Clonal Selection Algorithm for Dynamic Economic Dispatch with Nonsmooth Cost Functions

U. K. Rout, R. K. Swain, A. K. Barisal, R. C. Prusty

Abstract— This paper presents clonal selection algorithm to solve the Dynamic Economic Dispatch Problem (DEDP) of generating units considering valve point loading effects. It determines the optimal operation of units with predicted load demand over a certain period of time with an objective to minimize total production cost while the system is operating with ramp rate limits. This paper presents DED based on clonal selection technique for determination of the global or near global optimum dispatch solution. In the present case, load balance constraints, operating limits, valve point loading, ramp constraints and network loss coefficient are incorporated. Five unit test systems with non-linear characteristics of the generators are considered to illustrate the effectiveness of the proposed method. The feasibility of the proposed method is demonstrated and compared to those reported in the literature. The results are promising and show the effectiveness of the proposed method.

Index Terms— Clonal Selection Algorithm, Dynamic Economic load dispatch, Power generation operation and Control, Ramp rate limits

1 INTRODUCTION

THE dynamic load dispatch is an important optimization task of power system operation and control. The main objective of the dynamic economic dispatch is to minimize the cost of generation, subject to physical and operational constraints. In traditional economic dispatch has quadratic cost function. In reality, a generating unit can not exhibits a convex fuel cost fuction.for a practical power system problem. Therefore, non-convex characteristics will come due to steam valve effect. Overwhelming literature, however, deals mostly with static economic dispatch, i.e. the horizon is divided into periods and dispatch is optimized period-by-period. Accurate modeling of the DED problem will be improved when the valve point loadings in the generating units are taken into account. Furthermore, they may generate multiple local optimum points in the solution space. Some traditional optimization methods have been applied to solve the DED problems. The traditional methods such as gradient projection method [1], lagrangian relaxation (LR) [6] and dynamic programmings are used to solve the DED problem. These methods were facing problems to give optimal solution due to their non-linear and non-convex characteristic of generating unit. The stochastic search algorithm such as particle swarm optimization (PSO)[5,14,26], differential evolution (DE) [16,17], genetic algorithm (GA)[2,7], evolutionary programming (EP)[3,4,8,9], simulated annealing (SA)[10,15], and tabu search algorithm (TSA)[11] may prove to be very effective in solving non-linear economic dispatch problems without any restriction on the shape of the cost curves. Although these heuristic methods do not always guarantee discovering the global optimal solution in finite time, they often provide fast, reasonable and near global optimal solutions. All of these methods are probabilistic rules to update their candidates' positions in the solution space. The disadvantage of this method is requirement of large memory. So, the combination of the heuristic methods and deterministic method are required to solve the complex optimization problems. Heuristic methods are used for search purpose; to find near global optimum solution. Combining EP with sequential quadrature programming (SQP) [12] and PSO with SQP has been used to solve DED problem [13] because they can give near global optimal solution. It is very difficult to set the tuning parameters of optimization technique and exploring new ideas for solving the DED problem.

This paper proposes new optimization approaches, to solve dynamic dispatch problems using clonal selection principle. This is a very complex biological system, which accounts for resistance of a living body against harmful foreign antigens. It based on the principle of pattern recognition and clonal selection principle, whereby clonal selection principle (invariable called AIS) is implemented on learning and memory acquisition tasks. In AIS receptors presents on the antibody are responsible for antigen antibody interaction. In this interaction, different antibody has different affinity towards an antigen and binding strength is directly proportional to this affinity. AIS effectively exploit these interactions and corresponding affinity by suitable mapping it to fitness (objective function) evaluation, constraints satisfaction or other relevant amenities of optimum research. [18]-[25].

This work suggests a methodlogy using clonal selection algorithm to obtain the optimal generation dispatch solutions for dynamic dispatch problem in deregulated power system. The proposed methodology has been applied to five units test system to show its effectiveness and applicability. The results obtained from the proposed methodology are compared with

- U. K. Rout is with Badriprasad Institute of Technology, Sambalpur, Orissa and currently pursuing Ph.D program in electric power engineering in BPUT, Orissa, India. Email:umesh6400@gmail.com
- R.K. Swain, Professor in KIST, Bhubaneswar, Orissa, India.
- A.K. Barisal and R.C. Prusty are with the Department of Electrical Engineering VSSUT, Burla, India. Email:a_barisal@rediffmail.com

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the reported results given in literature..

