Knowledge Based Evolutionary Programming: Cultural Algorithm Approach for Constrained Optimization

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Abstract. A cultural approach to solve the problem defined by the economic load dispatch in power systems is presented in this paper. The practical problems of economic load dispatch have non-smooth cost functions with equality and inequality constraints that make the problem of finding the global optimum difficult using any mathematical approaches. Our approach is based on the concept of a cultural algorithm and is applied to constrained optimization problems in which a map of the feasible region is used to guide the search more efficiently. It combines cultural algorithm with evolutionary programming technique in such a way that a simple evolutionary programming (EP) is applied as a based level search, which can give a good direction to the optimal global region, and a domain knowledge (using the concept of cultural algorithm) is used as a fine tuning to determine the optimal solution at the final. The effectiveness and feasibility of the proposed method is tested on a practical thirteen generator system. Results obtained by the proposed method are compared with the other evolutionary methods. It is seen that the proposed method can produce comparable results.

1 Introduction

Economic load dispatch is one of the important tasks in the operation of power systems. The main objective is allocate the generation of the committed units in such a manner that overall operating cost is minimum satisfying a set of linear and non-linear constraints. Previous efforts on solving ELD problems have employed various conventional methods like lambda iteration, quadratically constrained programming, gradient methods etc [18], [1], [10]. These early methods were unable to meet the exact requirement leaving some approximate values which are basically not optimal value & hence a huge revenue loss occurs for nonlinear characteristics in practical systems due to valve point loading, prohibited operating zones and ramp rate limits of generators. After evolution of artificial intelligence technique, several population-based optimization methods are used to play the important role to solve the problem of economic load dispatch.

In the past decade, the global optimization techniques like genetic algorithms (GA) [4], particle swarm optimization (PSO) [8], evolutionary programming [9] etc which

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are form of probabilistic heuristic algorithm, has been successfully used to solve economic load dispatch problems.

Reynolds adds a new technique Cultural Algorithm as a vehicle for modeling social evolution and learning the behavioral traits [13]. Cultural algorithm is basically a global optimization technique which consists of an evolutionary population space whose experiences are integrated into a Belief space which influences the search process to converge the problem in a direct way. Cultural algorithms have been successfully applied to global optimization of constrained problems [14].

In this paper, an alternative approach to cultural algorithm has been proposed to solve the ELD problems. We worked on cultural algorithm embedded in evolutionary programming to solve the economic dispatch problem involving valve point loading effect. Embedding an EP into a CA framework [6] was developed to investigate the influence of global knowledge on the solution of optimization problem and it is successful to solving non-constrained optimization problem in previous work [5]. In this paper we use EP embedded in CA to solve constrained optimization problem.

2 Problem Formulation

The pure Economic Load Dispatch (ELD) problem is one of the major problems in power system operation and planning. The classical ELD problem may be described by minimizing the total fuel cost of the generating units under several operating constraints. The fuel cost curve for any unit is assumed to be approximated by segments of quadratic functions of the active power output of the generator. For a given power system network, the problem may be described as optimization (minimization) of total fuel cost as defined by (1) under a set of operating constraints.

$$FC(P_g) = \sum_{i=1}^{n} \left(a_i P_i^2 + b_i P_i + c_i \right) \tag{1}$$

where $FC(P_g)$ is the total fuel cost of generation in the system (\$/hr), a_i, b_i, c_i are fuel cost coefficients of the i th generating unit, P_i is power generated by the i th unit , and n is the number of thermal units. The coefficients a_i, b_i and c_i are generally obtained by curve fitting.

