

CAPACITOR PLACEMENT FOR LOSS REDUCTION IN RADIAL DISTRIBUTION NETWORKS: A TWO STAGE APPROACH

V.Usha Reddy **Dr.T.Gowri Manohar**

Sri Venkateswara University, Tirupati.

Email: vyza_ushareddy@yahoo.co.in , tgmanohar1973@rediffmail.com

P.Dinakara Prasad Reddy

Sri Venkateswara University, Tirupati.

Email: pdinakarprasad@gmail.com

Abstract: The paper presents a new evolutionary technique i.e. Differential Evolution Algorithm with Loss sensitivity factor method for optimizing the sizes and locations of shunt capacitors in radial distribution network to minimize the active power losses with the improvement of voltage profiles of different buses. The technique is applied on IEEE 34 buses network. The results are compared with ones of previous studies using heuristics methods and the same network tests.

Keywords: capacitor placement, Loss sensitivity factor, Differential Evolution method.

1. INTRODUCTION

It is known that the flow of reactive current in an electric network produces supplementary power loss and increases the voltage drop. Comparing to transport network, the distribution networks have low voltage and a large current which produce the losses by Joule effects relatively higher than in the transport networks (more than 13% of the losses). To improve the load flow, the quality of energy and to avoid as well a new investment on building a new grid, we have to reduce the losses by installing shunt capacitors in the appropriate places. In the literature we can find many different optimization techniques in away to optimize locations, sizes and numbers of capacitors.

H. N. Ng, M.M.A. Salama and A.Y.Chikhani, [1] have proposed an algorithm based on fuzzy capacitor placement for estimating the shunt

Compensation level necessary to improve the voltage level and reduce the active power losses.

M. D. Reddy and V. C. V. Reddy [4] have proposed a method with two levels to find the placement and the size of shunt capacitors. They used a fuzzy algorithm to Search the optimal placement and real genetic algorithm to find the optimal size of capacitors.

R. S. Rao and S. V. L. Narasimham [3] have also presented a method with two levels. In the first level they have used the loss sensitivity factors to search the appropriate buses which will receive the compensation capacitors. And in the second level they have used the Plant Growth Simulation Algorithm (PGSA) to determine the shunt compensation level at the placement of the optimal candidate in away to improve the voltage profile and to reduce the active power losses.

In this paper a new evolutionary technique i.e. Differential Evolution algorithm with loss sensitivity factor method is presented which perform the optimization of the size, number and the placement of the shunt capacitors. These have lead to reduce the investment cost of new reactive energy sources and the active power losses with the voltage levels improvement.

2. LOSS SENSITIVITY FACTOR BASED CAPACITOR LOCATION

To identify the location for capacitor placement in distribution system Loss Sensitivity Factors have been used. The loss sensitivity factor is able to predict which bus will have the

biggest loss reduction when a capacitor is placed. Therefore, these sensitive buses can serve as candidate buses for the capacitor placement. The estimation of these candidate buses basically helps in reduction of the search space for the optimization problem. As only few buses can be candidate buses for compensation, the installation cost on capacitors can also be reduced.

Consider a distribution line with an impedance $R + jX$ and a load of $P_{eff} + jQ_{eff}$ connected between 'i' and 'j' buses as given below in Fig.1.

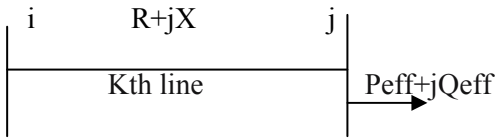


Figure 1: A distribution line with an impedance and a load.