2 PROBLEM FORMULATION

2.1 Dynamic Load Dispatch

The objective of the dynamic economic dispatch is to minimize the generator output economically over a certain period of time under various systems and operational constraints. The problem is formulated as follows.

$$Min = \sum_{t=1}^{T}\sum_{i=1}^{N} F_{it}(p_{it}) \qquad (1)$$

Where F Total operating cost over whole dispatch periods

T Numbers of hour in the time horizon;

N Number of dispatchable units;

$F_{it}(P_{it})$ The fuel cost in terms of its real power output P_{it} at a time t. Taking into account the valve point-point effects, the fuel cost function of the thermal generating unit is expressed as the sum of a quadratics and sinusoidal functions.

$$F_{it}(P_{it}) = a_i P_i^2 + b_i P_i + c_i + |\, e_i(\sin(f_i(P_{i\min} - P_i))\,| \qquad (2)$$

a_i, b_i, c_i, e_i and f_i are constants of fuel cost function of unit i subject to the following.Real power balance constraint

$$\sum_{i=1}^{N} P_{it} - P_{Dt} - P_{lt} = 0\,;\, t = 1,2,....T \qquad (3)$$

Where P_{Dt} is the total assumed load demand during at a time t; P_{lt} the transmission loss at a time t. Real power operating limits

$$P_{it\min} \le P_{it} \le P_{it\max} \;\; i = 1,2,....T \;\; t = 1,2,....T \qquad (4)$$

Where $P_{i\min}$ and $P_{i\max}$ are the minimum and maximum real power outputs of ith generator, respectively.

Generator unit ramp rate limits

$$P_{it} - P_{i(t-1)} \le UR_i \;\; i = 1,...n \qquad (5)$$

$$P_{i(t-1)} - P_{it} \le DR_i \;\; i = 1,...n \qquad (6)$$

UR_i and DR_i are ramp up and ramp down rate limits of ith generator respectively and these are expressed in MW/h.

3 CLONAL SELECTION ALGORITHM

The artificial immune system is a very intricate biological system, which accounts for resistance of living body against foreign antigens. It works on the principle of pattern recognition system. Learning and memory are the main characteristics system. Learning and memory are the main characteristics of immune system.The natural immune system is parallel adaptive system. The antibodies are produced by lymphocytes through clonal proliferation. In order to initiate clonal concept in optimization, the affinity concept is transferred to fitness or objective function evaluation and constraint satisfaction.

