DIFFERENTIAL EVOLUTION BASED OPTIMAL REACTIVE POWER DISPATCH FOR VOLTAGE STABILITY ENHANCEMENT

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ABSTRACT

Reactive power dispatch (RPD) is one of the important tasks in the operation and control of power system. This paper presents a Differential Evolution (DE) - based approach for solving optimal reactive power dispatch including voltage stability limit in power systems. The monitoring methodology for voltage stability is based on the L-index of load buses. The objective is to minimize the real power loss subjected to limits on generator real and reactive power outputs, bus voltages, transformer taps and shunt power control devices such as SVCs. The proposed algorithm has been applied to IEEE 30-bus system to find the optimal reactive power control variables while keeping the system under safe voltage stability limit and is found to be effective for this task. The optimal reactive power allocation results obtained using DE are compared with other methods. It is shown that the objective function value is less than those of other methods.

Keywords: Optimal Reactive Power Dispatch; Differential Evolution; Voltage Stability L-index; Power System Loss

1. INTRODUCTION

To solve the RPD problem, a number of conventional optimization techniques [1-2] have been proposed. These include the Gradient method, Non-linear Programming (NLP), Quadratic Programming (QP), Linear programming (LP) and Interior point method. Though these techniques have been successfully applied for solving the reactive power dispatch problem, still some difficulties are associated with them. One of the difficulties is the multimodal characteristic of the problems to be handled. Also, due to the non-differential, non-linearity and non-convex nature of the RPD problem, majority of the techniques converge to a local optimum. Recently, Evolutionary Computation techniques like Genetic Algorithm (GA) [3], Evolutionary Programming (EP) [4] and Evolutionary Strategy [5] have been applied to solve the optimal dispatch problem. In this paper, GA based approach has been proposed to solve the RPD problem.

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 [6-23].

Voltage Stability is becoming an increasing source of concern in secure operation of present-day power systems. The problem of voltage instability is mainly considered as the inability of the network to meet the load demand imposed in terms of inadequate reactive power support or active power transmission capability or both1. Voltage collapse is a local load bus problem and depends mostly on load conditions in the system. There exist two major techniques viz, static approach and dynamic approach for this analysis. Although not very accurate, yet the static technique has gained wide acceptance for its inherent virtues, eg, simplistic approach, faster execution and less memory consumption. The static voltage stability is primarily associated with the reactive power support. The real power (MW) loadability of a bus in a system depends on reactive power support that the bus can receive from the system. Several analytical tools have been presented in the literature for the analysis of the static voltage stability of a system. This paper is mainly concerned with analysis and enhancement of steady state voltage stability based on *L*-index [24]. An algorithm is proposed using new operational load flow (OLF) and optimization of reactive power control variables using LP technique. Simulated case studies conducted on two Indian power networks of 82 and 217 buses are presented for illustration purposes.

2. VOLTAGE STABILITY L-INDEX

Consider an n-bus system having 1, 2…g, generator buses (g), and g+1,g+2…n the load buses(r=n-g-s) and t number of OLTC transformers. The transmission system can be represented using a hybrid representation, by the following set of equations

$$\begin{bmatrix} V_L \\ I_G \end{bmatrix} = H \begin{bmatrix} I_L \\ V_G \end{bmatrix} = \begin{bmatrix} Z_{LL} & F_{LG} \\ K_{GL} & Y_{GG} \end{bmatrix} \begin{bmatrix} I_L \\ V_G \end{bmatrix} \quad (1)$$

where

V_L, I_L are the voltage and current vectors at the load buses

V_G, I_G are the voltage and current vectors at the generator buses

$Z_{LL}, F_{LG}, K_{GL}, Y_{GG}$ are the sub-matrices of the hybrid matrix H.

The H matrix can be evaluated from the Y bus matrix by a partial inversion, where the voltages at the load buses are exchanged against their currents. This representation can then be used to define a voltage stability indicator at the load bus, namely L_j which is given by,

$$L_j = \left| 1 + \frac{V_{0j}}{V_j} \right| \quad (2)$$

where,

$$V_{0j} = -\sum_{i \in G} F_{ji} V_i \quad (3)$$

The term V_{0j} is representative of an equivalent generator comprising the contribution from all generators.

