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Differential Evolution Approach for Contingency Constrained Reactive Power Planning

This paper presents a Differential Evolution (DE) approach for solving the contingency constrained optimal Reactive Power Planning (RPP) problem. Differential evolution is a simple population based algorithm with the ability in searching global optimum solution of non-linear and non convex optimization problems. While solving the RPP problem using Differential Evolution, the voltage magnitudes are taken as continuous variables, whereas the transformer tap setting and the reactive power generation of capacitor are taken as discrete variables. The proposed algorithm has been applied to find the optimal reactive power control variables in IEEE 30-bus system, 76 bus Indian system and IEEE 57-bus system under normal and contingency states. The results are promising and show the effectiveness and robustness of the proposed approach.

Keywords: - Differential evolution, Reactive Power Planning, Contingency, Voltage profile Enhancement

Nomenclature

G_{ij}, B_{ij}	Conductance and Susceptance of transmission line Connected between i^{th} and j^{th} bus.
P_i, Qi	Real and Reactive power injection of i^{th} bus.
P_s	Real power generation of slack bus.
Q_{ci}	Reactive power source installation at bus i.
Q_{gi}	Reactive power generation at bus i.
V_{gi}	Generator voltage magnitude at bus i.
t_k	Tap setting of transformer at branch k.
N_l	Set of number of load level duration.
N_E	Set of branch numbers.
N_C	Set of number of possible reactive power source installation buses.
N_T	Number of tap-setting transformer branches.
N_{PV}	Number of voltage buses.
N_B	Total number of buses.
N_{PQ}	Number of load buses.
N_{B-1}	Total number of buses excluding slack bus.
h	Per unit energy cost.
d_l	Duration of load level (h).
g_k	Conductance of branch k.
V_i	Voltage magnitude at bus i.
e_i	Fixed reactive power source installation cost at bus i.
C_{ci}	Per unit reactive power source purchase cost at bus i.

2. Introduction

Reactive Power Planning in power systems is a very important issue in the expansion planning and operation of power systems because it leads to increased transmission capability, reduced losses and improved power factor using shunt capacitors that have been very commonly installed in transmission networks. By applying capacitors adjacent to

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loads, several advantages are obtained. Some of them are improved power factor, reduced transmission losses, increased transmission capability, improved voltage control and improved power quality.

The goal of reactive power planning is to determine the location and amount of shunt reactive power compensation devices to be installed in the system to maintain satisfactory voltage profile during normal and anticipated contingency conditions at minimum cost. It is one of the most complex problems in power systems, as it requires the simultaneous minimization of two objectives. The first objective deals with minimization of real power losses in reducing the operation cost and improving the voltage profile. The second objective minimizes the allocation cost of additional reactive power sources.

The application of optimization techniques to power system planning and operation has been an active research area in the recent past. Mathematical programming techniques such as gradient method [1], Newton method [2], quadratic programming [3], linear programming [4-7], mixed integer programming [8], decomposition method [9-12] and interior point method [13] have been applied to solve the reactive power optimization problems. Most of these conventional optimization methods use the first and second derivatives of the objective functions and its constraint equations as the search directions. The conventional optimization methods can only lead to local minimum and sometimes result in divergence in solving RPP problems. Further, the conventional methods cannot deal with the non-differentiable factor in the reactive power sources installation function in RPP.

Global optimization techniques such as Genetic algorithm (GA) [13,14] Tabu search [15] Evolutionary programming [16] Evolutionary strategy [17] and simulated annealing [18] have been recently applied to reactive power optimization leading to improved solutions. Iba [13] proposed a GA-based method to the reactive power allocation planning which utilizes unique intentional operations. The first is “interbreeding” which is a kind of crossover using decomposed subsystem. This idea is similar to agricultural plant breeding, since it assembles a whole system using good parts with various features. The second is “gene recombination” or “manipulation”.Urdaneta et.al [14] proposed a modified GA at an upper stage and successive linear programming at a lower stage for the solution of reactive power planning problem. The genetic algorithm is devoted to find the location of new reactive power sources and the magnitude of reactive power sources to be installed at the previously determined locations was calculated by means of linear program iterated successively with a fast decoupled load flow algorithm.Gan et.al [15] proposed a tabu search method for solving large scale var optimization and planning problem. Simulation result of real world power system problem is presented in this paper. A comparison between the tabu search and simulated annealing method in solving the RPP problem is also given. Lai et.al [16] proposed an evolutionary programming approach to solve the reactive power planning problem and compared with non linear programming approach for the IEEE 30-bus system and a practical system. Kwang et.al [17] proposed a comparative study of three evolutionary algorithms namely evolutionary programming, evolutionary strategy and genetic algorithm in solving the RPP problem. In this paper the reactive power planning problem is decomposed into P- and Q – optimization modules and each module is optimized by the three evolutionary algorithms in an iterative manner to obtain the global solution. Jwo et.al [18] proposed a hybrid expert system and simulated annealing method to solve the reactive power planning problem. In this paper expert system consisting of several heuristic rules was used to find a local optimum solution, which will be employed as an initial starting point of the second stage. It can deal with a mixture of continuous and discrete variables. Devaraj et.al [19] proposed an improved genetic algorithm approach for solving the multiobjective reactive power dispatch problem. Minimization of real power loss and total voltage deviation were the objectives of this reactive power optimization problem. In this approach, modifications were proposed to take into account the discrete nature of the transformer tap setting and capacitor bank. For effective genetic operation, the crossover and mutation operators which can directly deal with the floating point numbers and integers are used. Hamouz et.al [20] proposed a particle swarm optimization algorithm for optimal reactive power planning. In this paper, the problem was decomposed into real power and reactive power optimization sub problems. The real power optimization minimizes the operation cost by adjusting the real power generation, while reactive power optimization minimizes the operation cost and investments on VARS by adjusting the reactive power generation, transformer tap setting and capacitor setting. This paper is concerned with the application of Differential Evolution (DE) for reactive power planning in power systems including line flow and voltage profile improvement in power systems.

