

IMPROVED DIFFERENTIAL EVOLUTION APPROACH FOR MULTI OBJECTIVE REACTIVE POWER PLANNING INCORPORATING VOLTAGE STABILITY

First J.PREETHA ROSELYN

SRM University, Chennai,India
8939916663, preetha.roselyn@gmail.com

Second D.DEVARAJ

Kalasalingam University, Srivilliputhur,India
9842913053,deva230@yahoo.com

Third S.S.DASH

SRM University, Chennai,India
9884356933, munu_dash_2k@yahoo.com

Abstract: *This paper proposes the application of Improved Differential Evolution (IDE) algorithm to solve the Voltage Stability Constrained Reactive Power Planning (VSCRPP) problem. Minimization of total cost of energy loss and cost of VAR source installments are taken as the objectives incorporating static voltage stability constraints to analyze VAR support decisions in the Reactive Power Planning (RPP) problem. The maximum L-index of the load buses is taken as the indicator of voltage stability. In the proposed approach, generator bus voltage magnitudes, transformer tap settings and reactive power generation of capacitor bank are taken as the control variables and are represented as the combination of floating point numbers and integers. DE/randSF/1/bin strategy scheme of Differential Evolution with self tuned parameter which employs binomial crossover and difference vector based mutation is used for the VSCRPP problem. The proposed VAR planning model is implemented on two typical systems, IEEE 30-bus system and IEEE 57 bus test system using Improved DE. The simulation results of the proposed optimization approach is better than Modified Genetic Algorithm (MGA) with BLX- α crossover and non uniform mutation and other conventional methods.*

Key words: *Reactive Power Planning, Voltage Stability, L-index, Differential Evolution..*

1. Introduction.

Reactive power planning is one of the most challenging problems in power systems, as it involves the simultaneous minimization of two objective functions and hence falls in non smooth and non differentiable optimization problems. It is to plan for economic compensation strategy of new reactive power sources in next few years. The first objective deals with the minimization of operation cost by reducing real power loss and improving the voltage profiles. The second objective minimizes the allocation cost of additional reactive power sources. Thus the VAR planning aims at reduced VAR support to maintain feasible operation with acceptable voltage profiles. Conventional calculus based optimization algorithms like linear programming [1], nonlinear programming [2] and

Newton method [3] have been applied to solve the RPP problem. The conventional optimization methods may lead to local minimum and sometimes result in divergence in solving complex RPP problems.

Recently, Evolutionary computation techniques like Genetic Algorithm (GA) [4] and Evolutionary programming (EP) [5] have received greater attention to obtain global optimum for RPP problem. Lai et al [2] proposes an application of evolutionary programming approach to RPP problem. The test results are compared with conventional gradient based optimization method. In [6], an Integer-coded multi objective Genetic algorithm is applied to reactive power planning problem considering both intact and contingent operating states. The problem of voltage stability and voltage collapse has become a major concern in power system planning and operation. The reactive power support and voltage problems are intrinsically related. Ajjarapu et. al [7] proposed a method of determining the minimum amount of shunt reactive power support which indirectly maximizes the real power transfer before voltage collapse is encountered. A sequential quadratic programming algorithm is adopted to solve the optimal solution. Vaahedi et. al [8] proposed an algorithm for optimal Var planning which takes into account voltage profile and voltage stability margins simultaneously. A new and fast method for computing the minimum voltage stability margin (VSM) of power systems is presented in [9]. The computation of the minimum VSM (mVSM) allows forecasting the load increase worst scenario. The information regarding the mVSM and the corresponding load increase direction for which it occurs, along with the usual VSM, allows operators to take measures like preventive control actions to move the system to secure operating points. Bedoya et al [10] presents critical areas using sensitivities

and participation factors for reactive compensation or load shedding control actions. The work demonstrates that by using sensitivity analysis, a dependable shape of the critical areas can be obtained without the calculation of eigen values and eigen vectors. Wang et al [11] proposed a flexible compensation method based on multi scenario and reactive power divisions to adapt the changes in future environment.

