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Stochastic Optimization Tools for ELD Problem

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Abstract:- ELD determines the power to be generated by the committed units so that the total cost can be minimized while satisfying the required constraints. Here the cost function is highly non linear, non-convex and non differentiable. Therefore, classical optimization methods usually face problem to converge. This paper presents a comparative study of three different algorithms i.e. MPSO, clonal selection algorithm and gravitational search algorithm for solving the ELD problem. Simulation results were performed with different test cases and comparisons are performed. The simulation result reveals the comparative performance and suggested the best technique which is easy to implement, with less execution time.

Keywords: - Economic Dispatch, valve point effect, PSO, Clonal Selection, GSA

I. INTRODUCTION

Economic load dispatch is a vital part of the optimization task in power system generation, whose characteristics are complex and highly non linear, is to schedule the committed unit outputs, So that the required load demand can be fulfilled at minimum cost while satisfying equality and inequality constraints. In conventional ELD the cost function of all generators is approximately represented by a simple quadratic function and is solved by different optimization technique such as dynamic programming and non-linear programming techniques. However non-off these methods may be able to provide an optimal solution for they usually get stuck at a local optimum [1],[2]. Recently, as an alternative to the conventional mathematical approaches, modern heuristic optimal technique such as simulated annealing (SA), evolutionary programming (EP), genetic algorithm (GA), particle swarm optimization (PSO), neural networks and tabu search have been given much attention by many researches due to their ability to find global or quasi global optimum solutions. Although these heuristic methods do not always guarantee the global optimal solution in finite time, they often provide fast and reasonable solution. PSO is a population based, self-adaptive search optimization technique introduced by Kennedy and Eberhart in 1995.It solves nonlinear and non-continuous optimization problems very effectively and proves its success for many power system problems [17],[20].This paper proposes new optimization approaches, to solve ELD problems using improved gravitational search algorithm has shown the efficiency of GSA over others. In order to establish the capability of GSA to optimize the non-smooth cost function of 3 and 40 generator systems. The results obtained are compared with these of EP, PSO and AIS. The proposed methodology emerges out to be a robust optimization technique for solving ELD problem for various curve natures and power systems.

II. NONCONVEX ECONOMIC LOAD DISPATCH

The economic load dispatch problem can be described as an optimization (minimization) process with the following objective function

$$\text{Minimize } F(P_{Gi}) = \sum_{i=1}^{N} F_i(P_{Gi})$$

Subject to: Energy balance equation

$$P_D = \sum_{i=1}^{NG} P_{Gi}$$

And power balance equation

$$P_{Gi,min} \le P_{Gi} \le P_{Gi,max} \quad \text{(i=1, 2….NG)}$$

Here the loss part is not considered for simplicity. The fuel cost function without valve- point loading of the generating unit by

$$F_i(P_{Gi}) = a_i\, P_{Gi}{}^2 + b_i\, P_{Gi} + c_i \qquad {}^{\$}/_{h}$$

And the fuel cost function considering valve point loading (as shown in fig.1) of the generating unit are given as

$$F(P_{Gi}) = a_i\, P_{Gi}{}^2 + b_i\, P_{Gi} + c_i + \left| d_i \times sin\{e_i \times (P_i^{min} - P_i)\}\right|$$

Where a_i, b_i & c_i are the fuel cost coefficients of the ith unit and e_i and f_i are the fuel cost coefficient of the ith unit with valve-point effects. The generating units with multi-valve steam turbine exhibit a greater variation in the fuel cost functions. The valve-point effects introduce ripples in the heat rate curves.

III. MODIFIED PARTICLE SWARM OPTIMIZATION

Particle swarm optimization (PSO) is a population based stochastic algorithm developed by Dr. Ebehart and Dr. Kennedy in 1995. This algorithm was inspired by social behaviour of bird flocking. The system is initialized with a random population and searches for optimal solution by updating particle's position and velocity. In PSO, the particles fly through the problem space by following the current optimum position and velocity. PSO is having mainly two advantages i.e. easy to implement and few parameters to adjust.

