}\ (\vec{g}_{best}\ (t) - \vec{x}_i\ (t))$$

$$\vec{d}_{i,\ alt\ 2}\ (t) = \text{sign}\ (\vec{l}_{best}\ (t) - \vec{x}_i\ (t))$$

Each seeker is associated with an empirical direction called as pro-activeness direction as given as:

$$\vec{d}_{i,\ pro}\ (t) = \text{sign}\ (\vec{x}_i\ (t_1) - \vec{x}_i\ (t_2))$$

The proportional selection rule of search directions is given by:

$$d_{ij} = \begin{cases} 0, & \text{if } r_j \leq p_j^{(0)} \\ +1, & \text{if } p_j^{(0)} \leq r_j \leq p_j^{(0)} + p_j^{(+1)} \\ -1, & \text{if } p_j^{(0)} + p_j^{(+1)} < r_j \leq 1 \end{cases}$$

In a population of size *S*, for each seeker *i* ($1 \leq i \leq S$), the position update on each variable *j* is given by the following equation.

$$x_{ij}(t+1) = x_{ij}(t) + \alpha_{ij}(t) \times d_{ij}(t)$$

The position of the worst seeker of each subpopulation is combined with the best one in each of the other subpopulations using the following binomial crossover operator as expressed in (12)

$$x_{k_n j,worst} = \begin{cases} x_{lj,best}, & \text{if } rand_j \leq 0.5 \\ x_{k_n j,worst}, & \text{else} \end{cases}$$

In order to increase the diversity in the population, good information acquired by each subpopulation is shared among the subpopulations.

IV IMPLEMENTATION OF SOA FOR ELD

The steps of the SOA, as implemented for the solution of the ELD problem of this work are as follows.

Step 1 Initialization: Read input data, set number of run counter, read cost curves of machines and B coefficients, set maximum population number, set lower and upper limits of each generator output, read SOA parameters, set termination criteria (i.e. maximum iteration cycles).

Step 2 Initialize the positions of the seekers in the search space randomly and uniformly.

Step 3 Set the time step t = 0

Step 4 Compute the objective function of the initial positions. The initial historical Best position among the population is achieved. Set the personal historical best position of each seeker to his current position.

Step5 Let t = t + 1.

Step 6 Select the neighbour of each seeker.

Step 7 Determine the search direction and step length for each seeker, and update his Position

Step 8 Update the position of each seeker.

Step 9 Compute the objective function for each seeker.

Step 10 Update the historical best position among the population and historical best Position of each seeker.

Step 11 Subpopulations learn from each other.

Step 12 Repeat from Step 5 till the end of the maximum iteration cycles/stopping Criterion.

Step 13 Determine the best string corresponding to optimum objective function value.

Step 14 Determine the optimal generation string corresponding to the grand optimum Objective function value.

V RESULTS AND DISCUSSIONS

SOA has been applied to solve the ELD problems in four different test cases for investigating its optimization capability. The software has been written in MATLAB language.

A. *TEST CASE 1: 20-GENERATING UNITS WITHOUT LOSS*

A system with 20 generators is taken as the test case 1. The system input data are available in Appendix A. The transmission loss is not considered for this case. For this test case load demand is 2500 MW.

TABLE 1 BEST RESULTS FOR 20-GENERATING UNITS WITH PD = 2500 MW

Unit	BBO [30]	LI [29]	HM [29]	SOA
P1	513.0892	512.7805	512.7804	593.75
P2	173.3533	169.1033	169.1035	150.82
P3	126.9231	126.8898	126.8897	50
P4	103.3292	102.8657	102.8656	53.5
P5	113.7741	113.6386	113.6836	89.97
P6	73.06694	73.571	73.5709	26.83
P7	114.9843	115.2878	115.2876	122.15
P8	116.4238	116.3994	116.3994	50
P9	100.6948	100.4062	100.4063	105.45
P10	99.99979	106.0267	106.0267	30.43
P11	148.977	150.2394	150.2395	292.07
P12	294.0207	292.7648	292.7647	452.52
P13	119.5754	119.1154	119.1155	130.22
P14	30.54786	30.834	30.8342	59.72
P15	116.4546	115.8057	115.8056	99.37
P16	36.22787	36.2545	36.2545	33.24
P17	66.85943	66.859	66.859	34.74
P18	88.54701	87.972	87.972	32.2
P19	100.9802	100.8033	100.8033	62.01
P20	54.2725	54.305	54.305	31.01
TG	2592.1011	2591.9670	2591.9670	2500
TGC ($/hr)	62456.77926	62456.6391	62456.6341	60166.97