Differential evolution (DE) [21, 22] is one of the recently developed evolutionary computation technique. Differential evolution improves a population of candidate solutions over several generations using the mutation, crossover and selection operators in order to reach an optimal solution. Differential evolution presents good convergence characteristics and requires few control parameters, which remain fixed throughout the optimization process and need minimum tuning. The DE technique can generate high quality solutions within shorter computation time and possess stable convergence characteristics than other stochastic methods. In this work, the DE algorithm is extended to handle mixed variables, such as transformer taps and reactive power sources. The performance of DE in solving the RPP problem is evaluated on IEEE 30, IEEE 57 bus test system and a practical 76 bus Indian system. Simulation results demonstrate that the proposed approach is superior to the existing methods for solving the reactive power planning problem.

3. Problem Formulation

The reactive power planning is concerned with determining the "optimal" reactive power control variables which results in minimum real power loss and reactive power source allocation cost while maximizing the voltage profile. The cost minimization comprises of two terms. The first term represents the total cost of energy loss given by

$$W_c = h\sum_{l \varepsilon N_i} d_l P_{loss}^l = h\sum_{l \varepsilon N_l} d_l \left[\sum_{\substack{k \in n_E \\ k=(i,j)}} g_k (V_i^2 + V_j^2 - 2V_i V_j Cos\ \theta_{ij} \right] \quad (1)$$

Where P_{loss} is the network real power loss during the period of load level *l*.

The second term represents the cost of reactive power source installation which has two components, the fixed installation cost and the purchase cost given by the equation

$$I_c = \sum_{i \in N_c} (e_i + C_{ci} \left| Q_{ci} \right|) \quad (2)$$

Here Q_{ci} *can* be either positive or negative corresponding to the installation of capacitance or reactance and so the absolute value is used to compute the cost.

The above two terms are put into one equation which can be easily adjusted by changing the parameters in W_c and I_c.

Minimize $F = W_c + I_c$ (3)

Subject to:

(i) Real power balance Equation:

$$P_i - V_i \sum_{j=1}^{N_B} V_j [G_{ij} \cos\theta_{ij} - B_{ij} \sin\theta_{ij}] = 0 \quad i = 1,2...N_{B-1} \tag{4}$$

(ii) Reactive power balance Equation:

$$Q_i - V_i \sum_{j=1}^{N_B} V_j [G_{ij} \sin\theta_{ij} - B_{ij} \cos\theta_{ij}] = 0 \quad i = 1,2...N_{PQ} \tag{5}$$

(iii) Slack bus real power generation limit:

$$P_S^{\min} \le P_S \le P_S^{\max} \tag{6}$$

(iv) Generator reactive power generation limit:

$$Q_{gi}^{\min} \le Q_{gi} \le Q_{gi}^{\max} \quad i \in N_{PV} \tag{7}$$

(v) Bus voltage limit:

$$V_i^{\min} \le V_i \le V_i^{\max} \quad i \in N_B \tag{8}$$

(vi) Capacitor reactive power generation limit:

$$Q_{ci}^{\min} \le Q_{ci} \le Q_{ci}^{\max} \quad i \in N_c \tag{9}$$

(vii) Transformer tap setting limit:

$$t_k^{\min} \le t_k \le t_k^{\max} \quad i \in N_T \tag{10}$$

(viii) Line flow limit:

$$S_l \le S_l^{\max} \quad l \in N_l \tag{11}$$

From the mathematical formulation of the RPP problem it is found that it is a non-linear combinatorial optimization problem**.** Conventional optimization techniques are not efficient in solving this complex optimization problem. In this work, DE is applied to solve the RPP problem. Section 4 presents the details of the DE-based approach for solving this complex optimization problem.

