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DIFFERENTIAL EVOLUTION APPROACH FOR OPTIMAL POWER FLOW SOLUTION

[1]K.Vaisakh, [2]L.R.Srinivas

[1]Professor, Department of Electrical Engineering, Andhra University, Visakhapatnam, AP, India-530003

[2]Assoc. Prof., Department of Electrical Engineering, SRKR Engineering College, Bhimavaram, W.G.Dist., AP, India - 534 204

E-mail: vaisakh_k@yahoo.co.in

ABSTRACT

This paper presents an algorithm for solving optimal power flow problem through the application of Differential Evolution (DE). The objective is to minimize the total fuel cost of thermal generating units having quadratic cost characteristics subjected to limits on generator real and reactive power outputs, bus voltages, transformer taps and power flow of transmission lines. The proposed method has been tested under simulated conditions on IEEE 30-bus system .The optimal power flow results obtained using DE are compared with other evolutionary methods. It is shown that DE total generation fuel cost is less expensive than those of evolutionary programming, tabu search, hybrid tabu search, and simulated annealing.

Keywords: *Optimal Power Flow; Differential evolution; Line flow constraints*

1. INTRODUCTION

Evolutionary Algorithms (EAs) are optimization techniques based on the concept of a population of individuals that evolve and improve their fitness through probabilistic operators like recombination and mutation. These individuals are evaluated and those that perform better are selected to compose the population in the next generation. After several generations these individuals improve their fitness as they explore the solution space for optimal value. The field of evolutionary computation has experienced significant growth in the optimization area. These algorithms are capable of solving complex optimization problems such as those with a non-continuous, non-convex and highly nonlinear solution space. In addition, they can solve problem that feature discrete or binary variables, which are extremely difficult.

Several algorithms have been developed within the field of Evolutionary Computation (EC) being the most studied Genetic Algorithms were first conceived in the 1960's when Evolutionary Computation started to get attention. Recently, the success achieved by EAs in the solution of complex problems and the improvement made in computation such as parallel computation have stimulated the development of new algorithms like Differential Evolution (DE), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO) and scatter search present great convergence characteristics and capability of determining global optima. Evolutionary algorithms have been successfully applied to many optimization problems within the power systems area and to the economic dispatch problem in particular [1-18].

2. OVERVIEW OF DIFFERENTIAL EVOLUTION

One extremely powerful algorithm from evolutionary computation due to it's excellent convergence characteristics and few control parameters is differential evolution. Differential evolution solves real valued problems based on the principles of natural evolution [11-15] using a population **P** of Np floating point-encoded individuals (1) that evolve over **G** generations to reach an optimal solution. In differential Evolution, the population size remains constant throughout the optimization process. Each individual or candidate solution is a vector that contains as many parameters (2) as the problem decision variables D. The basic strategy employs the difference of two randomly selected parameter vectors as the source of random variations for a third parameter vector. In the following, we present a more rigorous description of this new optimization method.

$$P = [Y_1^{(G)} \ldots\ldots\ldots\ldots\ldots\ldots Y_{Np}^{(G)}] \quad (1)$$

$$Y_i^{(G)} = [X_{1i}^{(G)}, X_{2i}^{(G)}, \ldots\ldots\ldots, X_{Di}^{(G)}]$$

$$i = 1,2,\ldots Np \quad (2)$$

Extracting distance and direction information from the population to generate random deviations result in an adaptive scheme with excellent convergence properties. Differential Evolution creates new offsprings by generating a noisy replica of each individual of the population. The individual that performs better from the parent vector (target) and replica (trail vector) advances to the next generation.

This optimization process is carried out with three basic operations:

- Mutation
- Cross over
- Selection

First, the mutation operation creates mutant vectors by perturbing each target vector with the weighted difference of the two other individuals selected randomly. Then, the cross over operation generates trail vectors by mixing the parameters of the mutant vectors with the target vectors, according to a selected probability distribution. Finally, the selection operator forms the next generation population by selecting between the trial vector and the corresponding target vectors those that fit better the objective function.

