Solution of Economic Dispatch Problem using Differential Evolution Algorithm

C.Kumar, T.Alwarsamy

Abstract – Economic Dispatch is the process of allocating the required load demand between the available generation units such that the cost of operation is minimized. There have been many algorithms proposed for economic dispatch out of which a Differential Evolution (DE) is discussed in this paper. The Differential Evolution (DE) is a population-based, stochastic function optimizer using vector differences for perturbing the population. The DE is used to solve the Economic Dispatch problem (ED) with transmission loss by satisfying the linear equality and inequality constraints. The proposed method is compared with Genetic Algorithm (GA), Particle Swarm Optimization (PSO) and Simulated Annealing (SA).

Keywords – Differential Evolution, Economic Dispatch, Genetic Algorithm, Particle Swarm Optimization, Simulated Annealing.

I. INTRODUCTION

Economic dispatch is the method of determining the most efficient, low-cost and reliable operation of a power system by dispatching the available electricity generation resources to supply the load on the system. The primary objective of economic dispatch is to minimize the total cost of generation while honoring the operational constraints of the available generation resources [1]. In the traditional ED problem, the cost function for each generator has been approximately represented by a single quadratic function and is solved using mathematical programming based optimization techniques such as lambda iteration method, gradient-based method [2]. These methods require incremental fuel cost curves which are piecewise linear and monotonically increasing to find the global optimal solution. This makes the problem of finding the global optimum solution challenging. Dynamic programming (DP) method [3] is one of the approaches to solve the non-linear and discontinuous ED problem, but it suffers from the problem of "curse of dimensionality" or local optimality. In order to overcome this problem, several alternative methods have been developed such as genetic algorithm (GA)], Particle swarm optimization (PSO), Simulated Annealing (SA) and Differential Evolution (DE).

A genetic algorithm (GA) [4] is a search heuristic that mimics the process of natural evolution. Genetic algorithms belong to the larger class of evolutionary algorithms (EA). The GA procedure is based on the principle of survival of the fittest. The algorithm identifies the individuals with the optimizing fitness values, and those with lower fitness will naturally get discarded from the population. But there is no absolute assurance that a genetic algorithm will find a global optimum. Also the genetic algorithm cannot assure constant optimization response times. These unfortunate genetic algorithm properties limit the genetic algorithms use in optimization problems.

Particle Swarm Optimization (PSO) [7] is motivated by social behaviour of organisms such as bird flocking and fish schooling. The PSO is an optimization tool, which provides a population-based search procedure. A PSO system combines local search methods with global search methods, but no guaranteed convergence even to local minimum. It has the problems of dependency on initial point and parameters, difficulty in finding their optimal design parameters, and the stochastic characteristic of the final outputs. Simulated annealing (SA) [10] is a global optimization method that distinguishes between different local optima. Starting from an initial point, the algorithm takes a step and the function is evaluated. Since the algorithm makes very few assumptions regarding the function to be optimized, it is quite robust with respect to non-quadratic surfaces. In fact, simulated annealing can be used as a local optimizer for difficult functions. The disadvantage of SA is its repeated annealing with a schedule is very slow, especially if the cost function is expensive to compute. The method cannot tell whether it has found an optimal solution. One algorithm that has become increasingly popular in the field of evolutionary computation is Differential Evolution (DE). DE [13, 14] is very appealing due to the great convergence characteristics that it presents when compared to other algorithms from evolutionary computation. Also the few control parameters of DE require minimum tuning and remain fixed throughout the optimization process. DE obtains solutions to optimization problems using three basic operations: Mutation, Crossover and Selection. The mutation operator generates noisy replicas (mutant vectors) of the current population inserting new parameters in the optimization process.

The crossover operator generates the trial vector by combining the parameters of the mutant vector with the parameters of a parent vector selected from the population. In the selection operator the trial vector competes against the parent vector and the one with better performance advances to the next generation. This process is repeated over several generations resulting in an evolution of the population to an optimal value.