4. Review of Differential Evolution Algorithm

Differential Evolution is an evolutionary computation algorithm developed by Storn and Price in 1995 [20]-[22] which solves real valued problems based on the principles of natural evolution. It is a heuristic optimization method which can be used to optimize nonlinear and non-differentiable continuous space functions. It has been extended to handle mixed integer discrete continuous optimization problem also. DE uses a population P of size N_P that evolves over G generations to reach the optimal solution. Each individual X_i is a vector that contains as many parameters as the problem decision variables D.

$$P^{(G)} = \left[X_1^{(G)}, \ldots\ldots, X_{N_P}^{(G)}\right] \tag{12}$$

$$X_i^{(G)} = \left[X_{1.i}^{(G)}, \ldots\ldots, X_{D,i}^{(G)}\right]^T, \quad i = 1, \ldots, N_P \tag{13}$$

The population size N_P is an algorithm control parameter selected by the user which remains constant throughout the optimization process. The optimization process in Differential Evolution is carried out using the three basic operations: Mutation, Crossover and Selection. The algorithm starts by creating an initial population of N_P vectors. Random values are assigned to each decision parameter in every vector as follows.

$$X_{j,i}^{(0)} = X_j^{\min} + \eta_j \left(X_j^{\max} - X_j^{\min} \right) \tag{14}$$

Where $i = 1,....., N_P$ and $j = 1,.....,D$; $X_j^{\min}$ and $X_j^{\max}$ are the lower and upper bounds of the j[th] decision parameter; and η_j is a uniformly distributed random number within [0, 1] generated for each value of j. $X_{j,i}^{(0)}$ is the j[th] parameter of the i[th] individual of the initial population. The main steps of the DE algorithms are given below:

Initialization
Evaluation
Repeat
Mutation
Crossover
Evaluation
Selection
Until *(termination criteria are met)*

Mutation

The mutation operator creates mutant vectors $\left(X_i^{'} \right)$ by perturbing a randomly selected vector X_a with the difference of two other randomly selected vectors X_b and X_c

$$X_i^{'(G)} = X_a^{(G)} + F\left(X_b^{(G)} - X_c^{(G)} \right) \quad i = 1,......, N_P \tag{15}$$

Where X_a X_b and X_c are randomly chosen vectors among the N_p population, and $a \neq b \neq c \neq i$. The scaling constant F is an algorithm control parameter used to adjust the perturbation size in the mutation operator and to improve algorithm convergence.

Crossover

The crossover operation generates trail vectors $\left(X_i^{''} \right)$ by mixing the parameters of the mutant vectors $\left(X_i^{'} \right)$ with the target vector $\left(X_i \right)$ according to a selected probability distribution,

$$X_{j,i}^{''(G)} = \begin{cases} X_{j,i}^{'(G)}, & if \quad \eta_j^{'} \leq C_R \quad or \quad j = q \\ X_{j,i}^{(G)}, & otherwise \end{cases} \tag{16}$$

Where $i = 1,....., N_P$ and $j = 1,.....,D$; q is a randomly chosen index $\in \{1,....., N_P\}$ that guarantees that the trail vector gets at least one parameter from the mutant vector; $\eta_j^{'}$ is a uniformly distributed random number within [0, 1] generated for each value of *j*.The crossover constant C_R is an algorithm parameter that controls the diversity of the population and aids the algorithm to escape from local minima. $X_{j,i}^{(G)}$, $X_{j,i}^{'(G)}$ and $X_{j,i}^{''(G)}$ are the *j*[th] parameter of the i^{th} target vector, mutant vector and trail vector at generation G, respectively.

Selection

The selection operation forms the population by choosing between the trail vectors and their predecessors (target vectors) those individuals that present a better fitness or are more optimal according to (17).

$$X_i^{(G+!)} = \begin{cases} X_i^{''(G)} & if \quad f\left(X_i^{''(G)}\right) \le f\left(X_i^{(G)}\right) \\ X_i^{(G)} & otherwise \end{cases}, i = 1,......, N_P \tag{17}$$

This process is repeated for several generations allowing individuals to improve their fitness as they explore the solution space in search of optimal values.

DE has three essential control parameters: the scaling factor (F), the crossover constant (C_R) and the population size (N_P). The scaling factor is a value in the range [0, 2] that controls the amount of perturbation in the mutation process. The crossover constant is a value in the range [0,1] that controls the diversity of the population. The population size determines the number of individuals in the population and provides the algorithm enough diversity to search the solution space.