The best generation costs reported for the algorithms in the literature like BBO {62456.77926} [30], Lambda iteration (LI) {62456.6391} [29], and Hopfield model (HM) {62456.6341} [29] are compared with the SOA-based best generation cost {60166.97}. Best solutions of the generation schedules, the generation costs etc are obtained from 125 trial runs of the SOA and other aforementioned algorithms are presented in Table 1. The convergence profile of the cost function of the test system is shown in Figure 1.

Figure 1. Convergence plot for 20 Units System

B. TEST CASE 2: 40-GENERATING UNITS WITHOUT LOSS

A system with 40 generators with transmission loss is not considered as the test case 2. The input data are given in [32]. The load demand is 10500 MW. The best generation cost{120928.04}obtained by the SOA is compared to those obtained by using IFEP {122624.3500} [32], hybrid EP and sequential quadratic programming (SQP) (EP-SQP) {122324} [31], PSO with local random search (LRS) (PSO-LRS) {122035.7946} [33], DE combination with SQP (DEC-SQP) {121741.9793} [34], new PSO (NPSO) {121704.7391} [33], new PSO with LRS (NPSO-LRS) {121664.4308} [33], combined PSO with real valued mutation (CBPSO-RVM) {121555.32} [40], ACO {121532.41} [35], self-organizing hierarchical PSO (SOH-PSO) {121501.14} [36], hybrid GA-pattern search-SQP (GA-PS-SQP) {121458.14} [31], quantum PSO (QPSO) {121448.21} [37], BBO {121426.953} [30], BF-NM {121423.63792} [38], DE/BBO {121420.8948} [39], real-coded GA (RCGA) {121418.5425} [40], improved coordinated aggregation-based PSO (ICA-PSO) {121413.20} [41], and PSO with both chaotic sequence

TABLE 2. BEST RESULTS FOR 40-GENERATING UNITS WITH PD=10500 MW

Unit	QPSO [37]	BBO [30]	DE [39]	ICA-PSO [41]	CCPSO [42]	SOA
P1	111.2	111.0465	110.7998	110.8	110.7998	114
P2	111.7	111.5915	110.7998	110.8	110.7999	109.68
P3	97.4	97.60077	97.3999	97.41	97.3999	99.67
P4	179.73	179.7095	179.7331	179.74	179.7331	171.57
P5	90.14	88.30605	87.9576	88.52	87.7999	82.73
P6	140	139.9992	140	140	140	114.65
P7	259.6	259.6313	259.5997	259.6	259.5997	255.92
P8	284.8	284.7366	284.5997	284.6	284.5997	300
P9	284.84	284.7801	284.5997	284.6	284.5997	300
P10	130	130.2484	130	130	130	229.37
P11	168.8	168.8461	168.7998	168.8	94	126.96
P12	168.8	168.8239	94	94	94	213.27
P13	214.76	21,47,038	214.7598	214.76	214.7598	140.76
P14	304.53	304.5894	394.2794	394.28	394.2794	252.18
P15	394.28	394.2461	394.2794	394.28	394.2794	297.69
P16	394.28	394.2409	304.5196	304.52	394.2794	385.11
P17	489.28	489.2919	489.2794	498.28	489.2794	488.16
P18	489.28	489.4188	489.2794	489.28	489.2794	490.32
P19	511.28	511.2997	511.2794	511.28	511.2794	488.38
P20	511.28	511.3073	511.2794	511.28	511.2794	526.41
P21	523.28	523.417	523.2794	523.28	523.2794	550
P22	523.28	523.2795	523.2794	523.28	523.2794	547.52
P23	523.29	523.3793	523.2794	523.28	523.2794	550
P24	523.28	523.3225	523.2794	523.28	523.2794	429.82
P25	523.29	523.3661	523.2794	523.28	523.2794	550
P26	523.28	523.4262	523.2794	523.28	523.2794	519.45
P27	10.01	10.05316	10	10	10	27.17
P28	10.01	10.01135	10	10	10	25.76
P29	10	10.00302	10	10	10	25.76
P30	88.47	88.47754	97	96.39	87.8	97
P31	190	189.9983	190	190	190	190
P32	190	189.9881	190	190	190	190
P33	190	189.9663	190	190	190	190
P34	164.91	164.8054	164.7998	164.82	164.7998	200
P35	165.36	165.1267	200	200	194.3976	200
P36	167.19	165.7695	200	200	200	199.98
P37	110	109.9059	110	110	110	75.75
P38	107.01	109.9971	110	110	110	104.81
P39	110	109.9695	110	110	110	90.13
P40	511.36	511.2794	511.2794	511.28	511.2794	550
TGC	121448.21	121426.95	121420.89	121413.2	121403.5362	120928.04