However, for more practical and accurate modeling of fuel cost function, the above expression is to be modified suitably. Modern thermal power plants consist of generating units having multi-valve steam turbines in order to incorporate flexible operational facilities. The generating units with multi-valve turbines have very different cost curve compared with that defined by (1) and exhibit a greater variation in the fuel cost curves. Typically, ripples are introduced in the fuel cost curve as each steam valve starts to operate. The valve-point effect may be considered by adding a sinusoidal function [16] to the quadratic cost function described above. Hence, the problem described by (1) is revised as follows:

$$FC_v(P_g) = \sum_{i=1}^{n} \left(a_i P_i^2 + b_i P_i + c_i + | e_i \times \sin\left(f_i \times \left(P_{i,\min} - P_i \right) \right) | \right) \tag{2}$$

where $FC_v(P_g)$ is total fuel cost of generation in (\$/hr) including valve point loading, e_i , f_i are fuel cost coefficients of the i th generating unit reflecting valve-point effect.

The cost is minimized with the following generator capacities and active power balance constraints as:

$$P_{i,\min} \le P_i \le P_{i,\max} \tag{3}$$

$$\sum_{i=1}^{n} P_i = P_D + P_L \tag{4}$$

where, $P_{i,\min}$ and $P_{i,max}$ are the minimum and maximum power generation by i th unit respectively, P_D is the total power demand and P_L is total transmission loss.

The transmission loss P_L can be calculated by using B matrix technique and is defined by (5) as

$$P_L = \sum_{i=1}^{n} \sum_{j=1}^{n} P_i B_{ij} P_j \tag{5}$$

where B_{ij} 's are the elements of loss coefficient matrix B.

3 Cultural Algorithm (CA)

The basic concept, principles & mechanisms of every evolutionary technique are based on how natural systems evolve to solve the complex computational problems. The CA works on the concept that, in advance societies the individuals get improvement by not only the information which it possesses due to heredity but by the information which are acquired after years of experience, which is called culture. This cultural evolution is an inheritance process that operates at two levels: the micro evolutionary level and the macro evolutionary level [13]. At the micro-evolutionary level, individuals are described in terms of behavioral traits (that could be socially accepted or unacceptable) which are passed from generation to generation using several socially motivated operators. At the macro-evolutionary level, individuals are able to generate “mappa”, or generalized descriptions of their experiences. Individual mappa can be merged and modified to form “group mappa” using a set of generic or problem specific operators. Both levels share a communication link.

The micro-evolutionary level refers to the knowledge acquired by individuals through generations which are stored to guide the behavior of the individuals. This acquired knowledge is stored in the search space called belief space in CA during the evolution of the population. Interaction between the two basic components i.e., population space and Belief space make cultural algorithm as a dual inheritance system. Population space is that where the information about individuals is stored and the belief space is where the culture knowledge is formed and maintained during the evolution of the population.

The frame work of CA can be described as shown in Fig.1.

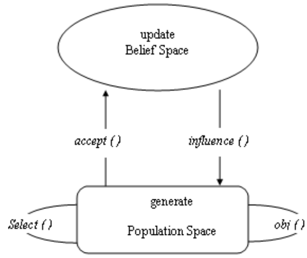

Fig. 1. Frame work of Cultural Algorithm

An acceptance function *accept ()* and updating function *update ()* play very vital role in belief space. After evolution of population space with a performance function *obj (), accept ()* will determine which individuals are kept aside for Belief space. Experiences of those elite individuals will update the knowledge of the Belief space via *update ().*These updated knowledge are used to influence the evolution of the population.

A pseudo- code description of cultural algorithm is described as follows,

```
Begin
        t = 0
        Initialize P^t
         Initialize B^t
         Repeat
              Evaluate P^t
              Update (B^t, accept (P^t))
              Generate (P^t, influence (B^t))
               t = t + 1
              Select P^t from P^(t-1)
              Until (Termination condition achieved)
 end
```

4 Overview of the Proposed Approach

The basic idea of using CA with evolutionary programming is to influence the mutation operator so that the current knowledge stored in the search space can be properly exploited. Cultural Algorithm belongs to the class of evolutionary algorithms which offers a unique strategy for optimization. The strategy used here is described by the following steps.