Real power loss in the line of the above Fig. 1 is given by $[I_k^2] * [R_k]$, which can also be expressed as,

$$P_{loss}[j] = \frac{(P_{eff}^2[j] + Q_{eff}^2[j])R[k]}{(V[j])^2} \quad (1)$$

Similarly the reactive power loss in the kth line is given by

$$Q_{loss}[j] = \frac{(P_{eff}^2[j] + Q_{eff}^2[j])X[k]}{(V[j])^2} \quad (2)$$

Where

$P_{eff}[j]$ = Total effective active power supplied beyond the bus 'j'

$Q_{eff}[j]$ = Total effective reactive power supplied beyond the bus 'j'

Now, the Loss Sensitivity Factors can be calculated as

$$\frac{\partial P_{loss}}{\partial Q_{eff}} = \frac{(2 * Q_{eff}[j]) * R[k]}{(V[j])^2} \quad (3)$$

$$\frac{\partial Q_{loss}}{\partial Q_{eff}} = \frac{(2 * Q_{eff}[j]) * X[k]}{(V[j])^2} \quad (4)$$

2.1 Candidate Bus Selection Using Loss Sensitivity Factor

The Loss Sensitivity Factor ($\partial P_{loss} / \partial Q_{eff}$) as given in eq. (3) has been calculated from the base case load flows. The values of loss sensitivity factors have been arranged in descending order and correspondingly the bus numbers are stored in bus position 'bpos [i]' vector. The descending order of ($\partial P_{loss} / \partial Q_{eff}$) elements of 'bpos [i]' vector will decide the sequence in which the buses are considered for compensation. At these buses of 'bpos [i]' vector, normalized voltage magnitudes are calculated by considering the base case voltage magnitudes given as below

$$Norm[i] = |V[i]|/0.95 \quad (5)$$

The 'Norm[i]' decides whether the buses need reactive compensation or not. The buses whose Norm[i] value is less than 1.01 can be selected as the candidate buses for capacitor placement. The following are the steps to be performed to find out the potential buses for capacitor placement

Step 1: Calculate the Loss Sensitivity Factor at the buses of distribution system using Eq. (3).

Step 2: Arrange the value of Loss Sensitivity Factor in descending order. Also store the respective buses into bus position vector bpos[i].

Step 3: Calculate the normalized voltage magnitude norm[i] of the buses of bpos[i] using Eq. (5)

Step 4: The buses who's Norm[i] is less than 1.01 are selected as candidate buses for capacitor placement.

3. DIFFERENTIAL EVOLUTION ALGORITHM

DE introduced by Storn and Price, is a branch of evolutionary algorithms for optimization problems over continuous domains. In DE, each variable's value in the chromosome is represented by a real number. DE can be categorized into a class of floating-point encoded evolutionary algorithms.

The theoretical framework of DE is very simple and DE is computationally inexpensive in

terms of memory requirements and CPU times. Thus, nowadays DE has gained much attention and wide application in a variety of fields. DE starts with the random initialization of a population of individuals in the search space and works on the cooperative behaviors of the individuals in the population. It finds the global optima by utilizing the distance and direction information according to the differentiations among the population. However, the searching behavior of each individual is adjusted by dynamically altering the differentiation's direction and step length. At each generation, the mutation and crossover operators are applied to individuals to generate a new population. Then, selection takes place and the population is updated.

3.1. Initialization

Before the population can be initialized, both upper and lower bounds for each parameter must be specified. b_L and b_U for which subscripts L and U indicate the lower and upper bounds, respectively. For example, the initial value ($g = 0$) of the j_{th} parameter of the i_{th} vector is

$$x_{j,i,0} = \text{rand}_j(0,1) \cdot (b_{j,U} - b_{j,L}) + b_{j,L} \quad (1)$$

The random number generator $\text{rand}_j(0, 1)$ returns a uniformly distributed random number from within the range $(0, 1)$, i.e. $0 \leq \text{rand}_j(0,1) < 1$. The subscript j indicates that a new random value is generated for each parameter.

3.2. Mutation

Once initialized, DE mutates and recombines the population to produce a population of N_p trial vectors. Equation (4) shows how to combine three different, randomly chosen vectors to create a mutant vector $v_{i,g}$

$$v_{i,g} = x_{r0,g} + F \cdot (x_{r1,g} - x_{r2,g}) \quad (2)$$

The scale factor $F \in (0,1+)$, is a positive real number that controls the rate at which the population evolves.

