Cultural Algorithm Based Constrained Optimization for Economic Load Dispatch of Units Considering Different Effects

Bidishna Bhattacharya, Kamal K. Mandal, Niladri Chakravorty

Abstract— This paper introduces an efficient evolutionary programming based approach of cultural algorithm which is a probabilistic optimum search method using genetics and evolution theory to solve different economic load dispatch problems. The proposed algorithm is a powerful population-based algorithm in the field of evolutionary computation which can efficiently search and actively explore solutions. Also it may be employed to handle the equality and inequality constraints of the ELD problems. The salient features of its knowledge space make the proposed cultural algorithm attractive in large-scale highly constrained nonlinear and complex systems. In this paper cultural algorithm combines with evolutionary programming technique to take care of economic dispatch problem involving constraints like power balance constraints, generator limit constraints, valve point loading effect, ramp rate limits, prohibited operating zone, and transmission losses etc because of cultural algorithm's flexibility. The effectiveness and feasibility of the proposed method is tested with one example of thirteen generator system considering valve point effect and one example of three generator system considering ramp rate limits, prohibited operating zone and transmission losses. Additionally the proposed algorithm was compared with other evolutionary methods like particle swarm optimization technique, genetic algorithm, evolutionary programming etc. It is seen that the proposed method can produce comparable results.

Index Terms— Cultural algorithm, cultural based evolutionary algorithm, evolutionary programming, ELD, prohibited operating zone, ramp rate limits, valve-point loading.

I. INTRODUCTION

Economic load dispatch (ELD) is one of the reliable planning tasks in the field of power system optimization [1]where the generation of the dedicated units are re-allocated in such a manner that overall operating cost is minimum satisfying a set of linear and non-linear constraints. Earlier efforts for finding minimum cost for ELD have applied various mathematical programming

methods and optimization techniques like lambda-iteration method [2], [3], the base point and participation factors method [2],[3], the gradient method [3],[4], a unit-based genetic algorithm method [5],[6] etc.

Unfortunately these early methods were incapable 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.

In light of the nonlinear characteristics of the units, the optimum planning of generation demands for techniques that do not have limitations on the shape of the fuel-cost curves. After evolution of artificial intelligence technique, several population-based optimization methods like genetic algorithms (GAs) [7], evolution strategies (ESs) [8], [9], evolutionary programming (EP) [10], and simulated annealing (SA) [11], [12] may prove to be very effective in solving nonlinear ELD problems without any restrictions on the shape of the cost curves.

Cultural algorithms (CAs) proposed by Reynolds [13] in 1994 are a class of models derived from the cultural evolution process. 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 functions, scheduling and real problems. Cultural Algorithm has been implemented for a few problem of Power System field such as substation planning [14], hydrothermal scheduling [15]. Economic load dispatch [16]. Recently L.D.S Coelho et al proposes cultural DE approach [17] with non-smooth fuel cost functions with valve point effect to achieve a better production cost compared to other heuristic optimization techniques.

In this paper, an alternative approach to cultural algorithm has been proposed to solve the ELD. We worked on evolutionary programming integrated to cultural algorithm to solve the economic dispatch problem involving valve point loading effect and network losses. Chung and Reynolds [18] developed the framework of embedding EP into CA to investigate the influence of global knowledge on the explanation of optimization problem. In this paper we worked on cultural algorithm having EP based population space which is dynamically controlled by the feasible region based records to direct the solutions towards the most promising region to solve constrained optimization problem efficiently.

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II. PROBLEM FORMULATION

A. Economic load Dispatch (ELD) Problem

The objective of an ELD problem is to find the optimal combination of power generations that minimizes the total generation cost while satisfying an equality constraint and inequality 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.

$$FC = \sum_{i=1}^{n} F(P_{gi}) = \sum_{i=1}^{n} a_i P_{gi}^2 + b_i P_{gi} + C_i \qquad (1)$$

Where FC is total fuel cost of generation in the system ($/hr), a_i, b_i and c_i are the cost coefficient of the i th generator, P_{gi} is the power generated by the i th unit and n is the number of generators.

The cost is minimized subjected to the following generator capacities and active power balance constraints.

(i) $P_{gi_{\min}} \le P_{gi} \le P_{gi_{\max}}$ for i=1,2,….n (2)

where $P_{gi_{\min}}$ and $P_{gi_{\max}}$ are the minimum and maximum power output of the i th unit.

(ii) $P_D = \sum_{i=1}^{n} P_{gi} - P_{loss}$ (3)

where P_D is the total power demand and P_{loss} is total transmission loss.