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C.Kumar, Department Electrical Engineering, SKP Engineering College, Anna University of Technology, Chennai, Tamilnadu, India. Mob.No.9994942022, Mail id: ckumarme81@gmail.com.
Dr.T.Alwarsamy, DOTE, Chennai, Tamilnadu, Mob. No9442006340, Mail id:talwarsamy@gmail.com

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In this paper, Differential Evolution is discussed to solve the ED problem by considering the linear equality and inequality constraints for a three units and six units system and the results were compared with GA, PSO and SA. The algorithm described in this paper is capable of obtaining optimal solutions efficiently.

II. PROBLEM FORMULATION

The objective of ED problem is to simultaneously minimize the total generation cost (*FT*) and to meet the load demand of a power system over some appropriate period while satisfying various constraints.

The objective function is

$$F_T = \min\left(\sum_{i=1}^{n} F_i(P_{Gi})\right) = \min\left(\sum_{i=1}^{n} A_i P_{Gi}^2 + B_i P_{Gi} + C_i\right) \quad (1)$$

Where: P_{Gi} Power generation of unit i, $F_i(P_{Gi})$: Generation cost function for P_{Gi} and *Ai*, *Bi*, *Ci*: Cost coefficients of ith generator. There are two constraints considered in the problem, i.e. the generation capacity of each generator and the power balance of the entire power system.

Constraint 1: Generation capacity constraint

For normal system operations, real power output of each generator is restricted by lower and upper bounds as follows:

$$P_{Gi}^{\min} \le P_{Gi} \le P_{Gi}^{\max} \quad (2)$$

Where $P_{Gi}^{\min} and P_{Gi}^{\max}$ are the minimum and maximum power generated by generator i, respectively.

Constraint 2: Power balance constraint

The total power generation must cover the total demand *PD* and the real power loss in transmission lines *PL*. This relation can be expressed as:

$$\sum_{i=1}^{n} P_{Gi} = P_D + P_L \quad (3)$$

Here a reduction is applied to model transmission losses as a function of the generators output through Kron's loss coefficients. The Kron's loss formula can be expressed as follows:

$$P_L = \sum_{i=1}^{n}\sum_{j=1}^{n} P_{Gi} B_{ij} P_{Gj} + \sum_{i=1}^{n} B_{oi} P_{Gi} + B_{oo} \quad (4)$$

where *Bij*, *Boi*, *Boo* are the transmission network power loss B-coefficients, which are assumed to be constant, and reasonable accuracy can be achieved when the actual operating conditions are close to the base case where the B-coefficients were derived. In the summary, the objective of economic power dispatch optimization is to minimize FT subject to the constraints (2) and (3).

III. OPTIMIZATION USING DIFFERENTIAL EVALUATION

Differential Evolution is one of the most recent population based stochastic evolutionary optimization techniques. Storn and Price first proposed DE in 1995 [13, 14] as a heuristic method for minimizing non-linear and non-differentiable continuous space functions. Differential Evolution includes Evolution Strategies (ES) and conventional Genetic Algorithms (GA). Differential Evolution is a population based search algorithm, which is an improved version of Genetic Algorithm. One extremely powerful algorithm from Evolutionary Computation due to convergence characteristics and few control parameters is differential evolution. Like other evolutionary algorithms, the first generation is initialized randomly and further generations evolve through the application of certain evolutionary operator until a stopping criterion is reached. The optimization process in DE is carried with four basic operations namely, Initialization, Mutation, Crossover and Selection.

3.1. Initialization

The algorithm starts by creating a population vector *of* size *P N* given by equation (5) composed of individuals that evolve over G generation. From the equation (6) each individual (*G*) *i X*, is a vector that contains as many elements as the problem decision variable. The population size *P N* is an algorithm control parameter selected by the user. Each individual or candidate solution is a vector that contains as many parameters as the problem decision variables D. In Differential Evolution the population size *P N*, remains constant throughout the optimization process.

$$P^{(G)} = \left[X_1^{(G)}, X_2^{(G)}, ...X_{Np}^{(G)}\right] \quad (5)$$

$$X_i^{(G)} = \left[X_{1i}^{(G)}, X_{2i}^{(G)}, ...X_{Di}^{(G)}\right]^T \quad i = 1,2,.........N_P \quad (6)$$