4.1 Initialization

The optimization process in CA is carried with the basic operations: initialization, modification of belief space, mutation and selection. The algorithm starts by creating a population vector P of size N_p composed of individuals that evolve over G

generations. Each individual X_i is a vector that contains as many elements as the problem decision variable. The population size N_p is an algorithm control parameter selected by the user. Thus,

$$P^{(G)} = \left[X_i^{(G)}, \ldots\ldots\ldots\ldots\ldots X_{N_P}^{(G)}\right]$$

$$X_i^{(G)} = \left[X_{1,i}^{(G)}, \ldots\ldots\ldots\ldots\ldots X_{D,i}^{(G)}\right]$$

$$i = 1, \ldots\ldots\ldots N_P$$

The initial population is chosen randomly in order to cover the entire searching region uniformly. A uniform probability distribution for all random variables is assumed in the following as

$$X_{j,i}^{(0)} = X_j^{\min} + \sigma_j (X_j^{\max} - X_j^{\min})$$

Where $i = 1, \ldots\ldots\ldots N_p$ and $j = 1, \ldots\ldots\ldots\ldots D$

Here D is the number of decision or control variables, $X_j^{\min}$ and $X_j^{\max}$ are the lower and upper limits of the j th decision variable and $\sigma_j \in [0,1]$ is a uniformly distributed random number generated anew for each value of j. $X_{j,i}^{(0)}$ is the j th parameter of the i th individual of the initial population.

4.2 Modification of Belief Space

The acceptance function controls the information flow from the population space to the belief space. The acceptance function determines which individuals and their behavior impact the belief space knowledge. Top individuals are selected to update the belief space.

The parameter values for the current selected individuals by the acceptance function are used to calculate the current acceptable interval of normative knowledge. So, the update of normative knowledge is as follows. Assuming X_i and X_k be the individuals with minimum and maximum values for parameter j between the accepted individuals in the current generation, then

$$l_j^{t+1} = \begin{cases} X_{i,j}^t, & \text{if } X_{i,j} \le l_j^t \text{ or } f(X_{i,j}^t) < L_j^t \\ l_j^t & \text{otherwise} \end{cases}$$

$$L_j^{t+1} = \begin{cases} f\left(X_{i,j}^t\right) & \text{if } X_{i,j} \le l_j^t \text{ or } f(X_{i,j}^t) < L_j^t \\ L_j^t & \text{otherwise} \end{cases}$$

and,

$$u_j^{t+1} = \begin{cases} X_{k,j}^t, & if\ X_{k,j} \le u_j^t\ or\ f(X_{k,j}^t) < U_j^t \\ u_j^t & otherwise \end{cases}$$

$$U_j^{t+1} = \begin{cases} f\left(X_{k,j}^t\right) & if\ X_{k,j} \le u_j^t\ or\ f(X_{k,j}^t) < U_j^t \\ U_j^t & otherwise \end{cases}$$

Where, l_j^t represents lower bound for parameter j at generation t and L_j^t denotes the performance score for it and u_j^t represents upper bound for parameter j at generation t and U_j^t denotes the performance score for it.

4.3 Mutation Operation

Mutation takes place for each variable of each individual, with the influence of the belief space. If the variable j of the parent is outside the interval given by the normative part of the constraints, then we attempt to move within such interval through the use of a random variable. *The current individual of n numbers of* candidate for parameter j can be selected by the formula given,

$$X_{i+n,j} = \begin{cases} X_{n,j} + |\left(u_j - l_j\right) * N_{n,j}(0,1)| & if\ X_{n,j} < l_j \\ X_{n,j} - |\left(u_j - l_j\right) * N_{n,j}(0,1)| & if\ X_{n,j} < u_j \end{cases}$$

u_j *and* l_j *represent the upper value and lower value of parameter* j of current elite in the belief space.

4.4 Selection Operation

Selection is the operation through which better offspring are generated. To improve the speed of the algorithm, we take advantage of the rules for performing tournament selection. After performing mutation, we will have a population of size 2*p* (*p* parents generate *p* children). Tournament is performed considering the entire population. Tournaments consists of *c* confrontations per individual, with the *c* opponents randomly chosen from the entire population. When the tournaments finish, the *p* individuals with the largest number of victories are selected to form the following generation.