3. DE OPTIMIZATION PROCESS

A. Initialization

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. Such values must lie inside the feasible bounds of the decision variable and can be generated by Eq. (3). In case a preliminary solution is available, adding normally distributed random deviations to the nominal solution often generates the initial population.

$$Y_{i,j}^{(0)} = Y_j^{\min} + \eta_j (Y_j^{\max} - Y_j^{\min}) \quad (3)$$

$$i = 1,2,\ldots\ldots\ldots Np \quad , \quad j = 1,2,\ldots\ldots\ldots D$$

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

B. Mutation

After the population is initialized, this evolves through the operators of mutation, cross over and selection. For crossover and mutation different types of strategies are in use. Basic scheme is explained here elaborately. The mutation operator is incharge of introducing new parameters into the population. To achieve this, the mutation operator creates mutant vectors by perturbing a randomly selected vector (Y_a) with the difference of two other randomly selected vectors (Y_b and Y_c) according Eq. (4). All of these vectors must be different from each other, requiring the population to be of at least four individuals to satisfy this condition. To control the perturbation and improve convergence, the difference vector is scaled by a user defined constant in the range [0, 1.2]. This constant is commonly known as the scaling constant (S).

$$Y_i^{'(G)} = Y_a^{(G)} + S(Y_b^{(G)} - Y_c^{(G)})$$

$$i = 1,2,\ldots\ldots\ldots Np \quad (4)$$

Where Y_a, Y_b, Y_c, are randomly chosen vectors $\in \{1,2,\ldots\ldots\ldots Np\}$ and $a \neq b \neq c \neq i$

Y_a, Y_b, Y_c are generated anew for each parent vector, S is the scaling constant. For certain problems, it is considered $a = i$.

C. Crossover

The crossover operator creates the trial vectors, which are used in the selection process. A trail vector is a combination of a mutant vector and a parent (target) vector based on different distributions like uniform distribution, binomial distribution, exponential distribution is generated in the range [0, 1] and compared against a user defined constant referred to as the crossover constant. If the value of the random number is less or equal than the value of the crossover constant, the parameter will come from the mutant vector, otherwise the parameter comes from the parent vector as given in Eq. (5).

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 the target vector in the trial vector. A randomly chosen parameter from the mutant vector is always selected to ensure that the trail vector gets at least one parameter from the mutant vector even if the crossover constant is set to zero.

$$X_{i,j}^{''(G)} = \begin{cases} X_{i,j}^{'(G)} & if \quad \eta_j^{'} \le C_R \quad or \quad j = q \\ X_{i,j}^{(G)} & otherwise \end{cases} \tag{5}$$

Where i = 1, 2, ……… Np

j = 1, 2, ……… D

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

Another type of crossover scheme is mentioned in [11].

$$X_{i,j}^{''(G)} = \begin{cases} X_{i,j}^{'(G)} & for \quad j = \langle n \rangle_D, \langle n+1 \rangle_D, ..., \langle n+L-1 \rangle_D \\ X_{i,j}^{(G)} & otherwise \end{cases} \tag{6}$$

Where the acute brackets $\langle \ \rangle_D$ denote the modulo function with modulus D. The starting index n is a randomly chosen integer from the interval [0, D-1]. The integer L is drawn from interval [0, D-1] with the probability Pr (L=v) = (CR) ^{v}. $CR \in [0,1]$ is the crossover probability and constitutes a control variable for the DE scheme. The random decisions for both n and L are made anew for each trial vector.

D. Selection

The selection operator chooses the vectors that are going to compose the population in the next generation. This operator compares the fitness of the trial vector and fitness of the corresponding target vector, and selects the one that performs better as mentioned in Eq. (6).

$$Y_i^{(G+1)} = \begin{cases} Y_i^{''(G)} & if \quad f(Y_i^{''(G)}) \le f(Y_i^{(G)}) \\ Y_i^{(G)} & otherwise \end{cases} \tag{7}$$

i =1, 2… Np

The selection process is repeated for each pair of target/ trail vector until the population for the next generation is complete.