In this paper, voltage stability level is included as an additional constraint in the RPP problem in the contingency state. The L-index proposed in [12] is used as the indicator of voltage stability. DE is an attractive optimization tool due to simplicity in coding, accuracy, convergence speed and robustness and hence drawn the attention of many researches all over the world. This paper proposes an Improved DE with self tuned parameters for VSC-RPP problem. DE/rand/1/bin scheme [13] is used for the RPP problem in which mutation scheme uses a randomly selected vector and only one weighted difference vector is used to perturb it. The mutation scheme is combined with binomial type crossover and with random scale vector. The simulation results are compared with modified genetic algorithm [17] in which BLX- α crossover and non uniform mutation scheme is used.

2. Voltage Stability Indicator

Kessel and Glavitch [12] proposed an index, namely, L-index to assess the voltage stability level of the power system. It is based on load flow analysis. Its value ranges from 0 (no load condition) to 1 (voltage collapse). The bus with the highest L-index value will be the most vulnerable bus in the system. The L-index calculation for a power system is briefly discussed below:

Consider a N-bus system in which there are N_g generators. The relationship between voltage and current can be expressed by the following expression:

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

where, I_G , I_L and V_G , V_L represent currents and voltages at the generator buses and load buses.

Rearranging the above equation we get,

$$\begin{bmatrix} V_L \\ I_G \end{bmatrix} = \begin{bmatrix} Z_{LL} & F_{LG} \\ K_{GL} & Y_{GG} \end{bmatrix} \begin{bmatrix} I_L \\ V_G \end{bmatrix} \quad (2)$$

$$\text{Here } F_{LG} = -[Y_{LL}]^{-1} [Y_{LG}] \quad (3)$$

The L-index of the j^{th} node is given by the expression,

$$L_j = \left| 1 - \sum_{i=1}^{N_g} F_{ji} \frac{V_i}{V_j} \angle(\theta_{ij} + \delta_i - \delta_j) \right| \quad (4)$$

where

V_i , V_j Voltage magnitude of i^{th} and j^{th} generator.

θ_{ij} Phase angle of the term F_{ji} .

δ_i , δ_j Voltage phase angle of i^{th} and j^{th} generator unit.

The values of F_{ji} are obtained from the matrix F_{LG} . The L-indices for a given load condition are computed for all the load buses and the maximum of the L-indices (L^{max}) gives the proximity of the system to voltage collapse. The indicator L^{max} is a quantitative measure for the estimation of the distance of the actual state of the system to the stability limit. The L-index has an advantage of indicating voltage instability proximity of current operating point without calculation of information about maximum loading point.

3. Problem Formulation.

The objective function in RPP problem comprises of two terms, namely, the total cost of energy loss and the cost of reactive power source installation which is given by:

$$\text{Minimize } f_c = W_c + I_c \quad (5)$$

The first term W_c represents the total cost of energy loss as follows:

$$W_c = h \sum_{l \in N_l} d_l P_{\text{loss}_l} \quad (6)$$

Where, P_{loss_l} is the network real power loss during the period of load level d_l and is given by equation:

$$P_{\text{loss}_l} = \sum_{\substack{k \in N_l \\ k=(i,j)}} g_k (V_i^2 + V_j^2 - 2V_i V_j \cos \theta_{ij}) \quad (7)$$

The second term I_c represents the cost of VAR source installments which has two components namely a fixed installation cost and variable cost.

$$I_c = \sum_{i \in N_c} (e_i + C_{ci} |Q_{ci}|) \quad (8)$$

Where Q_{ci} is reactive power source installation at

bus i and Q_{ci} can be either positive or negative, depending on whether the installation is capacitive or reactive. Therefore, absolute values are used to compute the cost. The above two equations are put in one equation to obtain a comprehensive one.

The RPP problem is subjected to the following equality and inequality constraints:

(i) Real power balance Equation:

$$P_i - V_i \sum_{j=1}^{N_B} V_j [G_{ij} \cos \delta_{ij} + B_{ij} \sin \delta_{ij}] = 0 \quad ;$$

$$i = 1, 2, \dots, N_{B-1} \quad (9)$$

(ii) Reactive power balance Equation:

$$Q_i - V_i \sum_{j=1}^{N_B} V_j [G_{ij} \sin \delta_{ij} - B_{ij} \cos \delta_{ij}] = 0 \quad ;$$

$$i = 1, 2, \dots, N_{PQ} \quad (10)$$

(iii) Slack bus real power generation limit:

$$P_s^{\min} \leq P_s \leq P_s^{\max} \quad (11)$$

(iv) Generator reactive power generation limit:

$$Q_{gi}^{\min} \leq Q_{gi} \leq Q_{gi}^{\max} \quad i \in N_{PV} \quad (12)$$

(v) Generator bus voltage limit:

$$V_{gi}^{\min} \leq V_{gi} \leq V_{gi}^{\max} \quad i \in N_B \quad (13)$$

(vi) Capacitor bank reactive power generation limit:

$$Q_{ci}^{\min} \leq Q_{ci} \leq Q_{ci}^{\max} \quad i \in N_c \quad (14)$$

(vii) Transformer tap setting limit:

$$t_k^{\min} \leq t_k \leq t_k^{\max} \quad i \in N_T \quad (15)$$

(viii) Line flow limit:

$$S_l \leq S_l^{\max} \quad l \in N_l \quad (16)$$

The reactive power planning problem is transformed into voltage stability constrained reactive power planning by including L^{\max} in the contingency state as additional constraint in the problem formulation. Hence from the above formulation it is found that the VSC-RPP problem is a combinatorial non-linear optimization problem. Generator voltage magnitudes are represented as floating point numbers and the discrete variables appear in the form of transformer tap setting and reactive power generation of VAR sources.

4. Proposed Differential Evolution

Differential Evolution [14] is a population-based stochastic search algorithm that works in the general framework of evolutionary algorithms. Unlike traditional Evolutionary Algorithms, DE variants perturb the generation population members

with the scaled difference of randomly selected and distinct population members. The optimization variables are represented as floating point numbers in the DE population. The proposed DE based algorithm is shown in Figure 1. It starts to explore the search space by randomly choosing the initial candidate solutions within the boundary. Differential evolution creates new off springs by generating a noisy replica of each individual of the population. The individual that performs better from the parent vector (target) and replica (trial vector) advances to the next generation. This optimization process is carried out with three basic operations namely, mutation, crossover and selection. In the proposed work, DE/randSF/1/bin strategy with self tuned parameter is used to solve the VSC-RPP problem. Here rand denotes randomly selected vector to be perturbed, 1 denotes the number of difference vectors considered for perturbation and bin stands for binomial type of crossover operator. This strategy remains the most competitive scheme based on accuracy and robustness of results. The details of these operators are given below:

a. Initialization of parameter vectors:

DE begins with a randomly initiated population of NP real parameter vectors known as genomes/chromosome which forms a candidate solution to multidimensional optimization problem and is expressed as:

$$X_{i,G} = x_{1,i,G}, x_{2,i,G}, x_{3,i,G}, \dots, x_{D,i,G}$$

Where G is the generation number and D is the problem's dimension. For each parameter of the problem, there will be minimum and maximum value within which the parameter should be restricted. Hence the j th component of i th vector is initialized as follows:

$$x_{j,i,0} = x_{j,\min} + rand_{i,j}[0,1] \cdot (x_{j,\max} - x_{j,\min}) \quad (17)$$

Where $rand_{i,j}[0,1]$ is a uniformly distributed random number lying between 0 and 1.

b. Mutation with Difference vectors:

After the population is initialized, the mutation operator is in charge of introducing new parameters into the population. The mutation operator creates mutant vectors by perturbing a randomly selected vector (X_{r1}) with the difference of two other randomly selected vectors (X_{r2} and X_{r3}). 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. The process can be expressed as follows:

$$V_{i,G} = X_{r1,G} + F(X_{r2,G} - X_{r3,G}) \quad (18)$$

where F is scaling constant.

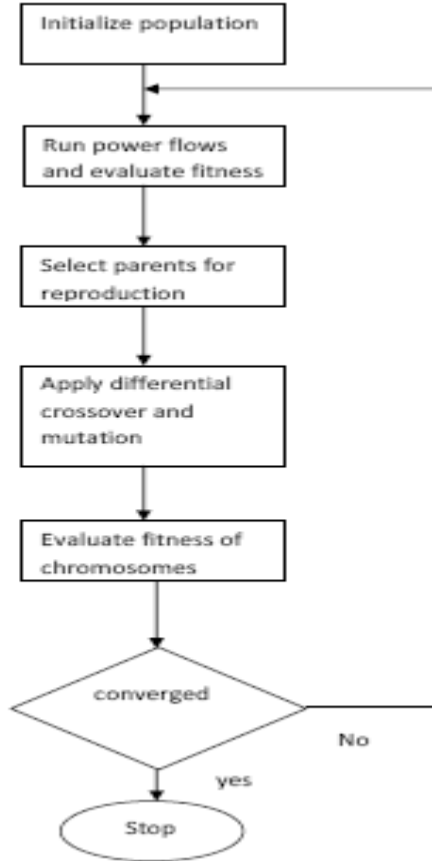


Figure 1. Flowchart of DE based algorithm

In this work, DERANDSF (DE with Random Scale Factor) is used in which the scaled parameter F is varied in a random manner in the range (0.4,1) by using the relation:

$$F = 0.5 \times (1 + \text{rand}(0,1)) \quad (19)$$

Where rand(0,1) is a uniformly distributed random number within the range [0,1]. This allows for the stochastic variations in the amplification of the difference vector and thus helps retain population diversity as the search progresses. The difference vector based mutation is believed to be the strength of DE because of the automatic adaptation in improving the convergence of the algorithm which comes from the idea of difference

based recombination operator i.e., Blend crossover operator (BLX)[16].

c. Crossover:

The crossover operator creates the trial vectors which are used in the selection process. A trial vector is a combination of mutant vector and a parent 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. In this work, binomial crossover is performed on each of the D variables. If the value of the random number is less or equal to the value of the crossover constant, the parameter will come from the mutant vector, otherwise the parameter comes from the parent vector. The crossover operation maintains diversity in the population preventing local minima convergence. The crossover constant must be in the range from 0 to 1. If the value of crossover constant is one then the trial vector will be composed of entirely mutant vector parameters. If the value of crossover constant is zero then the trial vector will be composed of entirely parent vector. Trial vector gets at least one parameter from the mutant vector even if the crossover constant is set to zero.

The scheme may be outlined as follows:

$$U_{i,j}(G) = \begin{cases} V_{i,j}(G) & \text{if } \text{rand}(0,1) \leq CR \text{ or } j = q \\ X_{i,j}(G) & \text{otherwise} \end{cases} \quad (20)$$

Where q is randomly chosen index in the D dimensional space.

CR is crossover constant

$X_{i,j}(G)$ is parent vector

$V_{i,j}(G)$ is mutant vector

d. Selection

To keep the population size constant over subsequent generations, the selection process determines which one of the target vector and trial vector will survive in the next generation and is outlined as follows:

$$X_i(G+1) = \begin{cases} U_i(G) & \text{if } f(U_i(G)) \leq f(X_i(G)), \\ X_i(G) & \text{if } f(X_i(G)) < f(U_i(G)) \end{cases} \quad (21)$$

Where f(X) is the objective function to be minimized. So if the new trial vector yields a better value of the fitness function, it replaces its target in the next generation; otherwise the target vector is retained in the population.

This process is continued until the

convergence criterion is satisfied. The termination condition is satisfied when the best fitness of the population does not change appreciably over successive iterations.

5. Differential Evolution Implementation

The following issues are addressed in the implementation of DE in VSC-RPP problem:

A. Problem Representation:

Generator bus voltages (V_{gi}), transformer tap positions (t_k) and reactive power generation of VAR sources (Q_{ci}) are the optimization variables for the VSC-RPP problem. The generator bus voltages are represented as floating point numbers, whereas the transformer tap position and the reactive power generation of VAR sources are represented as integers. The transformer tap setting with tapping ranges of $\pm 10\%$ and a tapping step of 0.025 p.u is represented from the alphabet (0,1,...8) and the VAR sources with limits of 1 and 5 p.u and step size of 1 p.u is represented from the alphabet (0,1,...5). With this representation, a typical chromosome of the RPP problem will look like the following:

0.981 0.970 .. 1.05 4 3 ... 1 -2 +1 ... +3
 $V_1 V_2 V_n Q_{c1} Q_{c2} Q_{cn} t_1 t_2 t_n$

B. Evaluation Function

In the reactive power optimization problem under consideration, the objective is to minimize the objective function which comprises the total cost of energy loss and VAR source installments of the system satisfying a number of equality and inequality constraints (5-12). For each individual, 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,

$$\text{Min } f = f_c + SP + \sum_{j=1}^{N_{PO}} VP_j + \sum_{j=1}^{N_q} QP_j + \sum_{j=1}^{N_l} LP_j \quad (22)$$