A. MPSO in Economic Dispatch

Step 1: Initialization

PSO is initialized with a number of random particles. Individual i's position and velocity at iteration 0 can be represented as the vector $X_i^0 = (P_{i1}^0, \dots\dots, P_{in}^0)$ and $V_i^0 = (V_{i1}^0, \dots\dots, V_{in}^0)$ respectively. Where n is the number of generators. In each iteration, each particle is updated by two "best" values. The first one is the best solution it has achieved so far. This value is called personal best P_{best} . Another "best" value that is tracked is the best value, obtained so far by any particle in the search space [10]. This best value is a global best and called G_{best}.The initial velocity of each individual is also created at random following the below strategy

$$(P_{j,min} - \epsilon) - P_{ij}^0 \le v_{ij}^0 \le (P_{j,min} + \epsilon) - P_{ij}^0$$

Step 2: Velocity and Position Update

For modification of the position of each individual, it is necessary to calculate the velocity of each individual in the next stage.

$$V_{k+1} = w * V_i^k + C1 \times rand1 \times [P_{best,i} - X_i^k] + C2 \times rand2 \times [G_{best} - X_i^k]$$

The coefficients $C1$ and $C2$ pull each particle towards P_{best} and G_{best} positions. The position is modified as below

$$X_i^{k+1} = X_i^k + V_i^{k+1}$$

Suitable selection of inertia weight w provides a balance between global and local explorations.

$$w = w_{max} - \frac{w_{max} - w_{min}}{iter_{max}} \times iter$$

Step 3: Position Modification Scheme

Due to over/under velocity, there is a chance that the resulting position of an individual may not always guarantee to satisfy the inequality constraints. So the scheme employed here is

$$P_{ij}^{k+1} = \begin{cases} P_{ij}^k + v_{ij}^{k+1} & if \quad P_{ij,min} \le P_{ij}^k + v_{ij}^{k+1} \le P_{ij,max} \\ P_{ij,min} & if \quad P_{ij}^k + v_{ij}^{k+1} < P_{ij,min} \\ P_{ij,max} & if \quad P_{ij}^k + v_{ij}^{k+1} > P_{ij,max} \end{cases}$$

Step 4: Updating P_{best} and G_{best}

The P_{best} of each individual at iteration $k+1$ is updated as follows

$$P_{best,i}^{k+1} = \begin{cases} X_i^{k+1} & if \quad TC_i^{k+1} < TC_i^k \\ P_{best,i}^k & if \quad TC_i^{k+1} \ge TC_i^k \end{cases}$$

Where, TC_i is the objective function value at the position of individual i .Lastly G_{best} is calculated at iteration $k+1$ i.e. the best evaluated position among all the position best values $(P_{best,i}^{k+1})$.

Step 5: Stopping Criteria

Here the stopping criterion is chosen as the predefined maximum iteration.

IV. CLONAL SELECTION PRINCIPLES

The natural immune system is a complex pattern recognition system that defends the body from foreign pathogens that is able to recognize all cells within the body as either self-cells or the non-self cells. It has a distributed task force that has the intelligence to take action from a local and global perspective using its network of chemical messengers for communication [18]. From the computational point of view, the natural immune system is parallel and distributed immune adaptive system It uses learning, memory and associative retrieval to solve recognition and classification tasks. There are two immune cells, viz. B-cells and T-cells. The body defence mechanism defends on action of antibodies to recognize and eliminate foreign cells called antigens. The antibodies are produced by lymphocytes through clonal proliferation. B-lymphocytes and T-lymphocytes are the two main components in the lymphocyte structure .The B-lymphocytes are the cells produced by the bone marrow and T-lymphocytes are the cells produced by the thymus. B-lymphocytes will produce only one antibody that is placed on its outer surface and acts as a receptor control mechanism of antibody production are then regulated by the action of T-lymphocytes. The lymphocytes will duplicate themselves through clonal proliferation. This is followed by the genetic operation on the clone of the plasma cells. Finally, antibodies are secreted and ready to bind antigens. Some of the lymphocytes will turn into long-lived B memory cell. These memory cells circulate through the blood, lymph and tissue, So that when exposed to a second antigen stimulus, they will differentiate into larger lymphocyte that can capable to produce high affinity antibodies to fight against the same antigens that stimulated the first response.

