HYBRIDIZATION OF ARTIFICIAL IMMUNE SYSTEM FOR OPTIMAL OPERATION OF POWER SYSTEM

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Abstract:

This paper presents Hybridization of Artificial Immune System (HAIS) and Sequential Quadratic Programming (SQP) based optimization technique to solve non-convex economic load dispatch (NCELD) problem of thermal plants. The presented methodology can take care of economic dispatch problems involving constraints such as power balance, generator limits, and valve point loading. The HAIS method is tested with two power system cases consisting of 6 and 13 thermal units. Comparisons are performed with other approaches under consideration.

Keywords: Artificial Immune System, Economic load dispatch, Non convex cost function, Sequential quadratic programming

1. Introduction:

The objective of the economic load problem (ELD) is to schedule the committed generating unit outputs so as to meet the required load demand at minimum operating cost while satisfying all unit and system equality and inequality constraints [1]. In traditional EDPs, the cost function of each generator is approximately represented by a simple quadratic function and is solved using mathematical programming [2] based on several optimization techniques, such as dynamic programming [3], linear programming [4], homogenous linear programming [5], and nonlinear programming technique [6]. However, real input-output characteristics display higher-order nonlinearities and discontinuities. Power plants usually have multiple valves that are used to control the power output of the unit. When steam admission valves in thermal units are first opened, a sudden increase in losses is observed. This leads to ripples in the cost function, which is known as the valve-point loading. The ELD problem with valve-point effects is represented as a non- smooth optimization.

Recently, stochastic optimization techniques such as Genetic algorithm (GA) [7-8], evolutionary programming (EP) [9-10], simulated annealing (SA) [11-12] and particle swarm optimization (PSO) [13-15] have been given much attention by many researches due to their ability to seek for the near global optimal solution. However, all the previous works mentioned above neglected the non-smooth characteristic of generator, which actually exist in the real power system.

In order to alleviate the aforementioned difficulties, this paper proposes a new optimization approach known as artificial immune system (AIS). AIS imitate the immunological ideas to develop some techniques used in various areas of research [16]. It works on the principle of pattern recognition (antibody and antigen) and clonal selection principle, whereby clonal selection principle called as AIS which is implemented to accomplish learning and memory acquisition tasks. AIS effectively exploit the interaction and corresponding affinity suitably mapping it to fitness evaluation, constraint satisfaction. AIS approach has been applied to solve economic load dispatch (ELD) problem [17].

This paper presents a novel optimization method based on Artificial Immune System Method (AISM) is applied to economic load dispatch in a practical power system. Under considering some nonlinear characteristics of a generator, such load demand, generators constraints, power loss and non-smooth cost function. The proposed methodology emerges as a robust optimization technique for solving the ELD problem for different size power system.

2. Problem Statement:

The prime objective of the ELD problem is to determine the most economic loadings of generators to minimize the generation cost such that the load demands in the scheduling horizon can be met and simultaneously, the operating constraints are satisfied. This constrained optimization problem can be written as:

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

where F is the total operating cost over the whole dispatch period, N is the no. of generating units and $F_i(P_i)$ is the fuel cost in terms of its real power output P_i. This minimization problem is subjected to a variety of constraints depending upon assumptions and practical implications like power balance constraints, generator output limits, transmission losses, ramp rate limits, etc. These constraints are discussed as follows:

a. Power balance constraint

The total generation should be equal to the total system power demand P_D plus the transmission loss which is represented as follows:

$$\sum_{i=1}^{N} P_i - P_D - P_L = 0 \tag{2}$$

where P_D is the total power demand and P_L is the transmission power loss in MW. The transmission loss must be taken into account in order to achieve proper economic dispatch. To calculate this transmission loss B coefficients method is used. The transmission loss is represented by B coefficients as:

$$P_L = \sum_{i=1}^{N}\sum_{j=1}^{N} P_i B_{ij} P_j \tag{3}$$

where P_i and P_j are real power injections at i^{th} and j^{th} buses respectively and B_{ij} are the loss coefficients, which are constants under certain assumed operating conditions. For AIS–SQP method, transmission loss is not considered hence the power balance constraint of Eq. (2) is as follows:

$$\sum_{i=1}^{N} P_i - P_D = 0 \tag{4}$$

b. Real power operating limits

The generated output of each unit should remain between its minimum and maximum limits. The following inequality constraint should be satisfied for each generator:

$$P_i^{\min} \le P_i \le P_i^{\max} \tag{5}$$

where $P_i^{\min}$ and $P_i^{\max}$ are the minimum and maximum real power output respectively of i^{th} generator.