The first step in the DE optimization process is to create an initial population of candidate solutions by assigning random values to each decision parameter of each individual of the population. 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 as in the following equation:

$$X_{i,j}^{(0)} = X_j^{\min} + \eta_j (X_j^{\max} - X_j^{\min})$$
$$i = 1,2,.......N_{P,}\ j = 1,2,.......D \quad (7)$$

Where $X_j^{\min}$ and $X_j^{\max}$ are respectively, the lower and upper bound of the decision parameter and η_j is a uniformly distributed random number within [0, 1] generated anew for each value of j.

$$X_i^{'(G)} = X_a^{(G)} + F(X_b^{(G)} - X_c^{(G)})$$
$$i = 1,2,...........N_P \quad (8)$$

Where *Xa*, *Xb* and *Xc*, are randomly chosen vectors $\in \{1,2,......N_P\}$ and a ≠ b ≠c ≠ i. *Xa*, *Xb* and *Xc*, are generated anew for each parent vector. The mutation factor F is a user chosen parameter used to control the perturbation size in the mutation operator and to avoid search stagnation.

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3.3. Crossover Operation

The crossover operation generates trial vectors by mixing the parameter of the mutant vectors with the target vectors. For each parameter, a random value based on binomial distribution is generated in the range [0, 1] and compared against a user defined constant referred as crossover constant. If the random number is less than the crossover constant the parameter will come from the mutant vector, otherwise the parameter comes from parent vector as in equation (9). The crossover operation maintains diversity in the population, preventing local minima convergence. The crossover constant (CR) must be in the range of [0, 1]. A crossover constant of one means the trial vector will be composed entirely of mutant vector parameters. A crossover constant near zero results in more probability of having parameters from target vector in trial vector. A randomly chosen parameter from mutant vector is always selected to ensure that the trial vector gets at least one parameter from mutant vector even if the crossover constant is zero. Trial vectors are generated according to

$$X_{i,j}^{''(G)} = \begin{cases} X_{i,j}^{'(G)} if \eta_j \le C_R or j = q \\ X_{i,j}^{(G)} otherwise \end{cases}$$

$$i = 1,2,........N_P, j = 1,2,..........D \qquad (9)$$

Where, q, is randomly chosen index $\in \{1,2,......D\}$ that guarantees the trial vector gets at least one parameter from mutant vector. η_j , is a uniformly distributed random number within [0, 1] generated a new for each value of j. $X_{i,j}^{(G)}$, is a parent vector; $X_{i,j}^{'(G)}$, is the mutant vector; $X_{i,j}^{''(G)}$, is a trial vector.

3.4. Selection Operation

Selection is the operation through which better offspring are generated. The evaluation (fitness) function of an offspring is compared to that of its parent. The parent is replaced by its offspring if the fitness of the offspring is better than that of its parent, while the parent is retained in the next generation if the fitness of the offspring is worse than that of its parent. The selection operator chooses the vector that is going to compose the population in the next generation. The selection is repeated for each pair of target / trial vector until the population for the next generation is complete. Thus, if f denotes the cost (fitness) function under optimization (minimization), then

$$X_i^{(G+1)} = \begin{cases} X_i^{''(G)} iff(X_i^{''(G)}) \le f(X_i^{(G)} \\ X_i^{(G)} otherwise \end{cases}$$