The optimization process is repeated for several generations. The iterative process of updating of belief space, mutation, and selection on the population will continue until a user-specified stopping criterion, normally, the maximum number of generations allowed, is met.

5 Structure of Solutions

In this section, an algorithm based on a cultural algorithm for optimal solution of economic load dispatch problem is described. For any population based algorithm the representation of individuals and their elements is very important. For the present problem, it is the candidate power generations of thermal units. The algorithm starts with the initialization process. Let $P^{(0)} = \left[X_1^{(0)}, X_2^{(0)}, \ldots. X_k^{(0)}, \ldots, X_{N_P}^{(0)}\right]$ be the initial population of N_P number of particles. For a system of n number of candidate generator, position of k th individual is of n-dimension and can be represented by $X_k^{(0)} = \left[PG_{k,1}^{(0)}, PG_{k,2}^{(0)}, \ldots\ldots, PG_{k,j}^{(0)}, \ldots\ldots, PG_{k,n}^{(0)}\right]$

The element $PG_{k,j}^{(0)}$ represents a randomly selected power generation satisfying the constraints given by (3).

6 Simulation Results

The proposed algorithm has been applied on a sample test system to verify its feasibility and effectiveness. The algorithm has been written in MATLAB and run a 3.0 MHZ, 1GB RAM PC. The test system consists of 13 thermal generating with the effects of valve point loading .Cost coefficients and generation limits of thirteen units System are taken from [4].

Table 1. Results for 13-Generatiors system

Unit	Generation (MW)	Unit	Generation (MW)
P_1	408.4368	P_8	58.9985
P_2	222.6675	P_9	111.5505
P_3	262.9531	P_{10}	73.6298
P_4	80.9229	P_{11}	69.8230
P_5	139.9683	P_{12}	70.0545
P_6	100.7569	P_{13}	62.1934
P_7	138.0447	Total Generation (MW)	1800

The parameter values are selected by trial and error method. The following values are selected for optimal results. Population size is 10, mutation probability is taken as 0.75, and maximum iterative generation number is 500. The load demand is taken as 1800 MW.

The optimal results are shown in Table 1. It is seen from Table 1, that optimal fuel cost is obtained 17683($/h). Table 2 compares the solution obtained by the proposed method with other methods like Particle Swarm Optimization [17], Genetic Algorithm [2], Evolutionary Programming [15] etc. It is seen that the best result using CA is comparatively lower than the other studies presented here.

Fig.2 shows convergence characteristics for a demand of 1800 MW.

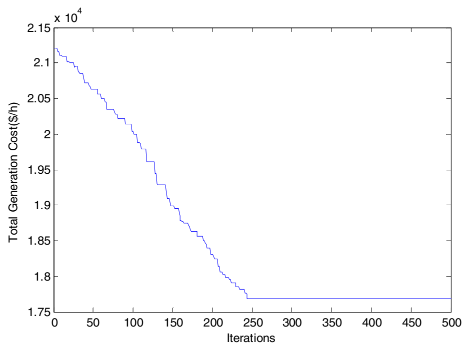

Fig. 2. Convergence characteristics of fuel cost

Table 2. Comparison of best fuel costs among different methods

Optimization Technique	Fuel Cost (\$/h)
PSO	18030.72
EP	17994.07
GA	17975.3437
DE	17963.83
CDEMD	17961.944
CA	17683.00

7 Conclusions

Economic Load Dispatch in one of the important problem for power systems operation. In this paper, a novel cultural algorithm has been proposed to solve Economic Load Dispatch problems. The proposed method has been tested on 13-generator systems with valve point effects. The results obtained by the proposed method are compared with other methods like GA, DE, EP, PSO etc. It is found that that proposed method can produce comparable results.

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