3. Artificial Immune System (AIS)

Artificial immune system (AIS) [16] mimics the biological principles of clone generation, proliferation and maturation. The main steps of AIS based on clonal selection principle are activation of antibodies, proliferation and differentiation on the encounter of cells with antigens, maturation by carrying out affinity maturation process, eliminating old antibodies to maintain the diversity of antibodies and to avoid premature convergence, selection of those antibodies whose affinities with the antigen are greater.

In order to emulate AIS in optimization, the antibodies and affinity are taken as the feasible solutions and the objective function respectively. Real number is used to represent the attributes of the antibodies. Initially, a population of random solutions is generated which represent a pool of antibodies. These antibodies undergo proliferation and maturation. The proliferation of antibodies is realized by cloning each member of the initial pool depending on their affinity.

4. Sequential Quadratic Programming:

Sequential quadratic programming (SQP) [17] is widely used to solve practical optimization problems. It outperforms every other nonlinear programming method in terms of efficiency, accuracy and percentage of successful solutions. At each major iteration, an approximation is made of the Hessian of the Lagrange function using Broyden-Fletcher-Goldfarb-Shanno (BFGS) quasi-Newton updating method. This is then used to generate a Quadratic Programming (QP) sub-problem whose solution is used to form a search direction for a line search procedure. As the objective function to be minimized is non-convex, SQP requires a local minimum for an initial solution. In this chapter, SQP is used as a local optimizer for fine-tuning the better region explored by AIS. Here, the formulation of SQP subroutine is taken from [17].

For each iteration, a QP is solved to obtain the search direction which is used to update the control variables. QP problem can be described as follows:

Minimize the following:

$$\nabla F(P_k)^T d_k + \frac{1}{2} d_k^T \mathrm{H}_K d_k \tag{6}$$

subject to the following constraints:

$$g_i(P_k) + [\nabla g(P_k)]^T d_k = 0 \qquad i = 1,\ldots,m_e \tag{7}$$

$$g_i(P_k) + [\nabla g(P_k)]^T d_k \le 0 \tag{8}$$

$$i = m_e + 1, \ldots, m$$

where

H_k : the Hessian matrix of the Lagrangian function at the k^{th} iteration

d_k : the search direction at the k^{th} iteration

P_k : the real power vector at the k^{th} iteration

$g(P_k)$: constraints from Eq. (4) to Eq. (5)

m_e : number of equality constraints

m : number of constraints

$$L(P, \lambda) = F(P) + g(P)^T \lambda \tag{9}$$

where λ is the vector of Lagrangian multiplier.

H_k is calculated using quasi-Newton formula given by:

$$\mathrm{H}_{k+1} = \mathrm{H}_k + \frac{q_k q_k^{\mathrm{T}}}{q_k^{\mathrm{T}} S_k} - \frac{\mathrm{H}_k^{\mathrm{T}} S_k^{\mathrm{T}} S_k \mathrm{H}_k}{S_k^{\mathrm{T}} \mathrm{H}_k S_k} \tag{10}$$

where

$$S_k = \mathrm{P}_{k+1} - \mathrm{P}_k \tag{11}$$

$$q_k = \nabla L(P_{k+1}, \lambda_{k+1}) - \nabla L(P_k, \lambda_{k+1}) \tag{12}$$

For each iteration of the QP sub-problem the direction d_k is calculated using the objective function. The solution obtained forms a new iterate given by the following expression:

$$\mathrm{P}_{k+1} = \mathrm{P}_k + \alpha_k d_k \tag{13}$$

5. Proposed Hybrid Algorithm:

The proposed hybrid method uses the property of the AIS, which can give a good solution even when the problem has many local optimum solutions at the beginning and SQP, which has a local search property that is used to obtain the final solution. Algorithms are as follows:

1) Let $p_k = [\mathrm{P}_1, \mathrm{P}_2, \ldots\ldots, \mathrm{P}_i, \ldots\ldots\mathrm{P}_\mathrm{N}]^\mathrm{T}$, be the k th antibody of a population to be evolved and $k = 1,2,\ldots, \mathrm{N}_\mathrm{P}$. The elements of p_k are real power outputs of the committed N generating units. The initial value of real power output of the i^{th} unit is determined by setting

$P_i \sim U(P_i^{\min}, P_i^{\max})$, where $i = 1,2,\ldots,N$. $U(P_i^{\min}, P_i^{\max})$ denotes a uniform random variable ranging over $[P_i^{\min}, P_i^{\max}]$. Each antibody should satisfy the constraints given by Eqs. (2.4) and (2.5).

