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Conductor selection optimization in radial distribution system considering load growth using MDE algorithm

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Abstract. This paper presents optimal conductor selection of MV feeders in radial distribution system (RDS) planning to reduce power loss and improve voltage profile using Modified Differential Evolution (MDE) algorithm. To analysis the steady state of network in each step of optimization, a direct approach load flow which is both robust and efficient and has high convergence speed is used. In this paper, conductor selection will be performed considering the capital investment, power loss, and energy loss factors so that, constraints like maximum current capacity of feeders and allowed voltage drop of nodes are satisfied. Also, the effect of load growth on the conductor selection and the cost of energy losses is considered. The proposed method is implemented on 32 bus network and the results are compared with other refernce.

Keywords: optimal conductor selection, modified differential evolution algorithm, power loss reduction and voltage profile improvement

1 Introduction

The optimum planning of power distribution networks is one of the most important research fields for electrical engineers. That is because of the close proximity of these networks to the ultimate consumers and of their great length, which has as a consequence increased capital investment and increased operational costs because of their losses. The ultimate aim of this research is to plan distribution networks which satisfy the growing demand for electricity, fulfill specific technical operational constraints and which are also characterized by the minimum overall cost (investment and operational cost). Power losses in the lines account for the bulk of the distribution system losses. The capital investment in laying distribution network lines accounts for a considerable fraction of total capital investment. In general, in most of the existing distribution systems, the conductors are not selected in a systematic way. Thus, the capital cost of conducting material and power loss in the feeders is more and also the maximum current carrying capacity and voltage limits are not generally satisfied. Therefore, considerable attentions have been given on optimal distribution systems planning over last few years.

In recent researches, many approaches have been proposed to solve power distribution system planning problem. In [1, 18], feeder cross section selection problem has fulfilled with using analytic methods considering allowable voltage drop so that, economic costs arising from investment cost, power and energy loss cost has minimized. In [19] an economical current density-based method and heuristic approach in combination for conductor size selection presented, but the solution obtained is sub-optimal. In [2, 4, 5, 11, 14] conductor selection problem has solved with heuristic optimization methods and the optimal conductor sizes are determined by minimizing the total cost consisting of cost of conductor and cost of losses and subject to the constraint on voltage drop at far end load points and maximum current carrying capacity of the feeder. In [6] , several financial and engineering factors are considered in the solution, which the intent will be the

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most economical when both capital and operating costs are considered. Ranjan et al. minimize investment cost, power and energy loss costs and also improves voltage profile with replacing existing conductors using evolutionary programming[10]. In addition to these, the effect of load growth on the conductor selection is considered in [15] with fuzzy evolutionary programming.Mohammadi et al. use genetic algorithm (GA), hybrid genetic and particle swarm optimization (HGAPSO), differential evolution (DE), PSO-DE, PSO and Imperialist Competitive (IC) algorithm to conductor selection problem respectively[3, 7–9, 12, 13].

This paper presents a method based on MDE algorithm for conductor selection in power radial distribution system planning considering effect of load growth. The selected conductors with proposed method consider maximum current carrying capacity of conductors as well as limit of allowable voltage drop for nodes. Additionally causes a compromise between investment costs (arising from feeder to be built, cost of maintenance and operation), power and energy loss cost, then make maximum saving.

2 Load flow analysis

The load flow solution provides the steady state condition of a power system. Because of the spread range of R and X, and radiality of the power distribution system, the load flow problem of the radial distribution network is included as an ill-condition problem. One of the major reasons, which make the load flow program diverge, is the ill-condition problem of the Jacobin matrix or Y admittance matrix.

In order to prevent this problem, the proposed direct approach of [17] is used. In this method, two matrices, which are developed from the topological characteristics of distribution systems, are used to solve load flow problem.

$$\begin{aligned} [B] &= [BIBC][I], \\ [\triangle V] &= [BCBV][B], \\ [\triangle V] &= [BCBV][BIBC][I] = [DLF][I]. \end{aligned} \tag{1}$$

The $BIBC$ matrix represents the relationship between bus current injections and branch currents, and the $BCBV$ matrix represents the relationship between branch currents and bus voltages Eq. (1). These two matrices are combined to form a direct approach for solving load flow problems.

$$\begin{aligned} I_i^k &= \left(\frac{P_i + jQ_i}{V_i^k}\right)^*, \\ [\triangle V^{k+1}] &= [DLF][I^k], \\ [V^{k+1}] &= [V^0] - [\triangle V^{k+1}]. \end{aligned} \tag{2}$$

The solution for distribution load flow can be obtained by solving Eq. (2) iteratively.