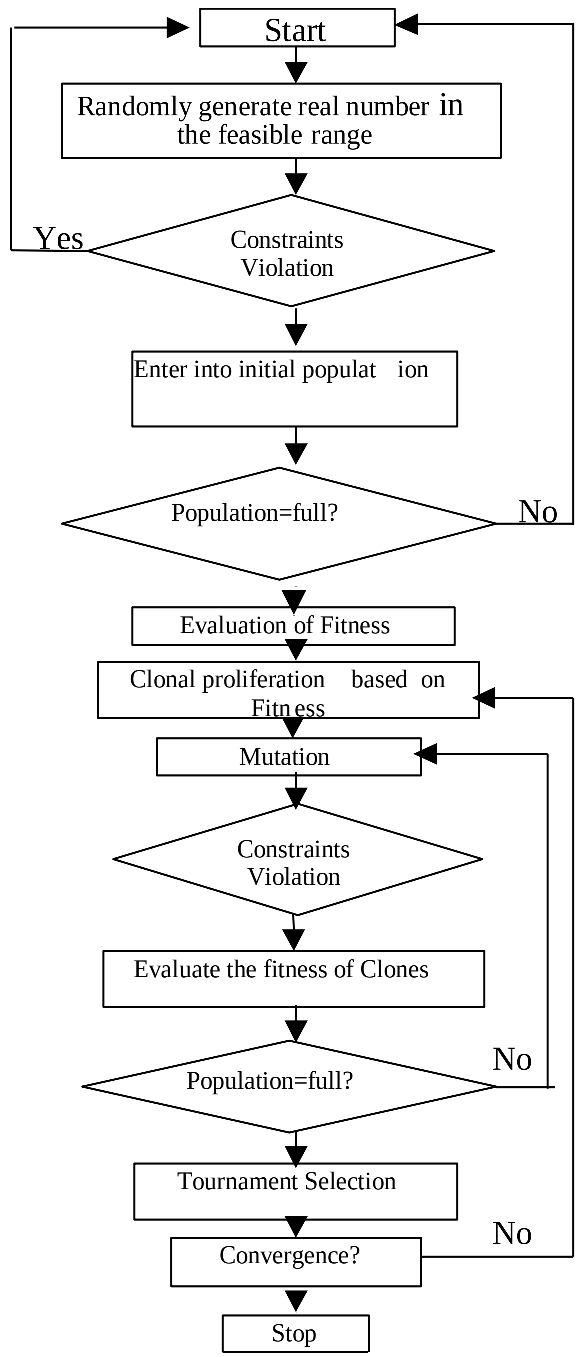

Fig. 1. Implementation of Clonal Selection Algorithm

Here, antigen represents constraints and antibody-antigen interaction refers to constraints satisfaction, i.e., higher the satisfaction of constraints more is the affinity.

Fig. 1.shows the procedures to implement the clonal selection

algorithm through a flow-chart. The algorithm starts with the random generation of real numbers to check for constraint violation. In case of any constraints violation, random data are generated again and again. This process is repeated iteratively until a deliberate fixed size of population is attained. When the population becomes full then each antibody is evaluated and clones are generated. The number of clones generated per antibody is dependent on the fitness values; i.e. larger the number of clones generated for the antibodies higher the fitness value. The mutation rate is adaptive which is similar to evolutionary programming [24]. Consequently, clones with higher fitness are made liable to undergo mutation to a lesser extent as compared to those with lower fitness. This is repeated till all the clones from the temporary clonal population are endured to mutation. Finally, tournament selection is done to select same number of muted clones as existed in the initial population. This completes one generation of the clonal selection algorithm. The convergence parameter is set when the best solutions of each generation cease to change. Thereby, stopping criteria is taken when either the satisfied convergence level is reached or the maximum number of generations is exhausted.

4 Clonal Selection Based Dynamic Economic Load Dispatch

The main objective of dynamic dispatch problem is to obtain the amount of real power to be generated by each committed generators, while achieving a minimum generation cost within the constraints. The section provides the solution methodology to the above-mentioned dynamic problems through clonal selection technique.

4.1 Representation of Antigen

For T intervals in the generation scheduling horizon, there is T dispatched for the *n* generators. An array of control variable vectors can be shown as

$$S=\begin{bmatrix} P_{11}P_{12}\dots P_{1T} \\ P_{21}P_{22}\dots P_{2T} \\ \\ P_{n1}P_{n2}\dots P_{nT}\end{bmatrix} \quad P=1,2,\dots M$$

Where P_{it} is the real power output of generator *i* at interval t

4.2 Initialization

For the complete M population, the candidate solution of each individual (generating unit's power output) is randomly initialized within the feasible range in such a way that is should satisfy the constraint given by Eq. (4). A component of a candidate is initialized as $P_{it} \sim U\ (P_{it\min,} P_{it\max})$,where U is the uniform distribution of the variables ranging in the interval of $(P_{it\min,} P_{it\max})$. Initialize the interaction count.

4.3 Affinity evaluation (objective function)

The affinity value of each antibody in the population set is evaluated using the equation (2).

4.4 Clonal Proliferation

The fittest antigen will be cloned (reproduced) independently and proportionally to their antigenic affinities, the higher the antigenic affinity, the higher the clones generated for each of the selected antigens. The equation for adaptive cloning process was developed based on the fittest antibody will produce more clones compared to weaker ones. Equation (7) is implemented to determine the number of clones is generated according the affinity measures or the fitness.

$$\text{Number of clones}_i=\left(1-\frac{f_i}{\sum_{i=1}^{i-20} f_i}\right)\times 200 \qquad (7)$$

f_i =Fitness value

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

4.5 Mutation

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 $(P_i, \eta_i), \forall_i \in \{1,\dots N_g\}$, Where η_i a strategy parameter [21]. Each antibody will go through the mutation process according to the expression given by equation 8 and 9.

$$\eta_i^{'}(j) = \eta_i(j)\exp(\tau^{'}(N(0,1) + \tau N_j(0,1)) \qquad (8)$$

$$P_i^{'}(j) = P(j) + \eta_i^{'}(j) N_j(0,1) \qquad (9)$$

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 anew for every i. and j. The factors $\tau = ((2(n)^{1/2})^{1/2})^{-1}$ and $\tau' = ((2n)^{1/2})^{-1}$ are commonly known as learning rates. An offspring $P_i^{'}$ is calculated using gaussian mutation.

n=No of population for an antibody.