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:

$$SP = \begin{cases} K_s (P_s - P_s^{\max})^2 & \text{if } P_s > P_s^{\max} \\ K_s (P_s - P_s^{\min})^2 & \text{if } P_s < P_s^{\min} \\ 0 & \text{otherwise} \end{cases} \quad (23)$$

$$VP_j = \begin{cases} K_v (V_j - V_j^{\max})^2 & \text{if } V_j > V_j^{\max} \\ K_v (V_j - V_j^{\min})^2 & \text{if } V_j < V_j^{\min} \\ 0 & \text{otherwise} \end{cases} \quad (24)$$

$$QP_j = \begin{cases} K_q (Q_j - Q_j^{\max})^2 & \text{if } Q_j > Q_j^{\max} \\ K_q (Q_j - Q_j^{\min})^2 & \text{if } Q_j < Q_j^{\min} \\ 0 & \text{otherwise} \end{cases} \quad (25)$$

$$LP_j = \begin{cases} K_l (S_l - S_l^{\max})^2 & \text{if } S_l > S_l^{\max} \\ 0 & \text{otherwise} \end{cases} \quad (26)$$

where, K_s , K_v , K_q and K_l are the penalty factors. The success of the penalty function approach lies in the proper choice of these penalty parameters. Using the above penalty function approach, one has to experiment to find a correct combination of penalty parameters K_s , K_v , K_q and K_l . In contingency state, voltage stability indicator, L^{\max} is included as additional constraint in the evaluation function and weightage is given to voltage stability rather than VAR cost and helps to improve the voltage security of the system. Since DE maximizes the fitness function, the minimization objective function f is transformed to a fitness function to be maximized as,

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

where k is a large constant.

5. Simulation Results

The proposed DE-based approach for contingency constrained VAR planning model incorporating voltage stability is applied in IEEE 30- bus and IEEE 57-bus test systems. The real and reactive loads are scaled up according to predetermined weighting factors to analyze the system under stressed condition. Generator excitation, switchable VAR compensators and transformer tap settings are considered as control variables for reactive power planning problem. The load buses are considered as

candidates for VAR installation. The program was written in MATLAB and executed on a PC with 2.4GHz Intel Pentium IV processor. The results of the simulation are presented below:

Case 1:IEEE 30-Bus System

The IEEE 30-bus system has 6 generators, 24 load buses and 41 transmission lines of which four branches (6-9), (6-10), (4-12) and (28-27) are with the tap changing transformer. Buses 30,29,26,25 and 24 are identified for reactive power injection based on maximum L-indices of load buses. The network and its datas are taken from [2]. The load voltage limits are 0.95 and 1.05 pu respectively.

Table 1. Controller Settings for Under Base Case for IEEE 30 Bus System

Control Variables	Initial Setting	Optimal Setting
Voltage Magnitudes		
V ₁	1.074;	1.0499;
V ₂	1.065;	1.0479;
V ₃	1.043;	1.0307;
V ₄	1.042;	1.0361;
V ₅	1.069;	1.0207;
V ₆	1.058;	0.9501.
Transformer Tap settings		
t ₁	0.981;	1.1;
t ₂	1.042;	1.1;
t ₃	1.029;	1.1;
t ₄	1.037;	0.9.
VAR source Installments		
Q6	0 ;	
Q17	0 ;	
Q13	0 ;	
Q27	0 ;	
Q30		0 ;
Q29		0 ;
Q26		0 ;
Q25		0 ;
Q24		0 ;
Var Installation cost,	0	0
I _c		
Cost of energy loss, W _c	2.6085 x 10 ⁶ \$/hr	2.3878 X10 ⁶ \$/hr
Reactive power additional cost, F _c	2.6085 x 10 ⁶ \$/hr	2.3878 X10 ⁶ \$/hr
Transmission loss	4.963 MW	4.543 MW
L ^{max}	0.1978	0.1568

Generator voltage magnitudes are treated as continuous variables whereas transformer tap-settings and shunt capacitor banks are treated as discrete variables with 9 levels and 6 levels respectively. The DE- based algorithm was tested with different parameter settings and the best results are obtained with the following setting:

- Population size : 30
- Crossover Rate : 0.7
- Scaled Parameter : variable random tuned value
- Number of generations: 150

Table 2 .Comparison of Fuel Cost

Method	Minimum cost, F _c
Conventional method [2]	4.0133x 10 ⁶ \$/hr
Evolutionary Programming [2]	2.6085 x 10 ⁶ \$/hr
Modified Genetic Algorithm	2.4314 X 10⁶ \$/hr
Proposed Differential Evolution	2.3878 X 10⁶ \$/hr