Control parameter selection

Proper selection of control parameters is very important for algorithm success and performance. The optimal control parameters are problem specific. Therefore, the set of control parameters that best fit each problem have to be chosen carefully. The most common method used to select the control parameter is parameter tuning. Parameter tuning adjusts the control parameters through testing until the best settings are determined. Typically the following ranges are good initial estimates: [23]: F= [0.5, 0.6], CR= [0.75, 0.90] and N_P= [3D, 8D].

In order to avoid premature convergence, F or N_P should be increased, or C_R should be decreased. Larger values of F result in larger perturbation and better probabilities to escape from local optima, while lower C_R preserves more diversity in the population thus avoiding local optima.

5. DE Implementation for RPP

While applying DE to solve the reactive power planning problem, the following issues need to be addressed.

1. Representation of the problem variables and
2. Formation of the evaluation function.

These two issues are described in this section.

A. Problem Representation

Each vector in the DE population represents a candidate solution of the given problem. The elements of that solution consist of all the optimization variables of the problem. For the reactive power planning problem under consideration, generator terminal voltages (V_{gi}), the transformer tap positions (t_k) and the Capacitor settings (Q_{Ci}) are the optimization variables. Generator bus voltage is represented as floating point numbers, whereas the transformer tap position and reactive power generation of capacitor are represented as integers.

B. Evaluation Function

Differential evolution searches for the optimal solution by maximizing a given fitness function, and therefore an evaluation function which provides a measure of the quality of the problem solution must be provided. In the reactive power optimization problem under consideration, the objective is to minimize the total cost while satisfying the constraints (4-11). The equality constraints are satisfied by running the Newton Raphson power flow algorithm. The inequality constraints on the control variables are taken into account in the problem representation itself, 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 becomes,

$$Min\ f = F + SP + \sum_{j=1}^{N_{PQ}} VP_j + \sum_{j=1}^{N_\tau} QP_j + \sum_{j=1}^{N_1} LP_j \tag{18}$$

Here, SP,VP_j ,QP_j and LP_j are the penalty terms for the reference bus generator active power limit violation, load bus voltage limit violation; reactive power generation limit violation and line flow limit violation respectively. These quantities are defined by the following equations:

$$SP = \begin{cases} K_s \left(P_s - P_s^{\max}\right)^2 & if\ \ P_s > P_s^{\max} \\ K_s \left(P_s - P_s^{\min}\right)^2 & if\ \ P_s < P_s^{\min} \\ 0 & otherwise \end{cases} \tag{19}$$

$$VP_j = \begin{cases} K_v (V_j - V_j^{\max})^2 & if\ \ V_j > V_j^{\max} \\ K_v (V_j - V_j^{\min})^2 & if\ \ V_j < V_j^{\min} \\ 0 & otherwise \end{cases} \tag{20}$$

$$QP_j = \begin{cases} K_q (Q_j - Q_j^{\max})^2 & if\ Q_j > Q_j^{\max} \\ K_q (Q_j - Q_j^{\min})^2 & if\ Q_j < Q_j^{\min} \\ 0 & otherwise \end{cases} \tag{21}$$

$$LP_j = \begin{cases} K_l (L_j - L_j^{\max})^2 & if\ L_j > L_j^{\max} \\ 0 & otherwise \end{cases} \tag{22}$$

Where, K_s, K_v, K_q and K_l are the penalty factors. Since DE maximizes the fitness function, the minimization objective function f is transformed to a fitness function to be maximized as,

$$\text{Fitness} = \frac{k}{f} \tag{23}$$

Where k is a large constant.

6. Results and Discussion

The proposed DE-based approach for solving the reactive power planning was applied to IEEE 30-bus, IEEE 57-bus test system and practical 76-bus Indian system. The generator active power generation was kept fixed except for the slack bus. The base power and parameters of costs are given in Table 1. The program was written in MATLAB and executed on a PC with 2.4 GHZ Intel Pentium IV processor. The results of the simulation are presented below.

Case 1: Reactive Power Planning in IEEE 30-bus system:

The proposed DE based approach for solving Reactive Power Planning problem was applied to IEEE 30-bus test system which is shown in figure 1. The IEEE 30 bus system has 6 generators, 24 load buses, 41 transmission lines, 4 transformer taps and 2 shunt elements. The transmission line parameters and the system base load are taken from [24]. The variable limits are given in Table 2. The real power settings of the generator are taken from [24]. The possible locations for capacitor installation are buses 10, 12,15,17,20,21,23,24 and 29. The proposed algorithm was run with minimization of total cost as the objective function. The total cost consisting of fixed installation cost, purchase cost and operating cost are calculated and minimized in the base case. The DE based algorithm was tested with different parameter settings and best results are obtained with the following setting:

No. of Generations	:	20
Population Size	:	100
F	:	0.5
CR	:	0.9

The DE algorithm reaches a minimum cost of 2,591,830$ in this case. The algorithm took 50 sec to reach the optimal solution. The optimal values of control variables are given in the second column of Table 3. Corresponding to these control variables, it was found that there was no limit violation. The minimum cost obtained by the proposed algorithm is compared with evolutionary programming [16] approach and the results are presented in Table 4. The minimum costs obtained in this method is less then the value reported in [16]. This shows the effectiveness of the proposed approach in solving the RPP problem.