2) As ED is a minimization problem, affinity is the inverse of the objective function and it is given by the following equation:

$$Affinity = \frac{1}{\sum_{i=1}^{N}\left[a_i + b_i P_i + c_i P_i^2 + \left|d_i \sin\left\{e_i\left(P_i^{\min} - P_i\right)\right\}\right|\right]} \qquad (14)$$

3) The antibodies are cloned directly proportional to their affinities, giving rise to a temporary population of clones.
4) The clones undergo maturation process through hyper-mutation mechanism whose rate is inversely proportional to their affinities. Each mutated clone must satisfy the constraints given by Eqs. (4) and (5).
5) The affinities of the mutated clones are evaluated.
6) Aging operator eliminates those individuals which have more than τ_B generations from the current population.
7) Tournament selection is done to select a new population of the same size as the initial population from the antibodies and mutated clones which are remained after application of aging operator. Select the solution which has the highest affinity value obtained so far.
8) Solve the ED problem using the SQP method with the selected solution obtained from AIS.

6. Simulations and Results:

The Hybrid AIS-SQP algorithms have been implemented for the solution of economic load dispatch with non-smooth cost functions on MATLAB 7.0 platform on a 3.06 GHz, Pentium-IV PC with 256 MB RAM. In case of AIS population size (N_P) is taken as 50. The following set of values is chosen after thorough investigation. N_P = population size = 50, N_C = No. of clones = 5, SPM = 12, NIT = No. of iterations = 200. The optimal result obtained by the proposed AIS-SQP method is found to be 1820.6 $ which is so far the minimum one among the other techniques as shown in Table 1 and Table 2.

7. Conclusions:

This paper employs the HAIS algorithm on constrained of economic dispatch problem. Comparative studies show significant improvement in fuel cost. The solution also has superior quality and very less fuel cost. According to the results, it can be concluded that the HAIS method can be effectively used to solve non-smooth as well as smooth constrained economic load dispatch problem. The proposed approach can be enriched by incorporating more realistic constraints to the problem and large size problems can be solved using this method.

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Table 1: Optimal solution for 6-unit system by Proposed Method

Output (MW)	**HAIS (proposed)**	**SA-PSO**	**SOH-PSO**	**PSO**
P_1	448.3546	446.71	438.21	447.4970
P_2	174.0576	173.01	172.58	173.3221
P_3	264.0924	265.00	257.42	263.4745
P_4	139.7022	139.00	141.09	139.0954
P_5	166.2479	165.23	179.37	165.4761
P_6	83.0011	86.78	86.88	87.1280
Total output	1275.4547	1275.7	1275.55	1276. 01
P_{loss} (MW)	12.4547	12.733	12.32	12. 9584
Total Gen. Cost ($)	15443.264	15447	15446.02	15,450

Table 2: Optimal solution for 13-unit system by Proposed Method

Output (MW)	EP	AIS	AIS-SQP
P_1	537.0592	628.3184	624.6347
P_2	75.9977	360.0000	348.5615
P_3	291.5525	299.1993	224.3853
P_4	160.3258	159.7330	112.4184
P_5	60.0000	109.8666	60.0000
P_6	106.2951	60.0000	60.0000
P_7	161.3267	60.0000	60.0000
P_8	108.5179	60.0004	60.0000
P_9	61.8441	60.0002	60.0000
P_{10}	46.9510	40.0000	40.0000
P_{11}	63.5265	40.0000	40.0000
P_{12}	56.0699	55.0000	55.0000
P_{13}	70.5337	67.8822	55.0000
Total output (MW)	1800	2000	1800
Total gen. cost ($)	1843.6	1986.0	1820.6