C. Clonal Selection Based Economic Load Dispatch

The developed AIS optimization technique using clonal Selection algorithm was implemented to solve the economic dispatch problem on a practical system having 3 and 40 generating units. Real number was used to represents the attributes of the antibodies. Each antibody attribute will be in a form of pair of real valued vector $(X_i, \eta_i), \forall_i \in \{1,....\mu\}$, Where η_i a strategy parameter [30]. Each antibody will go through the mutation process as per below equation

$$\eta_i^{'}(j) = \eta_i(j)\exp(\tau^{'}(N(0,1) + \tau N_j(0,1)) \quad x_i^{'}(j) = x(j) + \eta_i^{'}(j)N_j(0,1)$$

Where $N(0,1)$ is a normally distributed random number with zero mean and standard deviation equal to one. $N_j(0,1)$ is a random number generated for every i and j. The factor $\tau=((2(n)^{1/2})^{1/2})^{-1}$ and $\tau^{'}=((2n)^{1/2})^{-}1$ are commonly known as learning rates. An offspring $X_i^{'}$ is calculated using Gaussian mutation.

The presentation of clonal selection algorithm solving economic load dispatch problem is according to the following procedure and summarized into the flowchart given in figure (2)

a) Initial population is formed by a set of randomly generated real numbers. Where. Each antibody was tested for any constraints violation using equation (2) and (3). Only antibodies that satisfy the constraints are included in the population set.
b) The fitness value of each antibody in the population set is evaluated using equation (1).
c) Individual antibodies in the population are cloned separately, giving rise to a temporary set of cloned individuals.
d) The population of clones undergoes maturation process by implementing genetic operations i.e. mutation of cloned antibodies. The mutated clones are sorted and their fitness values are evaluated while satisfying constraints.
e) A new population of the same size as the initial population (μ) is selected from the muted clones based on their fitness values for the next generation
f) The new population will undergo the same process as stated in step a-e.
g) The process is repeated until the solution converged to an optimum value or it has reached a maximum iteration limit.

As other optimization technique, several parameters were implemented for comparison before its implementation such as the size and number of clones generated by each antibody. Based on the simulation results, the following parameters are found to be suitable: 20 members in a population pool and the number of proliferated clone are 720 for standard cloning. The equation for adaptive cloning process was developed based on fittest antibody will produce more clones compared to weaker ones.

$$\text{No. Of clones} = \left(1 - \frac{f_i}{\sum_{i=1}^{i-20} f_i}\right) \times 200$$

Where, f_i = Fitness values

$\sum f_i$ = Sum of fitness in a population

V. GRAVITATIONAL SEARCH ALGORITHM

Recently, Rashedi suggested a new heuristic search algorithm in 2009, namely Gravitational search Algorithm. The GSA could be considered as a small artificial world of masses. Here agents or particles are treated as objects and their performance is measured by their masses. All these objects attract each other obeying Newton's law of gravity, and this force causes a global movement of all the objects obeying law of motion towards the objects with heavier masses [20]. And the heaviest mass in the search space presents an optimum solution. It has been applied to solve various nonlinear functions successfully. It has the advantage, which enhance the exploration and exploitation abilities. In this paper, GSA algorithm has been proposed to solve economic dispatch with valve point effect for 3 and 40 generator test systems.

B. GSA in Economic Dispatch

Step-1(Initialization)

A set of agents called masses searches the optimum solution by obeying Newton's law of gravity and motion. Considering a system with N masses, position of i^{th} mass is defined as

$$X_i = \left(x_i^1, \ldots\ldots, x_i^d, \ldots\ldots, x_i^n\right) \qquad \text{for } i = 1,2..N$$

Step-2(Fitness Evaluation)

Assuming the equality of the gravitational and inertia mass

$$best(t) = \min_{j \in \{1,..N\}} fit_j(t)$$

$$worst(t) = \max_{j \in \{1,..N\}} fit_j(t)$$

And for a maximization problem

$$best(t) = \max_{j \in \{1,..N\}} fit_j(t)$$

$$worst(t) = \min_{j \in \{1,..N\}} fit_j(t)$$

Step-3(Evaluation of Gravitational Constant)