4. APPLICATION OF DE TO OPF

Differential Evolution has been applied to problems from several areas. Some power engineering problems have been solved with DE including: Distribution systems capacitors placement, harmonics voltage distribution reduction and passive shunt harmonic filter planning. DE has also been used in the design of filters, neural network learning, fuzzy logic application, and optimal control problems, among others.

The objective function of OPF

$$F_{COST} = \sum_{i=1}^{Ng} F_i = \sum (a_i P_{gi}^2 + b_i P_{gi} + c_i) \ \text{\$/Hr} \tag{8}$$

Subjected to the constraints

$$\begin{aligned} g(x,u) &= 0, \\ h(x,u) &\le 0. \end{aligned} \tag{9}$$

where g is the equality constraints and represent typical load flow equations.

h is the system operating constraints

E. Dependent Variables

X is the vector of dependent variables consisting of slack bus power P_{G1}, load bus voltages V_L, generator reactive power outputs Q_G, and transmission line loadings S_l. Hence, X can be expressed as

$$X^T = [P_{G1}, V_L, Q_G, S_l] \tag{10}$$

i.e.,

$$X^T = [P_{G1}, V_{L1}, ...V_{L\,Npq}, Q_{G1}, ...Q_{G\,Ng}, S_{l1}, ...S_{l\,Nl}]$$

where Npq, Ng, Nl are number of load buses, number of generators, and number of transmission lines, respectively.

F. Independent Variables

U is the vector of independent variables consisting of generator voltages V_G, generator real power outputs P_G, except at the slack bus P_{G1}, and transformer tap settings T. Hence, U can be expressed as

$$U = [V_G, P_G, T] \quad (11)$$

i.e.,

$$u^T = [V_{G1}, ...V_{G\,Ng}, P_{G2}.........P_{G\,Ng}, T_1,.........T_{Nt}]$$

where Nt is the number of the regulating transformers.

G. Initialization

The first step in this algorithm is to create an initial population. All the independent variables $[V_G, P_G, T]$ have to be generated according to formula (3), where each independent parameter of each individual in the population is assigned a value inside the given feasible region of the generator. This creates parent vectors of independent variables for the first generation. As they have created within their limits, they readily satisfy the corresponding inequality constraints. To find dependent variables $X^T = [P_{G1}, V_L, Q_G, S_l]$ corresponding to each individual, Newton-Raphson power flow solution is implemented.

After getting all vectors corresponding to dependent variables, constraint-handling method of penalty functions is applied to handle the inequality constraints related to dependent variables. Penalty factors corresponding to each dependent variable of each individual in population have to be calculated. If they violate a limit whether lower or upper, difference of that value and corresponding limit violated was taken as penalty index and it is multiplied with a constant so as to match with basic objective function i.e., fuel cost.

The penalty functions for slack bus power, voltages of load buses, line flows and reactive power generations are considered to calculate fitness of each population member. Fitness includes fuel cost function and also penalties corresponding to dependent variables. Inclusion of these penalties in fitness gives us a great opportunity to assign better fitness to that particular population member whose control parameters are within the operational limits in addition to minimum fuel cost.

$$Fit_P = \frac{1}{F_{COST} + (k1 * Spf_P) + (k2 * \sum_{i=1}^{Ng} Qgpf_{P,i}) + (k3 * \sum_{i=1}^{Npq} Vpf_{P,i}) + (k4 * \sum_{i=1}^{Nl} LFpf_{p,i})} \quad (12)$$

where

Slack bus penalty	$\rightarrow$	Spf
Line flows penalty	$\rightarrow$	$Lfpf$
Q_G Penalty	$\rightarrow$	$Qgpf$
Voltage penalty	$\rightarrow$	Vpf

5. DE IMPLEMENTATION RESULTS

The suitability of the proposed method has been tested for IEEE-30 bus shown in Fig.4. It is chosen as it is a benchmark system, has more control variables and provides results for comparison of the proposed method. The approach can be generalized and easily extended to large-scale systems.