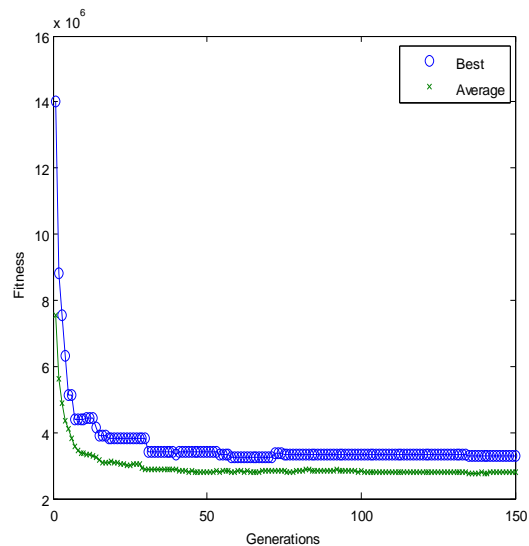


Figure 2. Convergence of DE-RPP algorithm for IEEE 30 bus system

The proposed approach took 184.75 secs to reach the optimal solution and is shown in Figure 2. Two sets of control variables are obtained for base case and contingency case. The optimal values of the control variables from the proposed algorithm along with

initial control variable setting are given in Table 1. The algorithm reached a minimum loss of 4.543 MW and the total cost is 2.3878×10^6 \$/hr. As indicated in Table 2, this total cost is less than the value reported in the literature for the IEEE 30-bus system under similar operating condition. For comparison, the RPP problem was solved using Modified Genetic Algorithm and it took 196.30 secs to reach the optimal solution. From this table, it is evident that the proposed Improved DE algorithm is more effective in reaching the optimal solution than the other evolutionary approaches.

Next contingency analysis was conducted on the system under base load condition. From the contingency analysis, line outages 28-27, 27-30 and 27-29 have been identified as severe cases with the L^{\max} values of 0.4165, 0.2352 and 0.2146 respectively. The L-indices of all the load buses are computed and is found that $L^{\max} = 0.1978$. The contingency state L^{\max} values were incorporated as additional constraints in the RPP problem and the DE/randSF/1/bin scheme based algorithm was applied to solve the VSC-RPP problem. The result of the VSC-RPP problem is given in Table 3. Under line outage 28-27, the maximum L-index has decreased from 0.4165 to 0.3836, a reduction of about 3.3% and the minimum voltage of the system has increased from 0.6721 to 1.0, an improvement of about 31%.

The real power savings and annual energy cost savings are calculated as follows:

$$P_{\text{save}} (\%) = \frac{P_{\text{loss}}^{\text{init}} - P_{\text{loss}}^{\text{opt}}}{P_{\text{loss}}^{\text{init}}} \times 100$$

$$W_C^{\text{save}} = h \cdot d_1 (P_{\text{loss}}^{\text{init}} - P_{\text{loss}}^{\text{opt}})$$

The real power savings from Improved DE is 8.46% and annual energy cost savings is \$ 227584.8 of those from evolutionary programming [15] in normal operating conditions. The comparison of voltage profile of the system before and after the application of improved DE and modified GA algorithms at the load buses for the contingency 28-27 are displayed in Figure 3. Improvement in the voltage profile of the system with the VSC-RPP algorithm is evident from this diagram. Further, before the application of the algorithm voltage violations were present in a few buses but they are corrected after the application of the proposed algorithm. Improvements in voltage stability and voltage profile have been achieved for the other contingency cases also. This shows the effectiveness of the proposed algorithm for voltage security improvement.

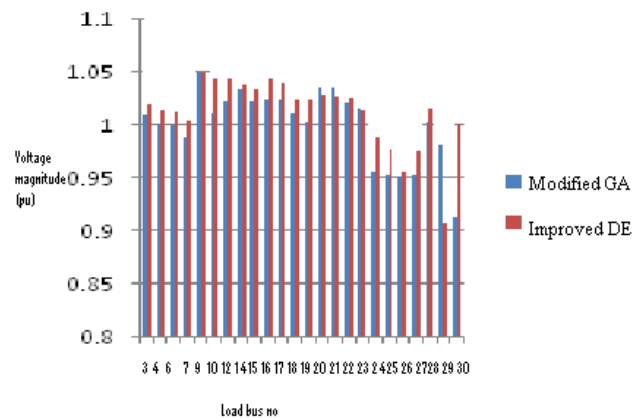


Figure 3. Voltage profile improvement for line outage 28-27 using proposed approach