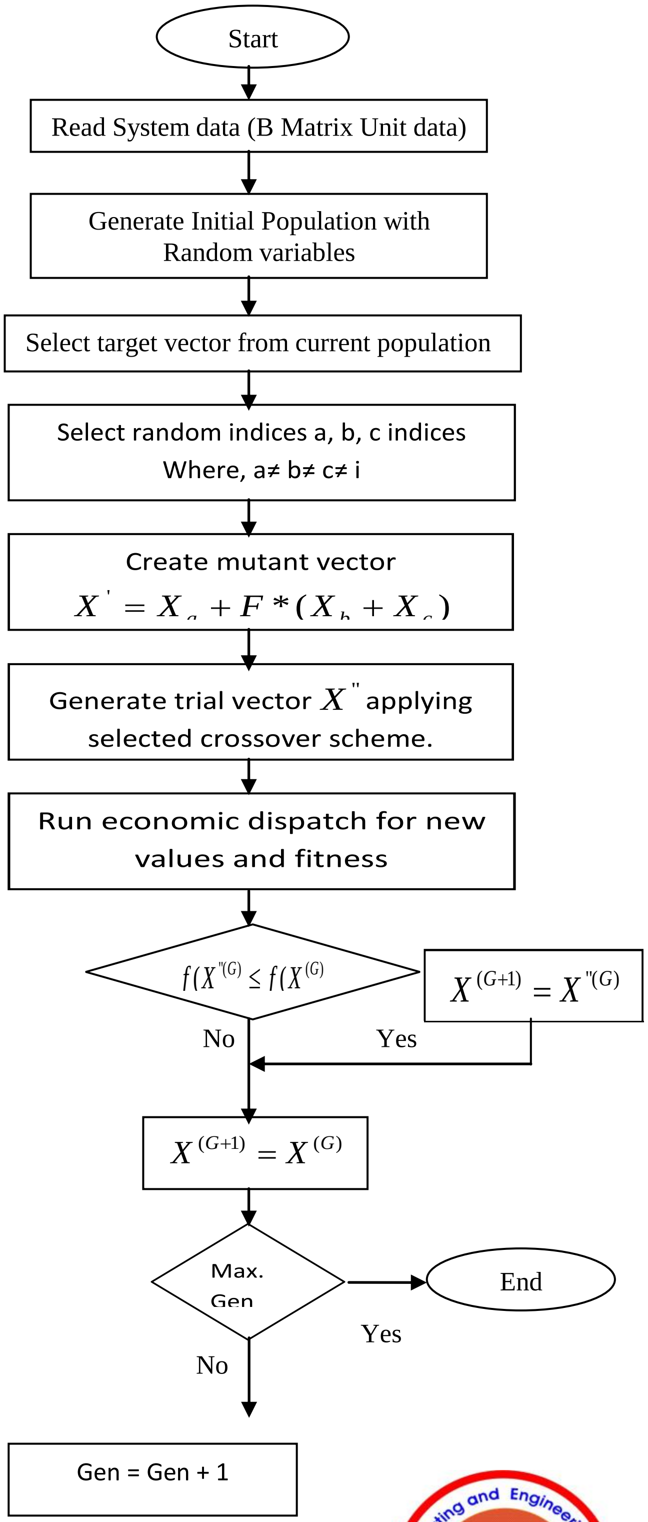
$$i = 1,2,.........N_P \qquad (10)$$

The optimization process is repeated for several generations. This allows individuals to improve their fitness while exploring the solution space for optimal values. The iterative process of mutation, crossover and selection on the population will continue until a user-specified stopping criterion, normally, the maximum number of generations allowed, is met. The other type of stopping criterion, i.e. convergence to the global optimum is possible if the global optimum of the problem is available.

IV. RESULTS AND DISCUSSION

Proposed DE Algorithm has been applied to ED problems in two different test cases for verifying its feasibility. These are a three units system and a six units system. Here, the result obtained from proposed DE [14, 15] method has been compared with GA [5, 6], PSO [8, 9] and SA [11, 12]. A reasonable B-loss coefficients matrix of power system network has been employed to calculate the transmission loss. The software has been written in MATLAB-7 language.