The gravitational constant, G, is initialized at the beginning and will be reduced with time to control the search accuracy

$$G(t) = G(G_0, t)$$

Step-4(Update the Gravitational and inertial mass)

We update the gravitational and inertial masses by the following equations:

$$M_{ai} = M_{pi} = M_{ii} = M_i \qquad i = 1,2, \ldots .N$$

$$m_i(t) = \frac{fit_i(t) - worst(t)}{best(t) - worst(t)}$$

$$M_i(t) = \frac{m_i(t)}{\sum_{j=1}^{N} m_j(t)}$$

Step-5(Calculate the total force)

The total force that acts on agent i in a dimension d be a randomly weighted sum of d^{th} components of the forces exerted from other agents:

$$F_i^d(t) = \sum_{j=1, j \neq i}^{N} rand_j F_{ij}^d(t)$$

Where $rand_j$ is a random number in the interval [0,1].At a specific time 't', we define the force acting on mass 'i' from mass 'j' as following:

$$F_{ij}^d(t) = G(t) \frac{M_{pi}(t) \times M_{aj}(t)}{R_{ij}(t) + \epsilon} \left(x_j^d(t) - x_i^d(t)\right)$$

where M_{aj} is the active gravitational mass related to agent j, M_{pi} is the passive gravitational mass related to agent i, G(t) is gravitational constant at time t, e is a small constant, and $R_{ij}(t)$ is the Euclidian distance between two agents i and j:

$$R_{ij}(t) = \left\| X_i(t), X_j(t) \right\|_2$$

Step-5 (Determination of Acceleration, Velocity and Position Updating)

By the law of motion, the acceleration of the agent i at time t, and in direction d, is given as follows:

$$a_i^d(t) = \frac{F_i^d(t)}{M_{ii}(t)}$$

Where, M_{ii} is the inertial mass of i^{th} agent.

Furthermore, the next velocity of an agent is considered as a fraction of its current velocity added to its acceleration. Therefore, its position and its velocity could be calculated as follows:

$$v_i^d(t+1) = rand_i \times v_i^d(t) + a_i^d(t)$$

$$x_i^d(t+1) = x_i^d(t) + v_i^d(t+1)$$

Where $rand_i$ is a uniform random variable in the interval [0, 1]. We use this random number to give a randomized characteristic to the search.

Step-6(Repeat)

Steps from 2 to 6 are repeated until the iterations reach the criteria. In the final iteration, the algorithm returns the value of positions of the corresponding agent at specified dimensions. This value is the global solution of the optimization problem also.

VI. SIMULATION RESULTS

In this paper, to access the efficiency of the proposed GSA approach is applied to 3 and 40 thermal units of ED problems in which objective function is non smooth because the valve point effect are taken into account. 50 independent runs were made for each of the optimization methods.

Test Case I

The input data for three-generator system are given in [4] and test data has given in table I. The maximum total power output of the generator is 850 MW. It can be observed that minimum generating cost is obtained by improved GSA technique and total generation cost is 8234.07 $/h. The execution time for all of GSA technique is 0.01s.The prime emphasis in this work to have comparative performance of PSO and AIS with respect to GSA. The result of this test case is shown in Table II.

TABLE I UNIT DATA FOR TEST CASE I (THREE-UNIT SYSTEMS)

Generator	P_{min}	P_{max}	a	b	c	e	f
1	100	600	561	7.92	0.001562	300	0.0315
2	100	400	310	7.85	0.001940	200	0.042
3	50	200	78	7.97	0.004820	150	0.063

TABLE II RESULT OF TEST CASE-I(WITH VALVE-POINT EFFECT)

EVOLUTION METHOD	MEAN TIME IN SEC.	BEST TIME IN SEC.	MEAN COST ($)	MAX. COST ($)	MIN COST ($)
CEP [7]	20.46	8.35	8235.97	8241.83	8234.07
FEP [7]	4.54	3.79	8234.24	8241.78	8234.07
MFEP [7]	8.00	6.31	8234.71	8241.80	8234.08
IFEP [7]	6.78	6.11	8234.16	8234.54	8234.07
MPSO [10]	---	----	---	---	8234.07
AIS	0.1	0.015	8234.11	8241.95	8234.07
GSA	0.1	0.01	8234.26	8236.54	8234.07