Table 3. Results of Optimization Under Contingency State for IEEE 30-Bus System

	Line outage 28-27 (125% Loaded condition)		Line outage 27-30 (125% Loaded condition)		Line outage 27-29 (125% Loaded condition)	
	Before optimization	After optimization	Before optimization	After optimization	Before optimization	After optimization
L^{\max}	0.4165	0.3553	0.2352	0.1737	0.2146	0.1601
V^{\min}	0.6721	0.9817	0.9565	0.9820	1.0201	1.0434
Base Case Loss	4.8549 MW					
Var installation cost	2.5518 X 10^6 \$/hr					

Case 2: IEEE 57 Bus Test System

The IEEE 57-bus system was chosen as the second test system to demonstrate the method's usefulness on a large system. The details of the IEEE 57-bus system are given below:

No of generators	: 4
No of synchronous condensers	: 3
No of load buses	: 50
No of transmission lines	: 80
No of tap changing transformers	: 16

The base load of the system is 1272 MW and 298 MVAR. The upper and lower bus voltage limits are 0.96 and 1.04 pu respectively. The proposed DE was applied to solve the RPP problem under base load condition and has brought the total cost to 1.005×10^7 \$/hr. To analyze the system under disturbance condition, contingency analysis was conducted at 1.25 times the base load condition. From the contingency analysis, line outage 46-47 is found to be the most severe case with the L^{\max} value of 0.4598. From the weak bus ranking, buses 30,32,31,33 and 34 were selected for reactive power injection. In contingency state, the voltage stability indicator, L^{\max} was incorporated in the RPP problem as an additional constraint and the proposed DE-based approach was applied to solve the VSC-RPP problem. As in the previous case, generator voltages, shunt capacitors and on load tap changing transformer were used as the control variables for improving the voltage security.

Table 4. Results of optimization under contingency state for IEEE 57 Bus test system

	Line outage 28-27 (125% Loaded condition)		
	Before optimization	After optimization (GA)	After optimization (DE)
L_{\max}	0.9066	0.6065	0.4729
V_{\min}	0.7581	0.8007	0.9820
Reactive power additional Cost (\$/hr)	4.3979×10^7	2.3654×10^7	1.2731×10^7
P_{loss} (MW)	83.38	44.26	23.9878

The optimal control variable setting after the application of the algorithm for the contingency is summarized in Table 4. From this table, it is found that the value of L^{\max} decreases after the application of the algorithm. The real power savings from

Improved DE is 45.8% when compared to modified genetic algorithm and annual energy cost savings is \$10659186 in critical contingency state (46-47) in 125% loaded condition. The voltage profile of the system before and after the application of the algorithm under contingency 46-47 are displayed in Figure 4. Improvement in voltage profile of the system after the application of the algorithm is evident from this result. The minimum voltage of the system has been increased by 22% by proposed DE. Hence the improvement in voltage profile of the system after the application of the proposed algorithm is evident from this result.

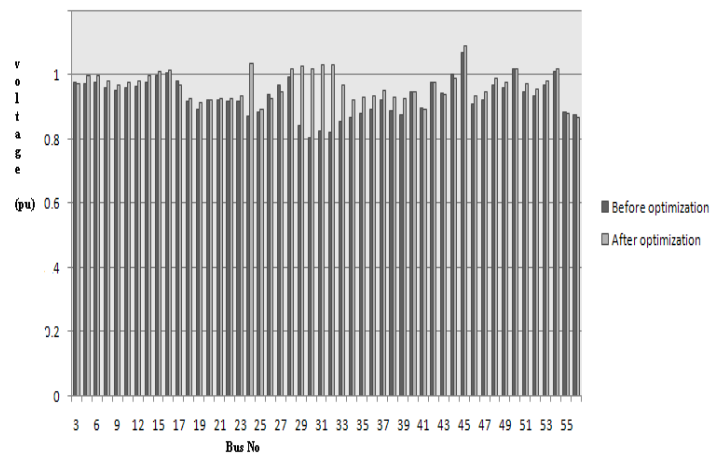


Figure 4 Voltage profile improvement for IEEE 57 bus system for line outage (46-47)