The index L_j can also be derived and expressed in terms of the power terms as the following.

$$L_j = \left| \frac{\overset{*}{S}_{j+}}{\overset{*}{Y}_{jj+} V_j^2} \right| \quad (4)$$

where,

$$S_{j+} = S_j + S_{jcorr} \quad (5)$$

* indicates the complex conjugate of the vector

$$S_{jcorr} = \Big(\sum_{\substack{i \in Loads \\ i \neq j}} \frac{\overset{*}{Z}_{ji}}{\overset{*}{Z}_{jj}} \frac{S_i}{V_i} \Big) V_j \quad (6)$$

$$Y_{jj+} = \frac{1}{Z_{jj}} \quad (7)$$

The complex power term component S_{jcorr} represents the contributions of the other loads in the system to the index evaluated at the node j.

It can be seen that when a load bus approaches a steady state voltage collapse situation, the index L approaches the numerical value 1.0. Hence for an overall system voltage stability condition, the index evaluated at any of the buses must be less than unity. Thus the index value L gives an indication of how far the system is from voltage collapse. This feature of this indicator has been exploited in our proposed algorithm to evolve a voltage collapse margin incorporated RPD routine. The L-indices for a given load condition are computed for all load buses. The equation for the L-index for j-th node can be written as

$$L_j = \left| 1.0 - \sum_{i=1}^{i=g} \left| F_{ji} \right| \frac{|V_i|}{|V_j|} \angle \theta_{ji} + \delta_i - \delta_j \right| \quad (8)$$

$$L_j = \left| 1.0 - \sum_{i=1}^{i=g} \frac{|V_i|}{|V_j|} (F_{ji}^r + jF_{ji}^m) \right| \quad (9)$$

* Indicates the complex conjugate of the vector

$$V_i = |V_i| \angle \delta_i, V_j = |V_j| \angle \delta_j$$

$$F_{ji} = |F_{ji}| \angle \theta_{ji}$$

$$F_{ji}^r = |F_{ji}| \cos(\theta_{ji} + \delta_i - \delta_j),$$

$$F_{ji}^m = |F_{ji}| \sin(\theta_{ji} + \delta_i - \delta_j) \quad (10)$$

It can be seen that when a load bus approaches a steady state voltage collapse situation, the index L approaches the numerical value 1.0. Hence for an overall system voltage stability condition, the index evaluated at any of the buses must be less than unity. Thus the index value L gives an indication of how far the system is from voltage collapse. This feature of this indicator has been exploited in our proposed algorithm to evolve a voltage collapse margin incorporated in RPD routine.

3. FORMULATION OF ORPD PROBLEM

The objective of RPD is to identify the reactive power control variables, which minimizes the real power loss (P_{loss}) of the system. This is mathematically stated as follows:

Minimize F= [f_1]

$$f_1 = P_{loss} = \sum_{\substack{k \in N_l \\ k=(i,j)}} g_k (V_i^2 + V_j^2 - 2V_i V_j \cos \theta_{ij}) \quad (11)$$

The reactive power optimization problem is subjected to the following constraints.

Equality Constraints:

These constraints represent load flow equation such as

$$P_i - V_i \sum_{j=1}^{N_g} V_j (G_{ij} \cos \theta_{ij} + B_{ij} \sin \theta_{ij}) = 0, \quad i \in N_B - 1 \quad (12)$$

$$Q_i - V_i \sum_{j=1}^{N_g} V_j (G_{ij} \sin \theta_{ij} - B_{ij} \cos \theta_{ij}) = 0, \quad i \in N_B - 1 \quad (13)$$

Inequality Constraints:

These constraints represent the system operating constraints. Generator bus voltages (V_{gi}), reactive power generated by the capacitor (Q_{ci}), transformer tap setting (t_k), are control variables and they are self-restricted. Load bus voltages (V_{load}) reactive power generation of generator (Q_{gi}) and line flow limit (S_l) are state variables, whose limits are satisfied by adding a penalty terms in the objective function. These constraints are formulated as