and crossover (CCPSO) {121403.5362} [42]. The best solutions of the generation schedules and the generation costs etc as obtained from 120 trial runs of the different algorithms are presented in Table 2. The convergence profile of the cost function is depicted in Figure 2.

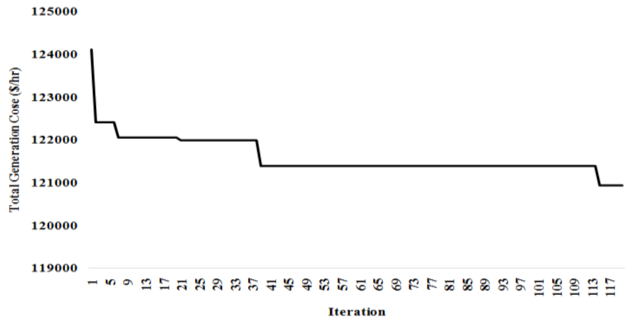

Figure 2. Convergence plot for 40 Units System

C. COMPARISON OF SOA WITH OTHER ALGORITHMS

i. SOLUTION QUALITY

It is noticed from Tables 1 and 2 that the minimum cost achieved by applying the SOA is the least one as compared to those achieved by earlier reported algorithms as mentioned in the respective tables. It emphasises on the fact that the SOA offers the best solution for the ELD problems considered.

ii. BEST GENERATION COSTS

It may be observed from Tables 1 and 2 that the minimum costs achieved by the SOA for Test System 1–2, are 60166.97 and 120928.04 $/h, respectively. Again, power mismatches are the least ones in the SOA as compared to those in the others. Hence, it can be concluded that for all the examples the performance of the SOA is found to be the best one.

VI CONCLUSION

In this paper, a novel seeker optimization algorithm, based on the act of human searching capability and understanding while performing any task, is applied to the solution of ELD problem. The proposed SOA is applied for 20 and 40 generating systems and the results are compared with other heuristic algorithms. It is revealed that the SOA has the ability to converge to a better quality near-optimal solution and possesses better convergence characteristics and robustness than other prevailing techniques reported in the recent literatures. It is also clear from the results obtained by different trials that the SOA is free from the shortcoming of premature convergence exhibited by the other optimization algorithms. The simulation results clearly reveal that the SOA may be used as an excellent optimizer for the solution of practical economic load dispatch problems of power systems.

REFERENCES

[1] Shaw B., GHOSAL S., MUKHERJEE V., and GHOSAL S.P., "Solution of Economic Load Dispatch Problems by a Novel Seeker Optimization Algorithm", International Journal on Electrical Engineering and Informatics, Vol. 3, No.1, 2011

[2] CHOUDHARY B.H., RAHMAN S.: 'A review of recent advances in economic dispatch', IEEE Trans. Power Syst., 1990, 5, (4), pp. 1248–1259

[3] HAPP H.H.: 'Optimal power dispatch – a comprehensive survey', IEEE Trans Power Appar. Syst., 1971, PAS-96, pp. 841–854

[4] WOOD A.J., WOLLENBERG B.F.: 'Power generation, operation and control' (Wiley, New York, 1984)

[5] CHEN C.L., WANG S.C.: 'Branch and bound scheduling for thermal generating units', IEEE Trans. Energy Convers.,1993, 8, (2), pp. 184–189