The IEEE-30 bus system consists of six generators, four transformers, 41 lines, and two shunt reactors. In DE solution for OPF, the total control variables are 15: six unit active power outputs, six generator bus voltage magnitudes, and four transformers tap settings and are given in Table 1. All generator active power, and generator bus voltages and transformer tap setting are considered as continuous for simplicity. The generators cost coefficients of the IEEE 30-bus test system are given in the Table 2.The limits of variables for the IEEE-30 bus system is given in Table 3.

In this section, the DE solution of the OPF is evaluated using the test system IEEE-30 bus system [7]. The results, which follow, are the best solution over the ten runs. The results are compared with EP and other methods.

TABLE I
SYSTEM DESCRIPTION OF CASE STUDY

Sl.No.	Variables	30-bus system
1	Buses	30
2	Branches	41
3	Generators	6
4	Generator buses	6
5	Shunts reactors	2
6	Tap-Changing transformers	4

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TABLE II
GENERATOR COST COEFFICIENTS OF IEEE 30-BUS SYSTEM

Bus No	Real Power Output limit (MW)		Cost Coefficients		
	Min	Max	a	b	c
1	50	200	0	2.00	0.00375
2	20	80	0	1.75	0.01750
5	15	50	0	1.00	0.06250
8	10	35	0	3.25	0.00834
11	10	30	0	3.00	0.02500
13	12	40	0	3.00	0.02500

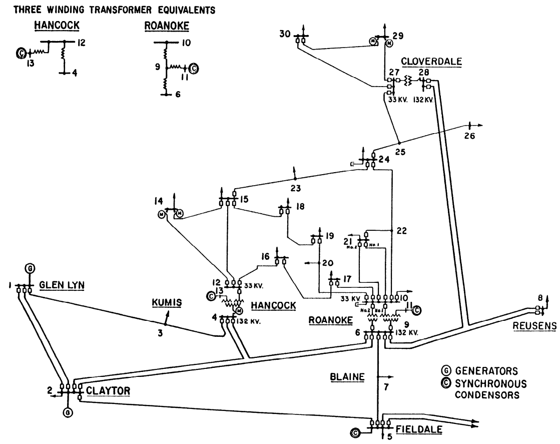

Figure 4: IEEE 30-bus system

TABLE III
LIMITS OF VARIABLES FOR IEEE 30-BUS SYSTEM

No.	Description	Units	Lower Limits	Upper Limits
1	Voltage PQ-bus	Pu	0.95	1.05
2	Voltage PV-bus	Pu	0.90	1.10
3	Transformer taps	Pu	0.90	1.10

TABLE V
OPTIMAL ACTIVE AND REACTIVE POWER GENERATION LEVELS FOR 30-BUS SYSTEM

Unit No.	Bus No	Generator unit real and reactive power control	
		Unit real power [MW]	Unit reactive power [MVAR]
1	1	177.3	-16.42
2	2	49.18	14.31
3	5	12.24	38.46
4	8	11.19	36.91
5	11	21.23	29.30
6	13	21.74	35.75

TABLE IV
DE PARAMETERS FOR BEST RESULTS OF OPTIMAL POWER FLOW FOR IEEE 30-BUS SYSTEM

Sl.No.	Parameters of Differential evolution	
	Parameters	Values
1	Population	20
2	Generations	100
	Penalty factors of fitness function	
5	Slack bus generation penalty factor	10,000
6	Reactive power penalty factor	1000
7	Load bus voltage penalty factor	1000
8	Line flows penalty factor	1000