Table 3: Optimal values of Control Variables of Case 1

Control Variables	**Control Variables Setting**
V_1	1.09
V_2	1.08
V_5	1.05
V_8	1.06
V_{11}	1.04
V_{13}	1.05
t_{6-9}	1.05

$t_{6\text{-}10}$	0.95
$t_{4\text{-}12}$	1.025
$t_{28\text{-}27}$	1.00
C_{10}	1
C_{12}	5
C_{15}	3
C_{17}	5
C_{20}	5
C_{21}	4
C_{23}	5
C_{24}	5
C_{29}	1
P_{loss} (MW)	4.72
Cost	**2,591,830**
Vmin	1.07

Table 4: Comparison of results of total cost

Method	Case 1	
	Total Cost($)	$P_{loss(MW)}$
EP[16]	2,608,500	4.963
PROPOSED METHOD	2,591,830	4.72

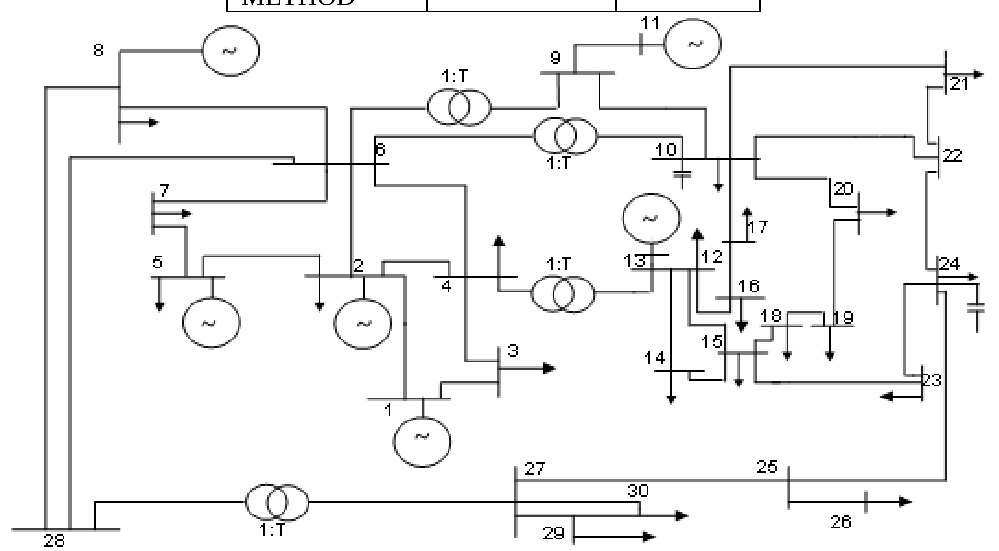

Fig.1. IEEE-30 bus test system

Case 2: Contingency Constrained Reactive Power Planning for IEEE 57-bus system:

The IEEE 57 bus system has 7 generators, 50 load buses, 80 transmission lines and 17 transformer taps. Two different cases are considered in this system. In case 1, the proposed DE algorithm is applied to minimize the total cost in base case without including the contingency constraint. In case 2, the algorithm is applied to minimize the total cost in base case after including contingency constraint. The possible locations of capacitor installation are buses 25, 30,32,34,35 and 53 to supply reactive power. The variable limits are given in Table 5. The DE based algorithm was tested with different parameter settings and best results are obtained with following setting:

No. of Generations	:	20
Population Size	:	100
F	:	0.5
CR	:	0.9

Table 6: Optimal values of Control variables of Case 2

Control Variable	Control Variables Setting	
	Case 1	Case 2
V_1	1.08	1.07
V_2	1.1	1.06
V_3	1.08	1.06
V_6	1.06	1.07
V_8	1.05	1.07
V_9	1.05	1.08
V_{12}	1.05	1.07
t_{4-18}	1.025	1.075
t_{4-18}	1.0	1.0
t_{21-20}	1.025	1.025
t_{24-25}	1.1	1.025
t_{24-25}	1.1	1.025
t_{24-26}	1.0	1.025
t_{7-29}	1.0	0.95
t_{34-32}	0.925	0.975
t_{11-41}	1.0	1.05
t_{15-45}	1.025	1.0
t_{14-46}	1.025	0.95
t_{10-51}	0.925	1.025
t_{13-49}	0.95	0.975
t_{11-43}	1.025	1.0
t_{40-56}	1.025	1.05
t_{39-57}	1.0	1.1
t_{9-55}	1.0	1.05
C_{25}	5	3
C_{30}	2	3
C_{34}	5	3
C_{32}	5	5
C_{35}	3	5
C_{53}	5	4
Loss (M W)	25.12	25.83
Cost ($)	**13,284,070**	**13,651,240**
Vmin	0.99	0.98
Time	52 sec	53 sec