[6] LEE K.Y., PARK Y.M., and ORTIZ J.L.: 'Fuel cost minimization for both real and reactive power dispatches', IEE Proc. C, Gener. Transm. Distrib., 1984, 131, (3), pp. 85–93

[7] LIN C.E., VIVIANI G.L.: 'Hierarchical economic dispatch for piecewise quadratic cost functions', IEEE Trans. Power Appar. Syst., 1984, PAS-103, pp. 1170–1175

[8] BAKIRTZIS A., PETRIDIS V., KAZARLIS S.: 'Genetic algorithm solution to the economic dispatch problem', Proc. Inst. Electr. Eng. Gener. Transm. Distrib, 1994, 141, (4), pp. 377–382

[9] LEE F.N., BREIPOHL A.M.: 'Reserve constrained economic dispatch with prohibited operating zones', IEEE Trans. Power Syst., 1993, 8, pp. 246–254

[10] SHEBLE G.B., BRITTIG K.: 'Refined genetic algorithm – economic dispatch example'. IEEE Paper 94 WM 199-0 PWRS, Presented at the IEEE/PES 1994, Winter Meeting.

[11] WALTERS D.C., SHEBLE G.B.: 'Genetic algorithm solution of economic dispatch with valve point loading', IEEE Trans. Power Syst., 1993, 8, (3), pp. 1325–1332

[12] MA H., EL-KEIB A.A., SMITH R.E.: 'A genetic algorithm-based approach to economic dispatch of power systems'. IEEE Conf., 1994

[13] GAING Z.-L.: 'Particle swarm optimization to solving the economic dispatch considering the generator constraints', IEEE Trans. Power Syst., 2003, 18, (3), pp. 1187–1195

[14] PARK J.B., LEE K.S., SHIN J.R., and LEE K.Y.: 'A particle swarm optimization for economic dispatch with non-smooth cost functions', IEEE Trans. Power Syst., 2005, 20, (1), pp. 34–42

[15] CHEN P.H., CHANG H.C.: 'Large scale economic dispatch by genetic algorithm', IEEE Trans. Power Syst., 1995, 10, (4), pp. 1919–1926

[16] YALCIONOZ T., ALTUN H., UZAM M.: 'Economic dispatch solution using a genetic algorithm based on arithmetic crossover'. Proc. IEEE Proto Power Tech. Conf., Proto, Portugal, September 2001

[17] FUNG C.C., CHOW S.Y., and WONG K.P.: 'Solving the economic dispatch problem with an integrated parallel genetic algorithm'. Proc. PowerCon Int. Conf., 2000, vol. 3, pp. 1257–1262

[18] FOGEL D.B.: 'Evolutionary computation: toward a new philosophy of machine intelligence' (IEEE Press, Piscataway, NJ, 2000, 2nd edn.)

[19] EBERHART R.C., SHI Y.: 'Comparison between genetic algorithms and particle swarm optimization'. Proc. IEEE Int. Conf. Evol. Comput., May 1998, pp. 611–616

[20] DAMOUSIS J.G., UNKIRLZIS A.G., DOKOPOULOS P.S.: 'Network constrained economic dispatch using real-coded genetic algorithm', IEEE Trans. Power Syst., 1995, 8, (4), pp. 198–205

[21] WONG K.P., WONG Y.W.: 'Genetic and genetic/simulated – annealing approaches to economic dispatch', Proc. Inst. Electr. Eng. Gener. Transm. Distrib., 1994, 141, (5), pp. 507–513

[22] YANG H.T., YANG P.C., HUANG C.L.: 'Evolutionary programming based economic dispatch for units with non-smooth fuel cost functions', IEEE Trans. Power Syst., 1996, 11, (1), pp. 112–118

[23] LIN W.-M., CHENG F.-S., TSAY M.-T.: 'An improved tabu search for economic dispatch with multiple minima', IEEE Trans. Power Syst., 2002, 17, (1), pp. 108–112

[24] SINHA N., CHAKRABARTI R., CHATTOPADHYAY P.K.: 'Evolutionary programming techniques for economic load dispatch', IEEE Trans. Evol. Comput., 2003, 7, (1), pp. 83–94