3.3. Crossover

To complement the differential mutation search strategy, DE also employs uniform

crossover. In particular DE crosses each vector with a mutant vector

$$u_{j,i,g} = \begin{cases} v_{j,i,g} & \text{if } (\text{rand}_j(0,1) \leq C_r \text{ or } j = j_{\text{rand}}) \\ x_{j,i,g} & \text{otherwise.} \end{cases} \quad (3)$$

The crossover probability $C_r \in [0,1]$ is a user-defined value that controls the fraction of parameter values that are copied from the mutant.

3.4. Selection

If the trial vector $u_{i,g}$ has an equal or lower objective function value than that of its target vector $x_{i,g}$ it replaces the target vector in the next generation. Otherwise the target retains its place in the population for at least one more generation. By comparing each trial vector with the target vector from which it inherits parameters DE more tightly integrates recombination and selection than do other EAs

$$x_{i,g+1} = \begin{cases} u_{j,i,g} & \text{if } f(u_{i,j}) \leq f(x_{i,j}) \\ x_{i,g} & \text{therwise.} \end{cases} \quad (4)$$

Once the new population is installed, the process of mutation, recombination and selection is repeated until the optimum is located, or a pre specified termination criterion is satisfied, e.g., the number of generations reaches a preset maximum g_{max} .

3.5. Algorithm to Find Capacitor Sizes

The basic procedure of DE is summarized as follows.

Step 1: Randomly initialize the population of individual for DE.

Step 2: Evaluate the objective values of all individuals, and determine the best individual.

Step 3: Perform mutation operation for each individual according to Eq. 2 in order to obtain each individual's corresponding mutant vector.

Step 4: Perform crossover operation between each individual and its corresponding mutant vector according to Eq.3 in order to obtain each individual's trial vector.

Step 5: Evaluate the objective values of the trial vectors.

Step 6: Perform selection operation between each individual and its corresponding trial vector

according to Eq.4 so as to generate the new individual for the next generation.

Step 7: Determine the best individual of the current new population with the best Objective value then updates best individual and its objective value.

Step 8: If a stopping criterion is met, then output gives its bests and its objective value
Otherwise go back to step 3.

4. TEST RESULTS

The proposed method for loss reduction by capacitor placement is tested on 34-bus radial distribution systems. The various control parameters used in the proposed algorithm are shown in table 1.

4.1 IEEE 34 BUS TEST NETWORK

The IEEE 34 bus test network with the proposed method is compared with the paper [4], [1], [3] in which better results are obtained with less number of capacitors. Here with this proposed method in which differential evolution algorithm is used gives a loss reduction of 52.92kw, which is better than the previous techniques.

Table1. Control Parameters

Control parameter	Definition
$N_p=30$	Population size
$F=0.8$	Mutation factor
$C_r=0.9$	Crossover probability
$50 < Q_c < 1500$	Capacitor size boundary
$g_{max}=500$	Maximum number of generation

The comparison of test results is shown below in table 2. This proposed DE based capacitor placement with Loss sensitivity factor Approach method gives promising results with less number of capacitor locations. The Voltage Magnitudes in P. U. of IEEE 34 distribution network before and after the compensation is shown in figure 2. In which the minimum voltage after compensation is higher than that of before compensation.