The optimal values of the control variables, loss, cost, and minimum voltage for case1 are given in second column of Table 6. The minimum cost obtained by this algorithm is compared with genetic algorithm approach [25] and the results are presented in Table 7. The cost obtained by this method is less than the value reported in [25]. Next, the single line contingency analysis is performed in IEEE 57- bus system. From the contingency analysis, the line outage 25-30 is identified as the severe contingency with a minimum voltage of 0.60. The voltage limit violated buses in contingency state are 23,24,25,26,27,28,29 and 33. The voltage violation occurred during this contingency is added as an additional constraint in case 2. The optimal values of the control variables, loss, cost, time and minimum voltage in this case are given in third column of Table 6. From table 6, it is found that the real power loss and total cost were increased after including the contingency constraint in base case, but the voltage violations which were present earlier have been completely alleviated. The voltage magnitudes of the above buses before optimization and after optimization are displayed in figure 2. From this figure, it was inferred that the voltage magnitudes of the severe buses were improved after the optimization. Also, it was inferred that the minimum voltage is raised from 0.60 to 0.98 after the application of the proposed DE algorithm. Further, before the application of the algorithm voltage violation violations were present in the buses. But, they are corrected after the optimization. Table 8 gives the voltage magnitude for a selected list of buses for contingency 25-30. Improvement in voltage profile at the load buses is evident from the results. The algorithm took 52 sec to reach the optimal solution. This shows the effectiveness of the proposed algorithm in solving the contingency constrained reactive power planning problem.

Table 7: Comparison of cost in base case for IEEE 57-bus system

Method	Total cost ($)	$P_{loss\ in\ MW}$
GA [25]	14,561,000	25.9654
Proposed Method	13,284,070	25.12

Table 8: Improvement of voltage profile for IEEE 57 bus system

S.No	Bus No	Voltage Magnitude	
		Before Optimization	After Optimization
1.	23	0.60	0.98
2.	24	0.62	1.00
3.	25	0.75	1.02
4.	26	0.76	1.01
5.	27	0.90	1.00
6.	28	0.92	0.99
7.	29	0.94	1.02
8.	33	0.91	1.01

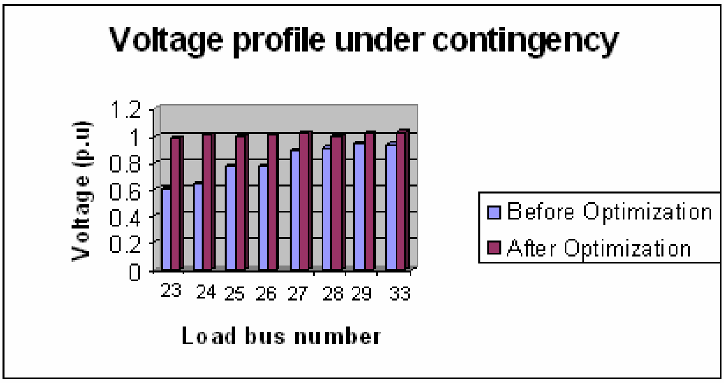

Figure 2: Voltage magnitudes of severe buses in contingency condition

Case 3: Reactive Power Planning of Practical 76-Bus Indian System:

The proposed DE approach was applied to solve the RPP problem in a practical Indian power system. The system under consideration is a regional grid of Indian power system , consisting of 13 generator buses, 63 load buses, 116 transmission lines , 18 tap changing transformers and switchable var compensators are located at 12 places. The total load on the system is 3668 MW and 2591 MVAR. The variable limits are given in Table 9. To obtain the optimal values of control variables the DE based algorithm was run with different parameter settings.

The best parameter settings are:

No of generation	:	20
Population size	:	100
F	:	0.2
CR	:	0.9

The algorithm reaches a minimum cost of 26,553,160 $. The algorithm took 55 sec to reach the optimal solution. The optimal control variable settings obtained in this case are given in Table 10. The loss obtained in this case is 50.28 MW which is less than the loss obtained by conventional linear programming method [26]. From the comparison, it is found that the proposed method is more effective in solving the RPP problem than the other methods.