(i) Voltage limits

$$V_i^{\min} \le V_i \le V_i^{\max} \quad ; i \in N_B \quad (14)$$

(ii) Generator reactive power capability limit

$$Q_{gi}^{\min} \le Q_{gi} \le Q_{gi}^{\max} \;;\; i \in N_g \quad (15)$$

(iii) Capacitor reactive power generation limit

$$Q_{ci}^{\min} \le Q_{ci} \le Q_{ci}^{\max} \;;\; i \in N_c \quad (16)$$

(iv) Transformer tap setting limit

$$t_k^{\min} \le t_k \le t_k^{\max} \;;\; k \in N_T \quad (17)$$

(v) Transmission line flow limit

$$S_l \le S_l^{\max} \;;\; l \in N_l \quad (18)$$

(vi) Voltage stability constraint

$$L_j \le L^{\max}; \quad j \in N_{PQ} \quad (19)$$

The equality constraints are satisfied by running the power flow program. The active power generation (P) (except the gi generator at the slack bus), generator terminal bus voltages (V) and transformer tap-settings (t) are the optimization gi k variables and they are self-restricted by the optimization algorithm. The active power generation at the slack bus (Pgs), load bus voltages (V) and reactive power generation (Q) and voltage stability load gi level (L) are state variables which are restricted through penalty function approach.

4. 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 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 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.

$$P = [Y_1^{(G)} ....Y_{Np}^{(G)}] \tag{19}$$

$$Y_i^{(G)} = [X_{1i}^{(G)}, X_{2i}^{(G)}, ..., X_{Di}^{(G)}]$$
$$i = 1,2, \ldots Np \tag{20}$$

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.

A. DE Algorithm

- Initialize population
- While stopping criteria are not satisfied,
- Create mutant vector with the difference vector and scaling constant
- Generate trial vectors applying the selected crossover scheme
- Select next generation members according to competition performance.

B. DE Optimization Process

1) 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. (21). In case a preliminary solution is available, adding normally distributed random deviations to the nominal solution often generates the initial population.

$$Y_{i,j}^{(0)} = Y_j^{\min} + \eta_j (Y_j^{\max} - Y_j^{\min}) \tag{21}$$
$$i = 1,2,\ldots, Np, \; j = 1,2,\ldots, D$$

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.

2) 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). 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).

$$Y_i^{'(G)} = Y_a^{(G)} + S(Y_b^{(G)} - Y_c^{(G)})$$
$$i = 1,2, \ldots\ldots Np \tag{22}$$

Where Y_a, Y_b, Y_c, are randomly chosen vectors $\in \{1,2,.........Np\}$ 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 $a = i$.

3) 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. Figure 3 shows how the crossover operation is performed.

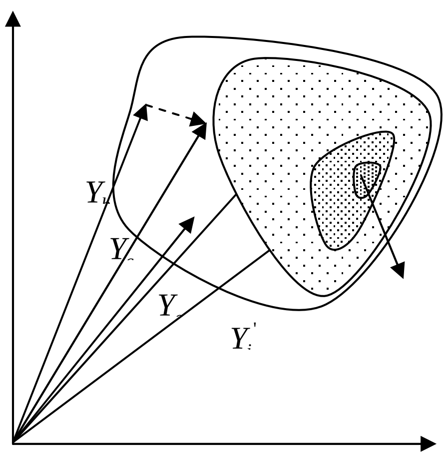

Figure 1: Mutation operator

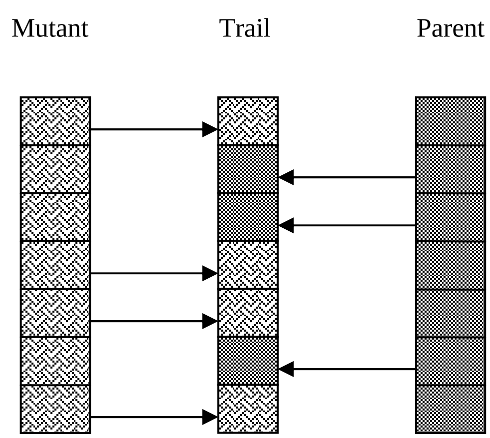

Figure 2: Crossover operator

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.