6. Conclusion

In this paper, Improved Differential Evolution algorithm with self tuned parameter has been applied to solve voltage stability constrained reactive power planning in power systems. The weak buses in the system were selected for reactive power injection. A multiobjective formulation of RPP problem has been developed in which candidate solutions are selected to reduce the reactive power installation cost and transmission loss while improving the voltage profile of the system. To improve the efficiency of the Differential Evolution algorithm in the search process, the optimization variables were represented in natural form. Further, of variable random scale vector to find the true global optimum in addition to binomial crossover and differential mutation vector is used. The simulation results of IEEE 30 bus

system and IEEE 57 bus test system shows that the proposed algorithm is effective in reducing the VAR installation cost and improving the voltage security of the system.

References

1. M.K.Mangoli., K.Y.Lee: *Optimal real and reactive power control using linear Programming*. In: Electric Power Systems Research . Vol 26(1993), p. 1-10.
2. L.L.Lai., J.T.Ma: *Application of Evolutionary programming to reactive power planning- Comparison with nonlinear programming approach..* In: IEEE Transactions on Power systems. Vol.12 .No.1. 1997. pp.198-206.
3. D.I.Sun, *Optimal power flow by Newton approach*. In: IEEE Transactions on PAS, Vol 103.No 10, 1984, pp 2864-2880.
4. K.Iba : *Reactive power optimization by Genetic algorithm*. In: IEEE Transactions on power systems, Vol 9, no 2, May 1994, pp 685-692.
5. 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*. In: IEEE transactions on Power Systems, Vol 13, no 1, Feb1998, pp 101-108.
6. A.J.Urdaneta., J.F.Gomez., E.Sorrentino., L.Flores., R.Diaz: *A combined genetic algorithm for optimal reactive power planning based on successive linear programming*. In: IEEE Transactions on Power Systems, Vol 14, No 4, 1999, pp 1292-1298.
7. Venkataranan Ajarapu, Ping Lin Lau, Srinivasa Battalu:*An optimal reactive power planning strategy against voltage collapse*. In: IEEE Transactions on Power Systems, Vol 10, No 2, May 1994.
8. E.Vaahedi, J.Taby., Y.Mansour., L.Wenyuan .,D.Sun: *Large scale voltage stability constrained optimal var planning and voltage stability applications using existing OPF/optimal VAR planning tools*. In: IEEE Transactions on Power Systems, vol.14, No.1, Feb 1999, pp.65-74.
9. Bedoya,D.B.. Castro,C.A., daSilva,L.C.P: *A method for computing minimum voltage stability margins of power systems, Generation Transmission and Distribution IET*. VOL 2, issue 5 pp 676-689,Sept 2008.
10. Bedoya, D., Bedrinana, M.F. Castro, C.A. da Silva, L.C.P. *Power system critical areas by using sensitivities and participation factors for online applications*. In: Transmission and Distribution conference and Exposition. Latin America, 2008 , IEEE/PES, Issue Date: 13-15, Aug 2008, pp 1-6.
11. Shihong Wang., H.Zang., Rui He., Q.M.Xiao., J.Chen., M.C.Xu : *A new reactive power planning based on system multiscenario operations*, Energy Procedia 14(2012), pp 782-784.
12. P.Kessel ., H.Glavitsh: *Estimating the voltage stability of power systems*. In : IEEE Transactions on Power systems, Vol 1, No 3, 1986, pp 346-354.
13. K.Price., R.Storn., J,Lampinen: *Differential Evolution- A practical approach to global optimization*, Berlin, Germany, Springer 2005.
14. Swagatam Das., Suganthan: *Differential Evolution: A survey of the state-of-the-Art*, IEEE Transactions on Evolutionary Computation, 2010, pp 1-26.
15. J.T.Ma., L.L.Lai: *Evolutionary Programming approach to reactive power planning*, IEE Proc-Gener.Transm.Distrib, Vol 143, No 4, July 1996.
16. L.J.Eshelman ., J.D.Schaffer,: *Real - coded genetic algorithms and interval schemata*”, in D.Whitley Edition, 1993, pp 187-202.
17. D.Devara.j, B.Yegnanarayana,: *A combined genetic algorithm approach for optimal power flow*, National power systems conference, NPSC-2000, Bangalore, India, 2000, pp 1866-1876.