Table 2. Results and Comparisons

	Before compensation	After Compensation							
		Fuzzy & Real Coded Genetic [4]	FES based [1]	Plant Growth [3]	Proposed Method				
Total real power loss(Kw)	221.72	168.95	168.98	169.14	168.8				
Location and optimal size (KVAR)		19	683						
		20	145						
		21	144	24	1500	18	1200	19	958
		22	143	17	750	21	639	20	229
		23	143	7	450	19	200	22	861
		24	143						
		25	228						
Total compensation (KVAR)		1629	2700	2039	2048				
Vmin(pu)	0.9417	0.9491	0.9490	0.9492	0.9495				

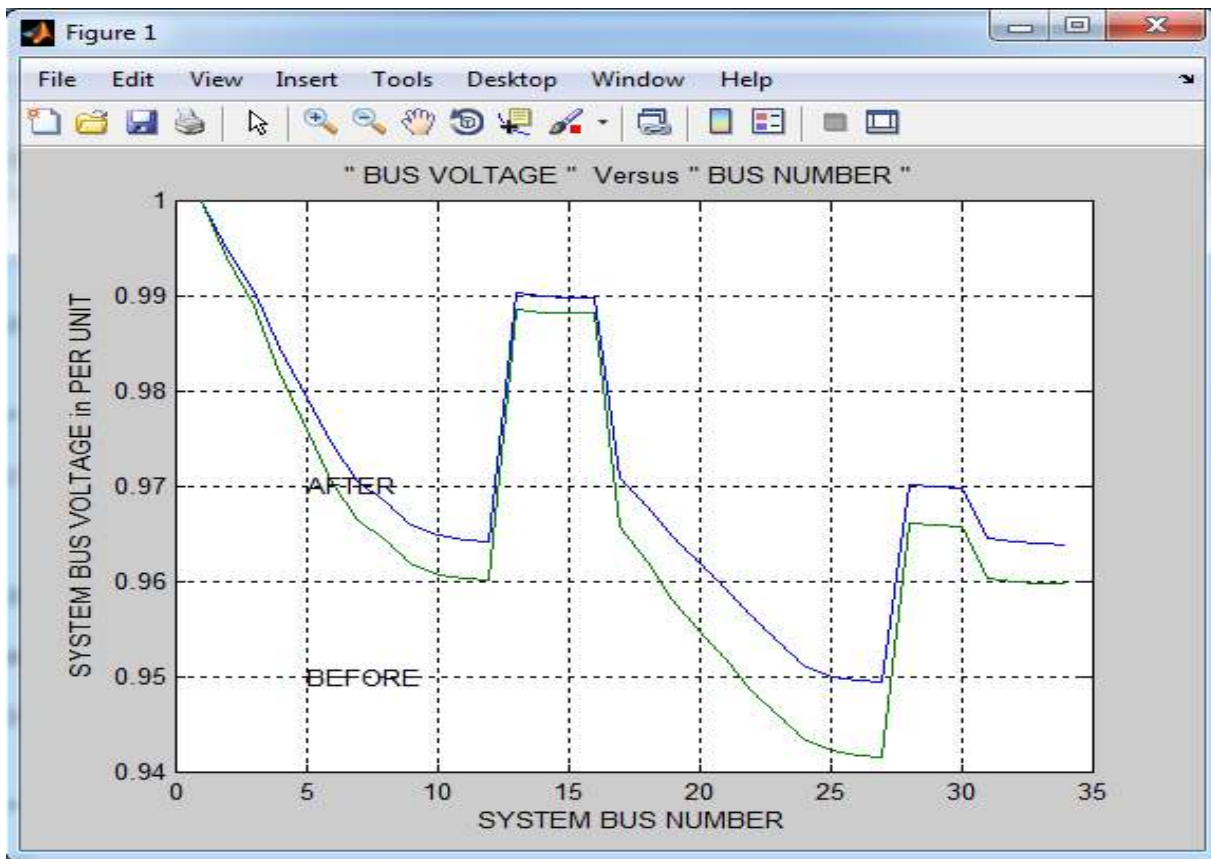


Figure 2. Voltage Magnitudes in P. U. of IEEE 34 distribution network

5. CONCLUSION

Through the comparison between the obtained results and previous results presented by different techniques, we notice clearly that the proposed new technique have given a best results and further less number of shunt capacitors are used in optimization. Consequently, we get further minimization of the active power losses and more improvement of different buses voltages. The algorithm is tested on 34 bus and the results are more promising.

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