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

Where $i = 1, 2 \ldots Np$ (23)

$j = 1, 2 \ldots D$

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].

$$X_{i,j}^{''(G)} = \begin{cases} X_{i,j}^{'(G)} & for \; j = \langle n \rangle_D, \langle n+1 \rangle_D, \ldots, \langle n+L-1 \rangle_D \\ X_{i,j}^{(G)} & otherwise \end{cases} \quad (24)$$

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.

4) 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.

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

$$i = 1, 2 \ldots Np \qquad (25)$$

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

5. DIFFERENTIAL EVOLUTION SOLUTION TECHNIQUE

In the ORPD problem, the elements of the solution consist of all the control variables, namely, generator bus voltages (V), the gi transformer tap-setting (tk), and the reactive power generation (Qci). These variables are represented continuous variables in the DE population.

Fitness Function: In the ORPD problem under consideration the objective is to minimize the total power loss satisfying the constraints given by equations (12) to (19). For each individual, the equality constraints given by equations (12) and (13) are satisfied by running Newton-Raphson algorithm and the constraints on the state variables are taken into consideration by adding a quadratic penalty function to the objective function.

With the inclusion of penalty function, the new objective function then becomes,

$$Min\,F = P_{loss} + K_v \sum_{i=1}^{N_{PQ}} (V_i - V_i^{\lim})^2 + K_q \sum_{i=1}^{N_g} (Q_{gi} - Q_{gi}^{\lim})^2 + K_f \sum_{i=1}^{N_l} (S_l - S_l^{\lim})^2 + K_l \sum_{j=1}^{N_{PQ}} (L_j - L^{\lim})^2 \qquad (26)$$

where K_v , K_q, K_f and K_l are the penalty factors for the bus voltage limit violation, generator reactive power limit violation, line flow violation and voltage stability limit violation, respectively. In the above objective function Vi lim and Qgi lim are defined as;

$$V_i^{\lim} = \begin{cases} V_i^{\min}; if\ V_i < V_i^{\min} \\ V_i^{\max}; if\ V_i > V_i^{\max} \end{cases}$$

$$Q_{gi}^{\lim} = \begin{cases} Q_{gi}^{\min}; if\ Q_{gi} < Q_{gi}^{\min} \\ Q_{gi}^{\max}; if\ Q_{gi} > Q_{gi}^{\max} \end{cases} \qquad (27)$$

The minimization objective function given by equation (26) is transformed to a fitness function (f) to be maximized as, where k is a large constant. This is used to amplify, the value of 1/F which is usually small, so that the fitness value of the chromosome will be in a wider range.

6. SIMULATION RESULTS

The details of the simulation study carried out on IEEE 30-bus system using the proposed DE-based method are presented here. 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. IEEE 30-bus system consists of 6 generator buses, 24 load buses and 41 transmission lines of which 4 branches (6-9), (6-10), (4-12) and (28-27) are with the tap-setting transformer. Generator parameters are given in the Appendix. The transmission line parameters of this system and the base loads are given in [1].

For the ORPD problem, the candidate buses for reactive power compensation are 10, 12, 15, 17, 20, 21, 23, 24 and 29. The DE-based ORPD algorithm was implemented using MATLAB code and was executed on a PC. Two different studies were performed with this system to show the significance of the proposed method and the use of the algorithm in a bigger system. In case 1 RPD problem is solved by the proposed method with 100% load level, case 2 is reactive power dispatch under network contingency with the incorporation of the voltage stability limit in both the cases.

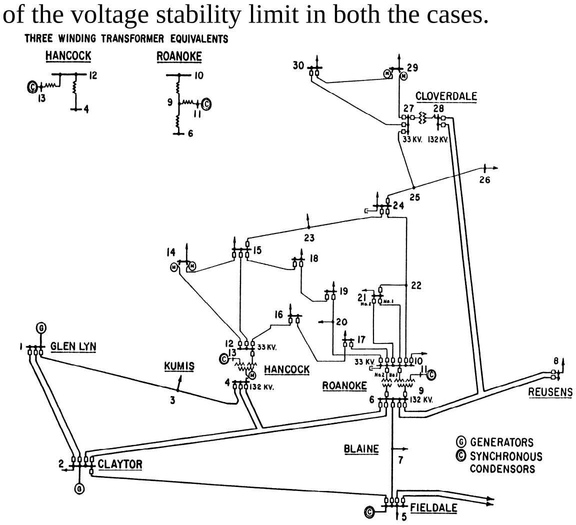

Figure 3: IEEE 30-bus system

The DE parameters used for the optimal power flow solution are given in Table III. They are treated as continuous controls. The results of these simulations are summarized next.