[25] PEREIRA-NETO A., UNSIHUAY C., SAAVEDRA O.R.: 'Efficient evolutionary strategy optimisation procedure to solve the nonconvex economic dispatch problem with generator constraints', Proc. Inst. Electr. Eng., Gen., Transm., Distrib., 2005, 152, (5), pp. 653–660

[26] PARK J.H., KIM Y.S., EOM I.K., LEE K.Y.: 'Economic load dispatch for piecewise quadratic cost function using Hopfield neural network', IEEE Trans. Power Syst., 1993, 8, (3), pp. 1030–1038

[27] LEE K.Y., SODE-YOME A., PARK J.H.: 'Adaptive hopfield neural network for economic load dispatch', IEEE Trans. Power Syst., 1998, 13, (2), pp. 519–526

[28] NARESH R., DUBEY J., SHARMA J.: 'Two phase neural network based modeling framework of constrained economic load dispatch', IEE Proc., Gener. Transm. Distrib., 2004, 151, (3), pp. 373–378

[29] GAING Z. L., "Particle swarm optimization to solving the economic dispatch considering the generator constraints," IEEE Trans. on Power Systems, Vol. 18, pp. 1187–1195, August 2003.

[30] BHATTACHARYA, P.K., CHATTOPADHYAY, "Biogeography-based optimization for different economic load dispatch problems," IEEE Trans. on Power Systems, Vol. 25, pp. 1064- 1077, May 2010.

[31] ALSUMAIT J. S., SYKULSKI A.K., and AL-OTHMAN., "A hybrid GA-PS-SQP method to solve power system valve-point economic dispatch problems," Applied Energy, Vol. 87, pp. 1773-1781, May 2010.

[32] SINHA N., CHAKRABARTI R, and CHATTOPADHYAY P.K., "Evolutionary programming techniques for economic load dispatch," IEEE Trans. on Evolutionary Computation, Vol. 7, pp. 83– 94, February 2003.

[33] SELVAKUMAR A.I., THANUSHKODI K., "A new particle swarm optimization solution to nonconvex economic dispatch problems," IEEE Trans. on Power Systems, Vol. 22, pp. 42–51, February 2007.

[34] COELHO L.D.S., MARIANI V.C., "Combining of chaotic differential evolution and quadratic programming for economic dispatch optimization with valve point effect," IEEE Trans. on Power Systems, Vol. 21, pp. 989–996, May 2006.

[35] POTHIYA S., NGAMROO I., KONGPRAWECHNON I., "Ant colony optimization for economic dispatch problem with non-smooth cost functions," International Journal of Electrical power and Energy System Vol. 32, pp. 478–487, June 2010.

[36] CHATURVEDI K.T., PANDIT M., SRIVASTAVA L., "Self-organizing hierarchical particle swarm optimization for nonconvex economic dispatch," IEEE Trans. on Power Systems, Vol. 23, pp. 1079-1087, August 2008.

[37] MENG K., DONG Z.K, WANG H.G., WONG K.P., "Quantum-inspired particle swarm optimization for valve-point economic load dispatch ", IEEE Trans. On Power System, Vol.25, pp.215-222, February 2010.

[38] PANIGRAHI P.K., RAVIKUMAR, PANDI V., "Bacterial foraging optimisation: Nelder–Mead hybrid algorithm for economic load dispatch," IET Proceedings of Generation Transmission and Distribution, Vol. 2, pp. 556–565, 2008.

[39] BHATTACHARYA P.K., CHATTOPADHYAY, "Hybrid differential evolution with Biogeography- based optimization for solution of economic load dispatch," to be appeared in IEEE Trans. on Power System.

[40] AMJADY N., RAD N.H.,"Non Convex Economic dispatch with AC constraints by a new real codded genetic algorithm", IEEE Trans. On power system, Vol.24, pp.1489-1502, Aug 2009.

[41] PARK J. B., JEONG W., SHIN J. R., and LEE K.Y.,"An improved particle swarm optimization for non-convex economic dispatch problems," IEEE Trans. On Power system, Vol.25, pp.156-166, February 2010.

[42] VLACHOGIANNIS J.G., LEE K. Y., "Economic load dispatch-A Comparative study of heuristic optimization techniques with an improved coordinated aggregation-based PSO," IEEE Trans. on power systems, vol.24, pp.991-1001, May 2009