Table 10: Optimal control variables for practical 76 bus Indian system

Vvar	Tvar	Cvar
0.99	0.975	3
1.02	1.00	5
1.03	1.025	3
1.05	1.025	3
1.00	1.00	3
1.05	1.025	5
1.06	0.975	3
1.01	0.975	3
0.98	1.00	3
1.02	0.975	3
1.01	1.025	2
1.05	1.10	2
1.04	1.00	
	0.975	
	1.00	
	0.925	
	0.975	
	1.05	
Cost = 26,553,160 $		
TL = 50.28 MW		
Vmin =0.95		

7. Conclusion

This paper has presented a differential evolution approach for solving the reactive power planning problem. The algorithm minimizes the operation cost and allocation cost of reactive power sources and voltage profile enhancement by adjusting the control variables such as generator voltage magnitude, setting of tap changing transformer and Capacitor setting. The proposed method formulates the reactive power problem as a mixed integer non-linear optimization problem and determines the control strategy with continuous and discrete control variables such as generator bus voltage, reactive power generation of capacitor banks and on load tap changing transformer tap position. To handle the mixed variables flexible representation scheme was proposed. Simulation results on IEEE 30-bus test system, IEEE 57-bus system and practical 76-bus Indian system demonstrate the effectiveness of the proposed approach in minimizing the cost and maximizing the voltage profile of the systems in base case and contingency conditions.

8. References

[1] F.F. Wu. G. Gross, J.F. Luini, P.M. Look, "A Two-stage Approach To Solving Large-scale Optimal power Flows," Power Industry Computer Applications Conference, 1979, PICA-79, *IEEE Conference Proceedings*, May 15-18, 1979, p.p.126-136.

[2] O. Crisan, M.A. Mohtadi, "Efficient identification of binding inequality constraints in optimal power flow Newton approach", Generation, Transmission and Distribution, IEE Proceedings C, vol.139, no.5, Sept. 1992, pp.365-370.

[3] A.D. Papalexopoulos, C.F. Imparato, F.F. Wu, "Large-scale optimal power flow: effects of initialization, decoupling and discretization," *IEEE Trans, on PAS*, vol.4, no.2, May 1989, p.p.748-759.

[4] K.R.C. Mamandur, R.D. Chenoweth, "Optimal control of reactive power flow for improvements in voltage profiles and for power loss minimization", *IEEE Trans. on PAS*, vol.100, no.7, July 1981, pp.3185-3193.

[5] A. Venkataramana, J. Carr, R.S. Ram Shaw, "Optimal reactive power allocation", *IEEE Trans. on PAS*, vol.PWRS-2, no.1, Feb. 1987, p.p.138-144.

[6] K. Iba, H. Suzuki, K.I. Suzuki, K. Suzuki, "Practical reactive power allocation/operation planning using successive linear programming", *IEEE Trans. on PAS*, vol3, no.2, May 1988, p.p.558-566.

[7] B. Venkatesh, G. Sadasivam, M.. Khan, "Optimal reactive power planning against voltage collapse using the successive multiobjective fuzzy LP technique", *IEEE Produceedings on Generation, Transmission and Distribution*, Vol.146, no.4 July 1999, pp.343-348.

[8] K. Aoki, M. Fan, A. Nishikori, "Optimal VAr planning by approximation method for recursive mixed-integer linear programming", *IEEE Trans. on PAS*, vol.4, no.4, Nov. 1988, pp.1741-1747.

[9] N. Deep, S.M. Shahidehpour, "Linear power optimization in a large power network using the decomposition approach," *IEEE Trans. on PAS*, vol.5, no.2, May 1990, pp.428-438.

[10] T.Gomez, I.J. Perez-Arriaga, J. Lumbreras, V.M. Parra, "A security constrained decomposition approach to optimal reactive power planning," *IEEE Trans. on PAS*, vol.6, no.3, aug.1991, pp. 1069-1076.

[11] Y.Y. Hong, D.I. Sun, S.Y. Lin, C-J Lin, "Multi-year multi-case optimal VAR planning," *IEEE Trans. on PAS*, vol.5, no.4, Nov.1990 p.p.1294-1301.

[12] N.I. Deeb, S.M. Shahidehpour, "Cross decomposition four multi-area optimal reactive power planning", *IEEE Trans. on PAS*, vol.8, no.4, Nov.1993, p.p.1539-1544.

[13] Iba.K,"Reactive power optimization by genetic algorithms", *IEEE Transactions on Power Systems*, Vol.9, No2, May 1994, pp.685-692.

[14] A.J. Urdaneta, J.F. Gomez, E. Sorrentino, L. Flores, R. Diaz, "A hybrid genetic algorithm for optimal reactive power planning based upon successive linear programming", *IEEE Trans. On PAS*, vol. 14, no.4, Nov.1999, pp.1292-1298.