V. FLOWCHART FOR DIFFERENTIAL EVOLUTION



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5.1. Case Study -1: Three units system

In this example, a simple system with three thermal units is used to demonstrate how the proposed approach works. The unit characteristics are given in Table 1. Now, Table 2 Provides the statistic results that involved the generation cost, evaluation value, and average CPU time

Table 1-Generating unit's capacity and Coefficients

Unit	P_{Gi}^{min}	P_{Gi}^{max}	A_i (\$/MW^2)	B_i (\$/MW)	C_i (\$)
1	50	250	0.00525	8.663	328.13
2	5	150	0.00609	10.04	136.91
3	15	100	0.00592	9.76	59.16

Load = 300 MW

$$B_{ij} = \begin{pmatrix} 0.000136 & 0.0000175 & 0.000184 \\ 0.0000175 & 0.000154 & 0.000283 \\ 0.000184 & 0.000283 & 0.00161 \end{pmatrix}$$

Table 2- Best Power output for three unit system

Unit output	MGA	PSO	SA	DE
P1 (MW)	208.99	209.001	207.64	207.637
P2 (MW)	86.0041	85.92	87.2783	87.2833
P3 (MW)	15.4163	15	15	15
Total Power Output (MW)	310.4099	309.9211	309.9205	309.9203
Total generation cost (\$/h)	3624.28	3621.75	3619.75	3619.8
Power Loss (MW)	10.4099	9.9833	9.9204	9.9204
Iteration time (sec)	0.0028	0.064	0.068	0.009
Total time (sec)	1.4065	3.2065	3.4017	4.503

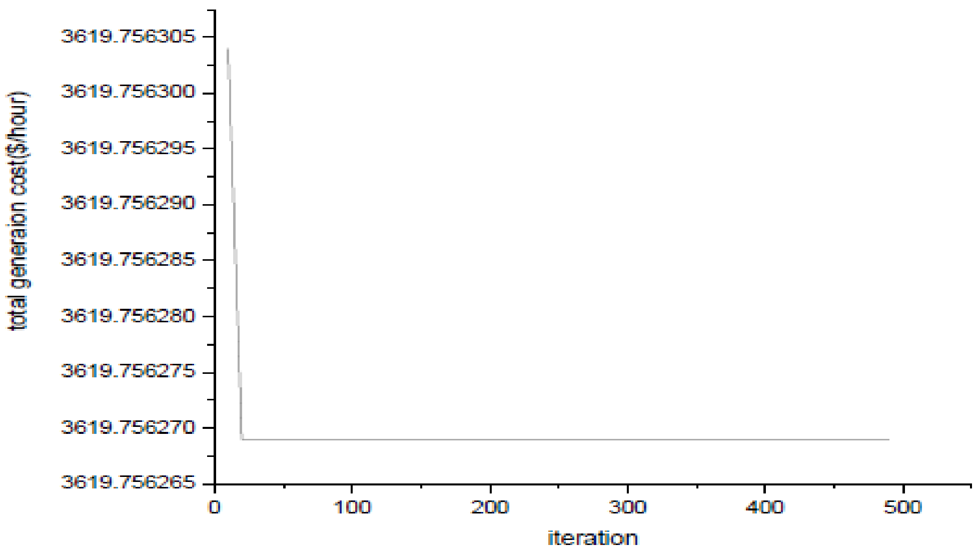

Figure 2. Convergence characteristic of Three-generator system

5.2. Case Study -2: Six units system

The system contains six thermal units and the load demand is 1263 MW. The characteristics of the six thermal units are given in Table 3. In normal operation of the system, the loss coefficients B with 100 MVA base capacities are given below. In this case, each individual PG contains six generator power outputs, such as P1, P2, P3, P4, P5, and P6, which are generated randomly. The dimension of the population is equal to 6 x 100. Table 4 provides the statistic results that involved the generation cost, evaluation value, and average CPU time.