Test Case II

This case study involved 40 thermal units with quadratic cost function together with the effects of valve point loading, as shown in Table III. The data of table III are also available in [7]. In this case load demand expected to be determined was 10500 MW. Table IV shows that the mean time, best time, the minimum cost and maximum cost are achieved by these optimization methods. The result obtained in GSA method gives better result than the result presented in Sinha [7] and park [10]. The performance of GSA approaches used in the case study of 40 thermal units proved superior to clonal selection and MPSO methods. This algorithm provides global solutions with high probability in an acceptable computing time. From Table IV one can observe the robustness and superiority to the existing heuristic methods. The comparative convergence characteristics of MPSO and GSA has been shown in Fig. 3

TABLE III UNITS DATA FOR TEST CASEV II (40 UNIT CASE)

Gen.	P_{min} (MW)	P_{max} (MW)	a	b	c	e	f
1	36	114	94.705	6.73	0.00690	100	0.084
2	36	114	94.705	6.73	0.00690	100	0.084
3	60	120	309.54	7.07	0.02028	100	0.084
4	80	190	369.03	8.18	0.00942	150	0.063
5	47	97	148.89	5.35	0.0114	120	0.077
6	68	140	222.33	8.05	0.01142	100	0.084
7	110	300	287.71	8.03	0.00357	200	0.042

8	135	300	391.98	6.99	0.00492	200	0.042
9	135	300	455.76	6.60	0.00573	200	0.042
10	130	300	722.82	12.9	0.00605	200	0.042
11	94	375	635.20	12.9	0.00515	200	0.042
12	94	375	654.69	12.8	0.00569	200	0.042
13	125	500	913.40	12.5	0.00421	300	0.035
14	125	500	1760.4	8.84	0.00752	300	0.035
15	125	500	1728.3	9.15	0.00708	300	0.035
16	125	500	1728.3	9.15	0.00708	300	0.035
17	220	500	647.85	7.97	0.00708	300	0.035
18	220	500	649.69	7.95	0.00313	300	0.035
19	242	550	647.83	7.97	0.00313	300	0.035
20	242	550	647.81	7.97	0.00313	300	0.035
21	254	550	785.96	6.63	0.00313	300	0.035
22	254	550	785.96	6.63	0.00298	300	0.035
23	254	550	794.53	6.66	0.00284	300	0.035
24	254	550	794.53	6.66	0.00284	300	0.035
25	254	550	801.32	7.10	0.00277	300	0.035
26	254	550	801.32	7.10	0.00277	300	0.035
27	10	150	1055.1	3.33	0.52124	120	0.077
28	10	150	1055.1	3.33	0.52124	120	0.077
29	10	150	1055.1	3.33	0.52124	120	0.077
30	47	97	148.89	5.35	0.01140	120	0.077
31	60	190	222.92	6.43	0.00160	150	0.063
32	60	190	222.92	6.43	0.00160	150	0.063
33	60	190	222.92	6.43	0.00160	150	0.063
34	90	200	107.87	8.95	0.0001	200	0.042
35	90	200	116.58	8.62	0.0001	200	0.042
36	90	200	116.58	8.62	0.0001	200	0.042
37	25	110	307.45	5.88	0.0161	80	0.098
38	25	110	307.45	5.88	0.0161	80	0.098
39	25	110	307.45	5.88	0.0161	80	0.098
40	242	550	647.83	7.97	0.00313	300	0.035

TABLE IV RESULT OF TEST CASE II (40 UNIT SYSTEM)

EVOLUTION METHOD	MEAN TIME IN SEC.	BEST TIME IN SEC.	MEAN COST ($)	MAX. COST ($)	MIN COST ($)
CEP [7]	1956.93	1955.48	124913.48	126902.89	123488.29
FEP [7]	1039.16	1037.30	124119.37	127245.59	122697.71
MFEP[7]	2196.10	2194.70	123489.74	124356.47	122647.57
IFEP [7]	1167.35	1165.70	123382.00	125740.63	122624.35
MPSO[10]	…	…	…	….	122252.26
AIS	3780.23	3762.12	123527.39	133904.49	122017.33
GSA	279.43	258 .68	121743.65	131656.27	121437,21