4.6 Selection

In implementation, it was assumed that the highest affinities were sorted in an ascending order. In selection, the offspring produced by mutation process will be sorted and calculate the best value from the offspring.

4.6 Stopping Criterion

There are various criteria available to stop a stochastic optimization algorithm. Some examples are tolerance, number of function evaluations and number of iterations. In this paper, maximum number of iterations is chosen as the stopping criterion, when there is no significant improvement in the solution. If the stopping criterion is not satisfied, the above procedure is repeated from clone with incremented iteration.

Table 1. Best Scheduling in MW of Five Unit System by CSA

Hour	P_1	P_2	P_3	P_4	P_5
1	17..587	98.797	31..374	125.2	140.47
2	10.802	98.478	64.773	125.22	139.61
3	12.077	98.947	103.68	125.11	139.81
4	10.711	98.52	112.75	173.11	140.83
5	10.545	96.88	108.92	209.17	139.14
6	38.336	102.59	112.78	210.26	151.65
7	12.907	98.522	112.55	210.04	199.96
8	12.379	98.481	112.99	210.12	228.91
9	39.893	103.79	113.71	210.73	231.56
10	64.216	98.298	112.55	209.6	229.44
11	74.548	100.32	114.12	210.54	231.07
12	74.584	99.335	113.53	234.15	229.56
13	64.774	97.845	112.88	209.17	229.54
14	46.19	99.501	112.59	210.21	231.11
15	16.659	99.09	112.97	206.27	227.62
16	11.014	86.428	104.11	157.42	227.78
17	10.492	88.48	111.9	125.21	228.22
18	38.967	103.6	116.44	126.02	230.52
19	47.613	98.732	112.04	174.14	230.24
20	64.243	98.474	112.61	208.88	229.97
21	38.517	98.575	112.87	209.8	229.92
22	10.723	98.077	111.66	162.04	230.16
23	10.605	98.113	112.62	124.56	186.96
24	10.998	81.325	112.24	124.26	138.64

5 Simulation Results

A clonal selection algorithm for the DED problem described above has been applied to five-unit test systems with non-smooth fuel cost function to demonstrate the performance of the proposed method. The five-unit test system [17] with non-smooth cost functions used to demonstrate the performance of the proposed method. The optimal generation dispatch with ramp rate limits is shown in Table 1. The simulations were carried out on a PC with a Pentium IV 2.8-GHZ processor. The software was developed using the MATLAB 7.01. The best solution obtained through the proposed method is compared to those reported in the recent literature. The number of clones will depend the fitness value. In order to obtain best performance the mummer of population is taken 20. The number of clones is 720. The total production cost of this proposed method is 43446.224$. Figure 2 shows the convergence characteristic of clonal selection algorithm for five-unit test system. Table 2 shows the comparison results for different methods.

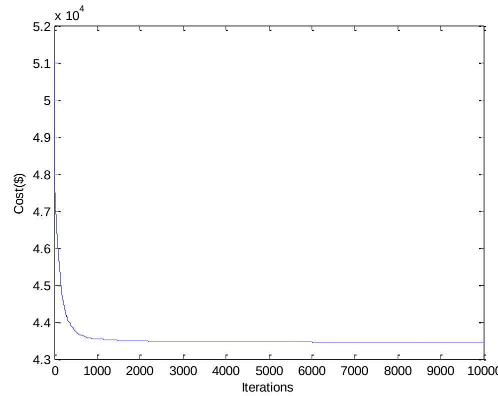

Figure 2 Convergence characteristics of 5 units test system

Table 2. Comparisons of results between SA, PSO and DE methodsTechnique Production Cost $ Cpu time (Sec)

SA [15]	47356	351.98
PSO[26]	50124	258.00
DE[17]	43213	376
Clonal	43446.22	242

6 Conclusion

An efficient algorithm based on one of the soft computing tools namely clonal selection algorithm is proposed in this paper to solve dynamic economic dispatch problem. The presented evaluation fuction model and optimally selected clones have enhanced the performance of the clonal selection algorithm. The effectiveness of the presented algorithm using 5unit test system has compared with reported in literature. The solution quality, reliability and computational efficiency show the superiority of the presented clonal selection algorithm. This algorithm can also be extended to solve DED, by inclusion of more inequality constraints such as line flows, voltage constraints, spinning reserves, etc. to obtain a more accurate dispatch solution for practical power system problems.

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