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

TABLE II
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	Trans. taps	Pu	0.90	1.10

TABLE III
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

C. Case 1: base case

In this case the system is optimized using the optimal reactive power dispatch method under base load condition for 100% load level. The real power settings of the generator are taken from [1]. To obtain the optimal values of the control variables the DE-based algorithm was run.

The optimal values of the control variables and power loss obtained are presented in Table IV. The minimum transmission loss obtained is 4.8500 MW which is smaller than the result obtained in [1] for the same IEEE 30-bus system. To illustrate the convergence of the algorithm, the relationship between the best fitness value of the ORPD results and the objective function (Ploss) are plotted against the number of generations in Figure 2. From the figure it can be seen that the proposed algorithm converges rapidly towards the optimal solution. This shows the effectiveness of the proposed method for the ORPD problem.

TABLE IV
CONTROL VARIABLES FOR THE 30-BUS SYSTEM

I. Generator voltages		II. Shunt Compensation		III. Transformer taps	
Gen bus	Value	SVC	Value	Tran. Tap	Value
1	1.0700	Q_{c10}	0.0426	T_{6-9}	0.9000
2	1.0629	Q_{c12}	0.0260	T_{6-10}	0.9000
5	1.0446	Q_{c15}	0.0275	T_{4-12}	1.0093
8	1.0430	Q_{c17}	0.0282	T_{28-27}	1.0119
11	1.0974	Q_{c20}	0.0458		
13	1.0613	Q_{c21}	0.0380		
		Q_{c23}	0.0531		
		Q_{c24}	0.0258		
		Q_{c29}	0.0309		

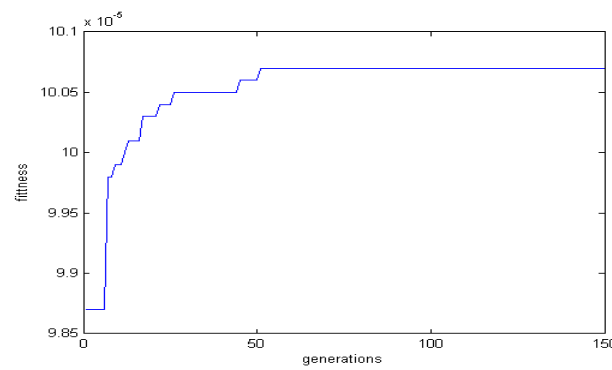

Figure 4: Fitness function value Vs Generations for case 1

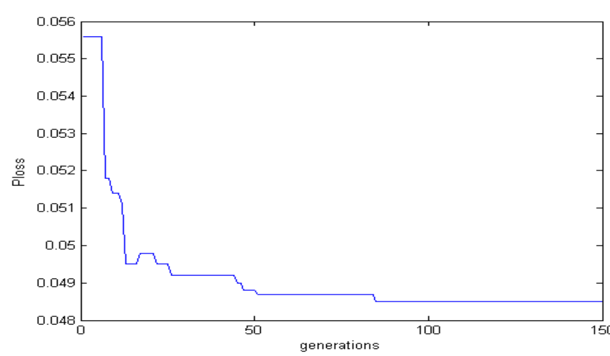

Figure 5: Objective function value Vs Generations for case 1

D. Case 2: contingency case

Again in this case, the same values of load condition and generator setting as in case 1 are followed. But a network contingency is considered in this case. Additional constraint in the form of limit on the maximum value of L-index as in normal condition is incorporated. This is done to restrict the maximum value of L-index under contingency condition from reaching a dangerously high value. For the network contingency, namely, line outage (4 -12), with the inclusion of the voltage stability constraint the DE-based algorithm was applied to obtain the optimal values of the control variables under normal condition, the result of which is given in the Table V. For these optimal values of control variables when line (4 -12) was removed it was found that the maximum value of L-index reached by the system is 0.1800 only. This improvement in voltage stability was achieved because of the restriction put on the maximum L-index value in the base case condition. Table VI shows the performance parameters of the reactive power dispatch obtained using DE-based RPD. This shows the effectiveness of the proposed algorithm for voltage security enhancement.