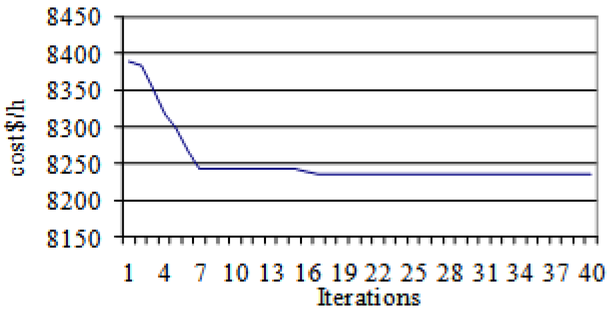

Fig.1 Convergence characteristics of the Test case-I (Clonal selection)

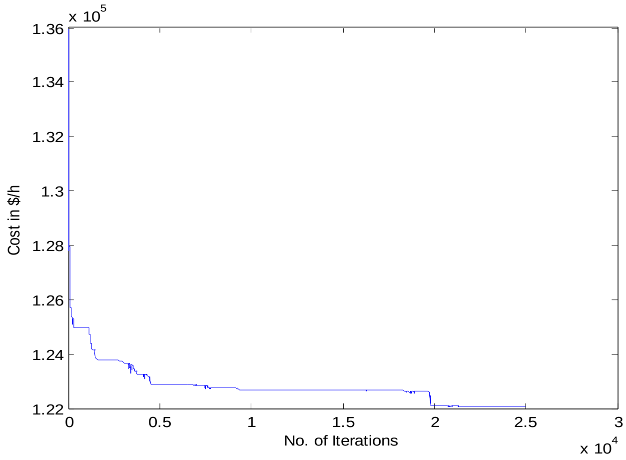

Fig.2 Convergence characteristics of Test case-II (Clonal Selection)

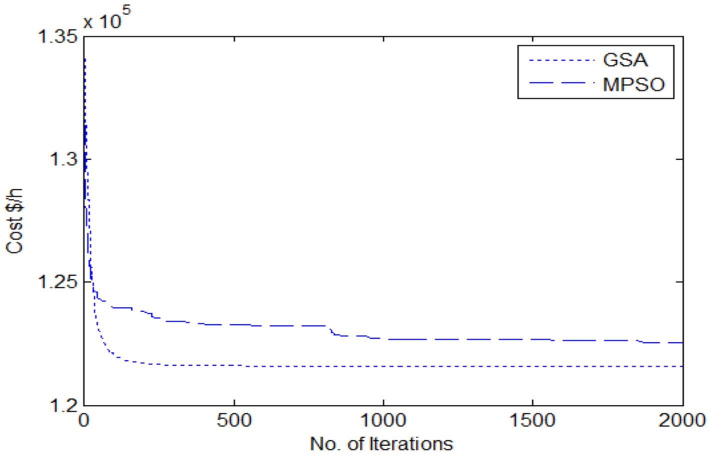

Fig.3 Convergence characteristics of the Test case-II (PSO and GSA)

CONCLUSION

A new approach to solve economic load dispatch problem is suggested. A comparative study carried out between the proposed technique, clonal selection and MPSO technique. The GSA algorithm gives better results with reduced computational time. Hence, the study shows that GSA could be a promising technique for solving complicated optimization problems in power systems. The GSA has provided the global solution satisfying the constraints with a high probability for 3-generator systems and provided a set of quasi optimums for 40-generator system, which are better than other heuristic methods.

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REFERENCES

[1]. C.E Lin and G.L.Viviani, "*Hierarchical Economic Dispatch for Piecewise Quadratic cost function''*, IEEE Trans.on power App Syst Vol PAS-103, no 6, pp 1170-1175,Jan 1984.