The transmission loss P_{loss} can be calculated by using B matrix technique and is defined by (4) as,

$$P_{loss} = \sum_{i=1}^{n} \sum_{j=1}^{n} P_{gi} B_{ij} P_{gj} \qquad (4)$$

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

In reality, the objective function of the ELD problem is considered as a set of non-smooth cost functions due to valve-point loadings and prohibited zone operation. This paper considers two cases of cost functions. The first case considers only the valve-point effect problem where the objective function is normally described as the superposition of a sinusoidal function and a quadratic function. The second case addresses only ramp rate limits, prohibited zones of power generation and transmission losses where the objective function is expressed as a quadratic function with several constraints.

B. ELD Problem Considering Valve Point Effects

For more rational and precise modeling of fuel cost function, the above expression of cost function is to be modified suitably. Modern thermal power plants are designed to have generating units with multi-valve steam turbines to incorporate flexible operational facilities but it gives a very different cost curve compared with that defined by (1) and exhibit a greater discrepancy 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 [19] to the quadratic cost function described above. Hence, the problem described by (1) is revised as follows:

$$FC_v = \sum_{i=1}^{n} a_i P_{gi}^2 + b_i P_{gi} + c_i + |\, e_i \times \sin\left(f_i \times \left(P_{gi_{\min}} - P_{gi}\right)\right) \qquad (5)$$

where FC_v 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.

C. ELD problem With Ramp Rate Limits and Prohibited Zone

Ramp Rate Limit

Practically, the operating range of all online units is constrained by their ramp rate limits for forcing the units to operate continuously between two adjacent specific operating periods [20], [21]. The generation may increase or decrease with corresponding upper and downward ramp rate limits. So, according to [3], [5], and [7], the inequality constraints due to ramp rate limits for unit generation changes are given as,

If power generation increases, $P_{gi} - P_{gi}^0 \le UR_i$ (6)

If power generation decreases, $P_{gi} - P_{gi}^0 \le DR_i$ (7)

Where P_{gi} is the power generation of unit i at previous hour and UR_i and DR_i are the upper and lower ramp rate limits respectively. The inclusion of ramp rate limits modifies the generator operation constraints (2) as follows,

$$\max\left(P_{gi_{\min}}, P_{gi}^0 - DR_i\right) \le P_{gi} \le \min\left(P_{gi_{\max}}, P_{gi}^0 + UR_i\right) \qquad (8)$$

Prohibited Operating Zone

Due to steam valve operation or vibration in a shaft bearing there are some restricted zones identified in the input-output curve. Because it is difficult to determine the prohibited zone by actual records of operations, the best cost-cutting measure can be achieved by avoiding operation in that specific areas those are in actual operation. Symbolically, for a generating unit i,

$$P_{gi_{\min}} \le P_{gi} \le P_{gi,1}^l$$

$$P_{gi,j-1}^u \le P_{gi} \le P_{gi,j}^l,\; j = 1,2,\ldots\ldots.n_i$$

$$P_{gi,n_i}^u \le P_{gi} \le P_{gi_{\max}}$$

where j is the number of prohibited zones of unit .

III. CULTURAL BASED EP ALGORITHM

A. Cultural Algorithm (CA)

Reynolds first proposed Cultural Algorithm (CA) as a vehicle for modeling social evolution and learning the behavioral traits [13]. It is a high level searching technique. This evolutionary technique follows the cultural evolution of the society. Every society consisting of several classes of people has some rules and regulations which are obeyed by them and their offspring.

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A particular class, whom we called the elite class, is selected on the basis of their knowledge & wealth. This elite class people define and regulate the norms.

The knowledge and concept of those people becomes the governing factor of the society. In this way culture or knowledge progresses from generations to generations making the new generation more up-to-date and fit for the survival. CA is nothing but the mathematical implementation of this learning procedure. The knowledge acquired by individuals through generations is 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.

In Fig. 1, the conceptual diagram of CA is shown. Belief space is basically a set of promising variable ranges that provide standards and guidelines within which individual adjustments can be made leading the individuals to go to the good range of solution. 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.

B. The Proposed Algorithm

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 suitably implemented. The proposed method is basically a probabilistic search technique, which generates the initial

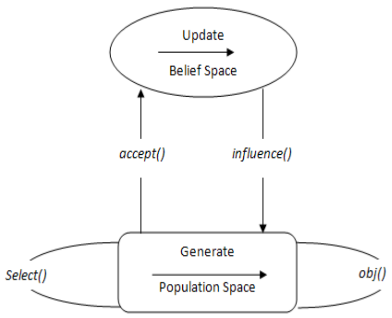

Fig 1. Cultural Algorithm Concept

parent vectors distributed uniformly in intervals within the limits and obtains global optimum solution over number of iterations. The main stages of this technique are initialization, acceptation and updating of belief space, creation of offspring vectors by mutation and competition and selection of best vectors to evaluate best solution. The implementation of the proposed algorithm is given below.