TABLE V
CONTROL VARIABLES FOR THE 30-BUS SYSTEM

I. Generator voltages		II. Shunt Compensation		III. Transformer taps	
bus No.	Value	SVC	Value	Tran. Tap	Value
1	1.0700	Q_{c10}	0.0140	T_{6-9}	1.0284
2	1.0625	Q_{c12}	0.0554	T_{6-10}	0.9000
5	1.0387	Q_{c15}	0.0421	T_{4-12}	1.0137
8	1.0403	Q_{c17}	0.0260	T_{28-27}	0.9850
11	1.0863	Q_{c20}	0.0484		
13	1.0646	Q_{c21}	0.0159		
		Q_{c23}	0.0194		
		Q_{c24}	0.0497		
		Q_{c29}	0.0288		

TABLE VI
PERFORMANCE PARAMETERS

Parameter	Values	
	Case 1	Case 2
P_{g1} (pu)(slack bus)	0.9985	1.0236
$L_{\max}$	0.1310	0.1800
P_{loss} (pu)	0.0485	0.0507

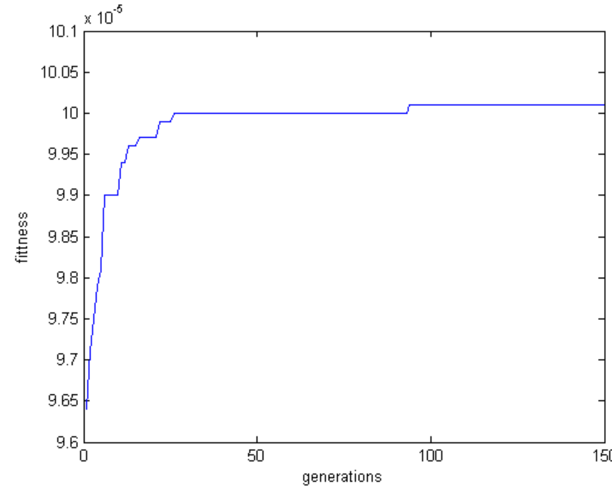

Figure 6: Fitness function value Vs Generations for case 2

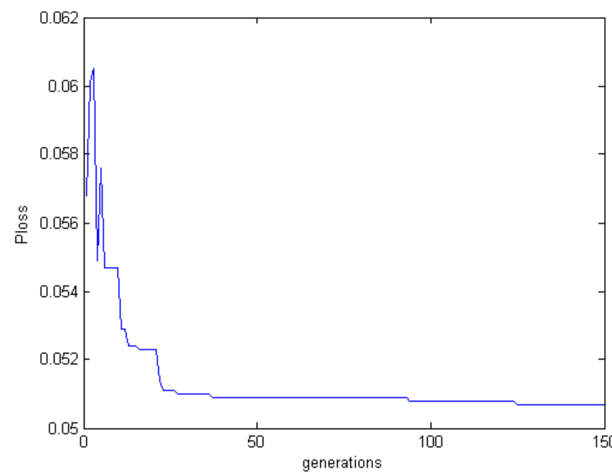

Figure 7: Objective function value Vs Generations for case 2

7. CONCLUSIONS

This paper presents a DE solution to the optimal reactive power allocation 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 RPD problem. The DE approach is useful for obtaining high-quality solution in a very less time compared to other methods.

Differential evolution algorithm is a stochastic optimization technique was employed as the optimization approach in determining the optimum values for the reactive power to be dispatched to establish voltage stability during contingency condition. Simulation results shows that the DE-based reactive power dispatch algorithm is able to improve voltage stability condition along with loss minimization in the system. Also, it is found that the results of the DE-based algorithm are always better than that obtained using conventional methods.

The future work in this area consists of the applicability of DE solutions to large-scale RPD problems of systems with several thousands of nodes. The continuous demand in electric power system network has caused the system to be heavily loaded leading to voltage instability. Voltage instability condition in a stressed power system could be improved by having an effective reactive power dispatch (RPD) procedures.

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