TABLE VI
CONTROL VARIABLES FOR THE 30-BUS SYSTEM

Sl. No.	I. Generator voltages		II. Power generation		III. Transformer taps	
	Gen voltage	Value	Pg	Value	Transf. Tap	Value
1	$\|V_{G1}\|$	1.060	P_{g1}	177.3	T_1	1.0657
2	$\|V_{G2}\|$	1.046	P_{g2}	49.18	T_2	0.9000
3	$\|V_{G5}\|$	1.100	P_{g5}	12.24	T_3	1.0468
4	$\|V_{G8}\|$	1.077	P_{g8}	11.19	T_4	0.9589
5	$\|V_{G11}\|$	1.022	P_{g11}	21.23		
6	$\|V_{G13}\|$	1.030	P_{g13}	21.74		

TABLE VII

COMPARISON OF THE TOTAL GENERATOR FUEL COSTS OF DE WITH TS, TS/SA, ITS, EP, AND IEP

Cost ($/hr)	Algorithm					
	TS	TS/SA	ITS	EP	IEP	DE
Best cost	802.502	802.788	804.556	802.907	802.465	802.230
Average cost	802.632	803.032	805.812	803.231	802.521	802.031
Worst cost	802.746	803.291	806.856	803.474	802.581	802.35

The DE parameters used for the optimal power flow solution are given in Table 4. They are treated as continuous controls. Table 5 shows the optimal setting of the generator bus active power and corresponding reactive generation for DE. Table 6 shows the optimal control variables obtained for the optimal power flow of the IEEE-30 bus system. Table 7 shows the comparison of the cost of generation for the IEEE-30 bus system for the above cases with other soft computing methods.

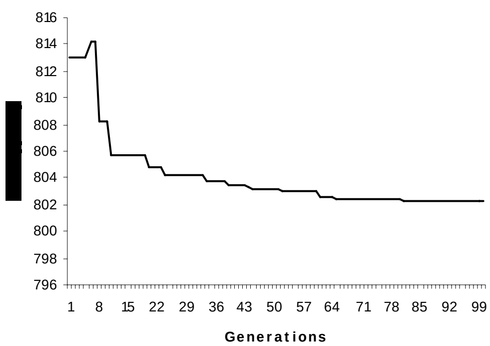

Figure 5: Cost Vs Generations

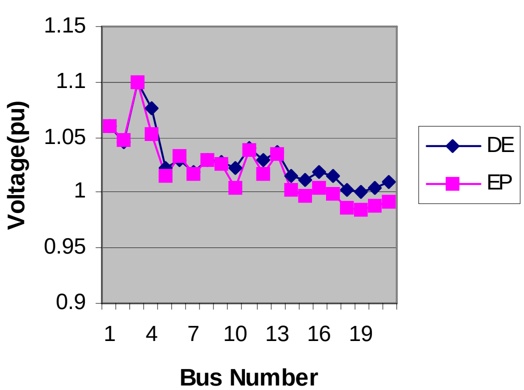

Figure 6: Bus voltage profiles

Figure 5 shows the convergence of DE for the optimal power flow problem. The operating costs of the best solution in the normal operation achieved by the DE and EP are, respectively, $802.230 and $802.907 per hour. It can be observed from Fig.5 that the convergence of DE is faster while obtaining a better solution in lesser computational time. Figure 6 shows the bus voltage profiles of the 30-bus system achieved by the DE and EP.

6. CONCLUSIONS

This paper presents a DE solution to the optimal power flow problem and is applied to an IEEE 30-bus power system. The main advantage of DE over other modern heuristics is modeling flexibility, sure and fast convergence, less computational time than other heuristic methods. And it can be easily coded to work on parallel computers. The main disadvantage of DE is that it is heuristic algorithms, and it does not provide the guarantee of optimal solution for the OPF problem. The DE approach is useful for obtaining high-quality solution in a very less time compared to other methods.

The future work in this area consists of the applicability of DE solutions to large-scale OFF problems of systems with several thousands of nodes, utilizing the strength of parallel computers.

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