Initialization

Initial population is one of the deciding factors for reaching the optimum solution. The initial population is composed of *K* parent individuals which are randomly created. Each element in a population is uniformly distributed within its feasible range. The initial population should satisfy all the constraints .The initialized parent vectors are ,

$$X_{i,j} = \begin{bmatrix} x_{11}x_{12}\cdots x_{1n} \\ x_{21}x_{22}\cdots x_{2n} \\ \vdots \\ x_{i1}x_{i2}\cdots x_{in} \end{bmatrix}$$

$i=1,2,\ldots k$ and n is the number parameters.

Belief space structure

In this paper two types of knowledge are used, one is situational knowledge and another is normative knowledge. For *j* number of parameters the formal syntax of the belief space used here is *<N[j],S[j]>,* where *S* stands for situational knowledge which is the set of best individuals and Normative belief *N* is a set of interval information for each domain variable. For domain variable *j, N[j]* is represented as *<I,L,U>*. *I* denote the closed interval, that is a continuous set of real numbers, *x*, and is represented as:

$$I = [l,u] = \{x \mid l \le x \le u$$

Usually, *l* (lower bound) and *u* (upper bound) are initialized as the given domain values. *L* represents the performance score of the individual for the lower bound and *U* represents the performance score of the individual for the upper bound.

Acceptance Function

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.

Updating the Belief Space

Here in this paper, the situational knowledge *S* consists of a current best solution and the elite *S* is updated by the following rule:

$$S = \begin{cases} x_{best};\ f(x_{best}) \le f(s) \\ s; otherwise \end{cases}$$

The parameter values for the current selected individuals by the acceptance function are used to determine the current satisfactory range of the normative knowledge. To update the normative knowledge minimum (x_i) and maximum (x_k) values for parameter j between the accepted individuals in the current generation are selected. Then the updated interval of normative knowledge is as follows,

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

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

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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.

Influence the population space

The influence function is liable for choosing the individuals of population space within the updated interval stored in belief space. The current individual of n numbers of candidate for parameter j can be selected by the formula given,

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

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

Mutation

Gaussian mutation is used for the parameter j an offspring vector $x_{i,j}^{'}$ is created from each parent by adding to each component of $x_{i,j}$, a Gaussian random variable with a zero mean and a standard deviation proportional to the scaled cost values of the parent trial solution, i.e.,

$$x_{i,j}^{'} = x_{i,j} + N\left(0, \sigma_i^2\right) \ for \ i = 1,2......n$$

Where $N\left(0, \sigma_i^2\right)$ represents a Gaussian random variable with mean 0 and standard deviation σ_i^2.

Selection

The selection technique used in this paper is the tournament selection method. The parent trial vectors x_i and the corresponding offspring $x_i^{'}$ (2k number) vectors compete with each other for survival within the contending group. The individuals who have the greatest number of wins will be the parents for the next generation. In this way the whole process goes on until the convergence of the program.

IV. IMPROVED CULTURAL EP ALGORITHM IMPLEMENT FOR ECONOMIC LOAD DISPATCH PROBLEM

A. Representation of Individual String

The generation power output of every unit is chosen as a gene and many genes comprise an individual which represent a candidate solution for the ELD problems. For example, suppose there are N units that should be operated to provide power to loads, then we define the *i*-th individual P_i as, $P_i = [P_{i1}, P_{i2}, ...P_{id}], i=2,.......N$, where N is the size of the population, d represents the generator number, and P_{id} means the generation power output of the *d*-th unit at *i*-th individual. We use real values to represent the genes in the individuals.

B. Handling of Constraint Condition

The value of each power in the population is constrained by the corresponding range. If the generation of power exceeded the span, then the method for creation of revised generation is,

if $P_{id} > P_{\max}$, then $P_{id} = P_{\max}$ and

if $P_{id} < P_{\min}$, then $P_{id} = P_{\min}$

Where $P_{\max}$ and $P_{\min}$ are the lower and upper bounds of the parameter respectively to be optimized in the d *d*imensional space.

V. IMPLEMENTATION AND SIMULATION RESULTS

Proposed algorithm has been implemented to ELD problems having two different generating systems to verify its viability and effectiveness. The algorithm has been written in MATLAB and run a 3.0 MHZ, 1GB RAM PC. The first test system consists of 3 generating units considering ramp-rate limits, prohibited operating zone and network losses and the second one consists of 13 thermal generating with the effects of valve point loading. The solution obtained by the proposed method has been compared with other methods like PSO, GA etc.

A. Description of the Test Systems

Test Case 1: A system with three generators with ramp rate and prohibited zone is used in this paper. The transmission loss is considered here. Cost coefficients and generation limits of three units system are taken from [22]. In Table I the data of ramp rate and prohibited zone is given. The solutions obtained from the proposed method are given in Table II. And a comparison of best results of different methods like GA, PSO etc is given in Table III. A convergence characteristic of the said system with load demand of 300MW is shown in Fig.2.