[15] D.Gan, Z.Qu and H.Cai,"Large scale Var optimization and planning by tabu search" *Electric Power System Research* 1996, 39(3), 195-204.

[16] L.L. Lai, J.T. Ma, "Application of evolutionary programming to reactive power planning-comparison with nonlinear programming approach, "*IEEE Trans. On PAS*, vol.12, no.1, Feb. 1997, p.p.198-206.

[17] K.Y. Lee, F.F. Yang, "Optimal reactive power planning using evolutionary algorithms: a comparative study for evolutionary programming, evolutionary strategy, genetic algorithm, and linear programming", *IEEE Trans. On PAS*, vol.13, no.1 Feb. 1998, p.p.101-108.

[18] W.S. Jwo, C.W. Liu, C.-C. Liu Y.-T. Hsiao, "Hybrid expert system and simulated annealing approach to optimal reactive power planning", *IEE Proceedings on Generation, Transmission and Distribution*, vol. 142, no.4, July 1995, pp.381-385.

[19] D.Devaraj,S.Durairaj and P.S.Kannan,"Real parameter genetic algorithm for multiobjective reactive power dispatch", *International Journal of Power and Energy Systems*,Vol.28,No.1,2008.

[20] Z.Al.Hamouz, S.F.Faisal and S.Al.Sharif, " Application of particle swarm optimization algorithm for optimal reactive power planning", *International Journal on control and Intelligent Systems*, Vol.35, No.1, 2007, pp 66-72.

[21] K.Price,"Differential Evolution: a fast and simple numerical optimizer", Biennial conference of the North American Fuzzy Information Processing Society NAFIPS, 19-22 Jun 1996,pp.524-527.

[22] R.Storm,"On the usage of differential evolution for function optimization", Biennial conference of the North American *Fuzzy Information Processing Society NAFIPS*, 19-22 Jun 1996, pp.519-523.

[23] R.Storm, K.Price,"Differential Evolution – a simple and efficient adaptive scheme for global optimization over continuous spaces", *Journal of Global Optimization*, vol.11, 1997, Dordrecht, pp.341-359.

[24] O. Alsac and B. Stott, "Optimal load flow with steady state security", *IEEE Transactions on Power Apparatus and Systems*, Vol. PAS – 93, 1974, pp 745 – 751.
[25] S.Subamalini, S.Durairaj, D.Devaraj,"Reactive power planning including FACTS devices using genetic algorithm", Proceeding of 14th National *Conference on Power Systems*, IIT, Roorkee, 27-29, December 2006.
[26] S.Durairaj, P.S.Kannan and D.Devaraj," Multi objective VAR dispatch using particle swarm optimization",*International Journal of Emerging Electric Power Systems*,Vol.4,Issue 1,2005,pp 1-16.

Appendix

Table 1: Base Power and parameter of costs

S_B	H	e_i	C_{ci}	d_l		
(MUA)	($/p.u.wh)	($)	($./p.u.VAR)	Case1	Case 2	Case 3
100	6000	1000	3000,000	8760	8760	8760

Table 2: Variable limits (p.u) of IEEE 30-bus test system

Bus	1	2	5	8	11	13
Q_g^{max}	1.5	0.6	0.48734	0.6245	0.4	0.45
Q_g^{min}	-0.2	-0.2	-0.15	-0.15	-0.1	-0.15

V^{max}	V^{min}	T^{max}	T^{min}	Q_c^{max}	Q_c^{min}
1.35	0.95	1.1	0.9	5.0	0.0

Table 5: Variable limits (p.u) of IEEE 57-bus test system

Bus	1	2	3	6	8	9	12
Q_g^{max}	2.0	0.50	0.60	0.25	2.0	0.9	1.55
Q_g^{min}	-1.4	-0.17	-0.1	-0.08	-1.4	-0.03	-1.5

V^{max}	V^{min}	T^{max}	T^{min}	Q_c^{max}	Q_c^{min}
1.35	0.95	1.1	0.9	5.0	0.0

Table 9: Variable limits (p.u) of Practical 76-bus Indian system

Bus	1	2	3	4	5	6	7	8	9	10	11	12	13
$Q_{g\,max}$	1.0	2.0	1.0	3.0	4.0	2.2	2.2	2.2	0.8	0.35	0.4	1.0	1.5
$Q_{g\,min}$	-0.6	-1.0	-0.5	-1.5	-2.0	-1.0	-1.0	-1.0	-0.4	-0.2	-0.5	-1.5	-1.0

V^{max}	V^{min}	T^{max}	T^{min}	Q_c^{max}	Q_c^{min}
1.35	0.95	1.1	0.9	5.0	0.0