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Table 3-Generating unit's capacity and Coefficients

Unit	P_{Gi}^{min}	P_{Gi}^{max}	A_i ($/MW²)	B_i ($/MW)	C_i ($)
1	100	500	240	7.0	0.0070
2	50	200	200	10.0	0.0095
3	80	300	220	8.5	0.0090
4	50	150	200	11.0	0.0090
5	50	200	220	10.5	0.0080
6	50	120	190	12.0	0.0075

$$B_{ij} = \begin{pmatrix} 1.7 & 1.2 & 0.7 & -0.1 & -0.5 & -0.2 \\ 1.2 & 1.4 & 0.9 & 0.1 & -0.6 & -0.1 \\ -0.1 & 0.1 & 0.0 & 0.2 & -0.6 & -0.8 \\ -0.5 & -0.6 & -0.1 & -0.6 & 12.9 & -0.2 \\ 0.2 & -0.1 & -0.6 & -0.8 & -0.2 & 15 \end{pmatrix}$$

$Bo_i = 10^{-3}$ [-0.3908 -0.1297 0.7047 0.0591 0.2161 -0.6635]
$B_{oo} = 0.056$

Table 4- Best Power output for six generator system

Unit output	GA	PSO	SA	DE
P1 (MW)	451.9702	432.9639	447.008	400.00
P2 (MW)	173.1626	170.5198	173.1887	186
P3 (MW)	261.1574	261.9009	263.9242	289
P4 (MW)	136.849	116.9111	139.0607	150
P5 (MW)	166.7021	190.4102	165.5824	200
P6 (MW)	85.6831	103.4931	86.6289	50
Total Power Output (MW)	1275.524	1276.199	1275.47	1275
Total generation cost ($/h)	15444.00	15458.56	15443.00	15192
Power Loss (MW)	0.0063	0.01281	0.1240	0.0124
Iteration time (sec)	0.0063	0.01281	0.1240	0.0124
Total time (sec)	3.182859	64.089	62.02	6.201792

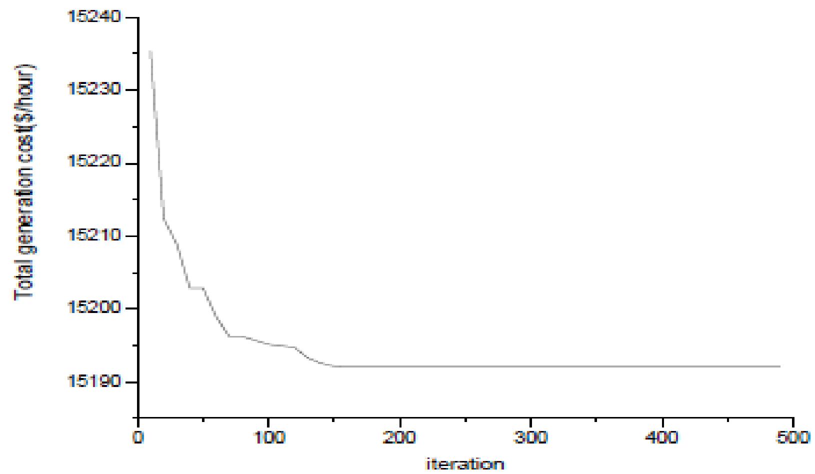

Fig 3. Convergence characteristics of Six Gen Systems

VI. CONCLUSION

The differential evolution algorithm has been successfully implemented to solve ED problems with the generator constraints as linear equality and inequality constraints and also considering transmission loss. The algorithm is implemented for three units and six units system. From the result, it is clear that the proposed algorithm has the ability to find the better quality solution and has better convergence characteristics, computational efficiency and less CPU time per iteration when compared to other methods such as GA, PSO and SA.

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AUTHORS PROFILE

C.Kumar is Research Scholar in the Department of Electrical and Electronics Engineering, Anna University of Technology, Coimbatore, India. He received M.E. Degree in Power System Engineering from Annamalai University, Chidambaram, India in the year of May 2005 and B.E. Degree in Electrical and Electronics Engineering from Madras University, Chennai in the year of May 2003. His Research Interest in the area of Power System Engineering.

Dr. T. Alwarsamy is Liaison officer**,** Directorate of Technical Education, Chennai, India. He received Ph.D degree in Bharathiyar University, Coimbatore, India and M.E. degree in Government College of Technology, Coimbatore, India in the year 1990, and B.E. degree in Thiagarajar College of Engineering, Madurai, India in the year of 1984. He worked as a Assistant Professor in the Department of Mechanical Engineering, Government College of Technology, Coimbatore, India.