[2]. D.C Walter and G.B. Sheble ,"*Genetic Algorithm Solution Economic Load dispatch With Valve Point Loading''*, IEEE Trans.on power Syst. Vol 8 no 3, August 1993, pp 1325-1332

[3]. P-H Chen and H-C Chang."*Large-Scale Economic Dispatch by Genetic Algorithm'',* IEEE Trans. on power Syst. Vol 10,no 4, Nov 1995 pp 1919-1926.

[4]. Th Back and H-P Schwefel, "*An Overview of Evolutionary Algorithm for Parameter Optimization ''*, IEEE Trans. on Evolutionary Computation .Vol 1,no 1 1993, pp 1-123

[5]. H.T Yang, P-C Yang and C.L Huang "*Evolutionary programming Solutions for Units with Non-Smooth Cost Functions*'', IEEE Trans.of power Syst. Vol 11,no 1, Feb 1996, pp 112-118.

[6]. K.P.Wong and j. Yuryevich. "*Evolutionary Programming Based Algorithm for Environmentally-constrained Economic Dispatch",* IEEE Trans. on power Syst., Vol 13,no 2,May 1998, pp 301-306.

[7]. N. Sinha, R. Chakrabarty and P. K. Chattopadhyay, "*Evolutionary Programming Techniques for Economic Dispatch ",* IEEE Trans. on Evol. Comput. Vol 7 pp 83-94, Feb 2003.

[8]. K.P.Wong and Y.W.Wong, "*Thermal generator Scheduling Using Hybrid Genetic/Simulated Annealing Approach*," IEE Proceedings Part-C Vol 142,July 1995,pp 372-380

[9]. J. kennedy and R.C Eberhart, "*Swarm Intelligence",* a Francisco, CA: Morgan Kaufmann, 2001

[10]. J.B.Park, K.S.Lee, J. Shin, K.Y.Lee, "*A particle Swarm Optimization for Economic Dispatch With Non-smooth Cost Function,"* IEEE Trans. on power Syst , Vol. 20,No,1,pp 34-42 Feb 2005

[11]. Y.Shi , R.C Eberhart, "*A Modified Particle Swarm Optimizer"*, in: Proceedings of the IEEE international Conference on Evolutionary Computation, 1998, pp 69-73

[12]. T.K.A Rahman, Z.M.Yasin, W.N.W.Abdullah, "*Artificial Immune Based for Solving Economic Dispatch in Power system"*, IEEE National Power and Energy Conference Proceeding, Malaysia 2004 pp 31-35

[13]. L.N.de Castro and J.Timis, "*Artificial Immune System:-A Novel Paradigm to Pattern Recognition, "*In Artificial Neural Networks in Pattern Recognition ,SOCO-2002,University of Paisley, U.K. pp 67-84,2002

[14]. D.Dasgupta and N.A. Okline, "*Immunity-Based Survey,"* in the Proceedings of IEEE international

[15]. Conference on System, Man and Cybernetics, vol., pp.369-374, oct.1997

[16]. L.N.de Castro, F.J. Zuben, Learning *and Optimization using through the clonal Selection* Principle,'' IEEE Trans. on Evolutionary Computation, vol.6, pp.239-251, June 2002.

[17]. L.N.de Castro and F.J. Von Zuben, *"Artificial Immune System: Part 1-Basic Theory and Applications*,'' Technical report, TR-DCA01/99 Dec.1999

[18]. F. M. Burnet. *"The Clonal Selection Theory of Acquired Immunity*, Cambridge University Press Cambridge, U.K, 1959

[19]. B. K. Panigrahi, S. R.Yadav, S.Agrawal and M.K.Tiwari, "*A clonal algorithm to solve economic load dispatch"*, Elect. Power syst. Res. Vol 77,pp 1381-1389 2007.

[20]. T.K.A Rahman, S.I Suliman and I.Musurin, "*Artificial Immune-Based Optimization Technique for Solving Economic Dispatch in Power System"*, Springer, pp 338-345, 2006.

[21]. E. Rashedi, H. N. Pour, and S. Saryazdi , "*GSA: A Gravitational Search Algorithm*," Information Sciences, Special Section on High Order Fuzzy Sets, vol. 179, pp. 2232-2248, 2009.