Test Case 2: A thirteen generator system with valve point loading is used in this paper. Cost coefficients and generation limits of thirteen units system are taken from [17].The transmission loss is not considered here. The best solution obtained from the proposed method is given in Table IV. In Table V a comparison with different methods like GA, PSO, EP etc has been given. A convergence characteristic of the said system with load demand of 1800MW is shown in Fig.3.

TABLE I DATA FOR 3-GENERATORS SYSTEM

Unit	P_{gi}^0	UR_i	DR_i	Prohibited zone
1	215	55	95	[105,117][165,177]
2	72	55	78	[50,60][92,102]
3	98	45	64	[25,32][60,67]

TABLE II
RESULTS FOR 3-GENERATORS SYSTEM

Unit	Unit Power output (MW)	Total Power Output (MW)	Power Loss (MW)	Fuel Cost ($/h)
P_1	191.6072			
P_2	87.3840	312.6490	12.6168	3625.9
P_3	33.6579			

B. Determination of Parameters for Proposed Algorithm

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 for thirteen generator system. And maximum iterative generation number 700 with population size 10 and mutation probability as 0.8 is taken for three generator system.

TABLE III
COMPARISON OF BEST RESULTS AMONG DIFFERENT METHODS (3 GEN SYSTEM)

Optimization Technique	Total Power Output (MW)	Power Loss (MW)	Fuel Cost ($/h)
APSO	312.797	12.8364	3634.3127
GA	323.89	24.011	3737.20
2 PHASE N.N	312.45	12.45	3652.6
PROPOSED METHOD	312.6490	12.6168	3625.9

TABLE IV
RESULTS FOR 13-GENERATORS 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

C. A Comparative Study with Other Methods

The optimal results are shown in Table II and Table IV. It is found from Table V, that optimal fuel cost for thirteen generator system are 18030.72($/h) in PSO [23], 17975.343($/h) in GA[24], 17994.07($/h) in EP[25] and 17963.83($/h) in DE[26]**.** In case of proposed algorithm the fuel cost is obtained as 17683($/h) for the same system, is comparatively lower than the fuel cost obtained in other method.

In case of three generator system for load demand of 300MW, the fuel cost is 3634.3127($/h) in APSO [27].In GA [28] it was 3737.20($/h) and 3652.6($/h) in 2PHASE N.N [28].But from the Table III it is seen that the fuel cost as well as the power loss obtained in proposed method is comparatively lower than the other methods.

TABLE V
COMPARISON OF BEST FUEL COSTS AMONG DIFFERENT METHODS (13 GEN SYSTEM)

Optimization Technique	Fuel Cost ($/h)
PSO	18030.72
EP	17994.07
GA	17975.3437
DE	17963.83
PROPOSED METHOD	17683.00

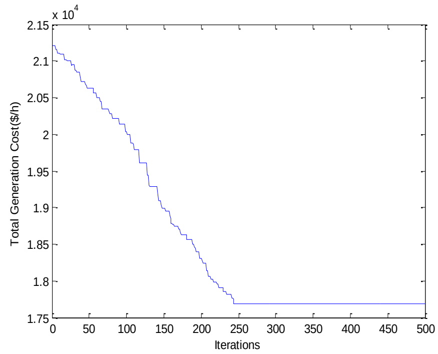

Fig.2 Convergence characteristics of fuel cost of thirteen generator system

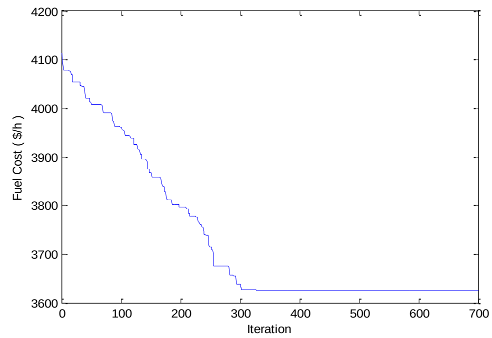

Fig.3 Convergence characteristics of fuel cost of three generator system

VI. CONCLUSION

This paper has proposed a different approach to cultural algorithm for the constrained ELD problem in power systems. As in this dual inheritance approach the offspring in population space is influenced by the parent's best experience, so the search technique of the proposed method is converted global search to local search. The simulation results have shown that the proposed method is better than other methods in terms of the convergence characteristics and accuracy. Practical generator operation is modeled using several non linear characteristics like ramp rate limits, prohibited operating zones. From this limited comparative study, it can be concluded that the applied algorithm can be effectively used to solve smooth as well as non-smooth constrained ELD problems.

In future, efforts will be made to incorporate more realistic constraints to the problem structure and the practical large sized problems would be attempted by the proposed methodology.

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