3 Modified differential evolution algorithm

Differential Evolution Algorithm (DEA) is a simple population based, stochastic parallel search Evolution algorithm for global optimization and is capable of handling non-differentiable, nonlinear and multimodal objective functions. In DEA the population consists of real-valued vectors with dimension D that equals the number of design parameters. The size of the population is adjusted by the parameter N_p. The initial population is uniformly distributed in the search space. Modification to DE algorithm is represented in [16] .

3.1 Initialization

Typically, each decision parameter in every vector of the initial population is assigned a randomly chosen value from within its corresponding feasible bounds:

$$X_{j,i}^{0} = X_j^{\min} + \mu_j (X_j^{\max} - X_j^{\min}),\ i = 1, \cdots, N_p,\ j = 1, \cdots, D, \tag{3}$$

where μ_j denotes a uniformly distributed random number within the range $[0, 1]$,generated anew for each value of j. $X_j^{\max}$ j and $X_j^{\min}$are the upper and lower bounds of the j^{th} decision parameter, respectively.

3.2 Mutation

The mutation operator creates mutant vectors $X_i^{'}$ by perturbing a randomly selected vector X_a with the difference of two other randomly selected vectors X_b and X_c, according to the following expression:

$$X_i^{'(G)} = X_a^{(G)} + F(X_b^{(G)} - X_c^{(G)}),\ i = 1, \cdots, N_p, \tag{4}$$

where a, b, and c are randomly chosen indices, such that $a, b, c \in \{1, \cdots, N_p\}$ and $a \neq b \neq c \neq i$. It should be noted that new (random) values for a, b, and c have to be generated for each value of i. The scaling factor F is an algorithm control parameter in the range $[0, 2]$ which is used to adjust the perturbation size in the mutation operator and improve algorithm convergence.
Modification to DE[16]:
The first modification to DE is to replace the random base vector $X_n^{(G)}$ a in the mutation Eq. (5) with the tournament best $X_{th}^{(G)}$. One highly beneficial method that deserves special mention is the DE/best/2/bin which perturbs the best solution found so far with two difference vectors based on a binomial distribution crossover scheme:

$$X_i^{'(G)} = X_{best}^{(G)} + F(X_a^{(G)} - X_b^{(G)} + X_c^{(G)} + X_d^{(G)}),\ i = 1, \cdots, N_p, \tag{5}$$

where X_a, X_b, X_c and X_d are randomly chosen vectors from the set $\{1, \cdots, N_p\}$, mutually different and different to the target vector. X_a, X_b, X_c and X_d are generated anew for each parent vector. X_{best} is the best solution found so far in the optimization process. This strategy dramatically improves the convergence rate of the algorithm.

Also, instead of using a fixed F throughout a run of DE, we use a random F in for each mutated point[16].

3.3 Crossover

In order to increase the diversity among the mutant parameter vectors, crossover is introduced. To this end, a trial vector $X_i^{''}$ is created from the components of each mutant vector $X_i^{'}$ and its corresponding target vector X_i, based on a series of D-1 binomial experiments of the following form:

$$X_{j,i}^{''(G)} = \begin{cases} X_{j,i}^{'(G)}, & \text{if } \rho_j \leq C_R \text{ or } j = p, \\ X_{j,i}^{(G)}, & \text{otherwise}, \end{cases} \qquad i = 1, \cdots, N_P,\ \ j = 1, \cdots, D, \tag{6}$$

where ρ_j denotes a uniformly distributed random number within the range $[0, 1)$, generated anew for each value of j. The crossover constant C_R which is usually chosen from within the range $[0, 1]$, is an algorithm parameter that controls the diversity of the population and aids the algorithm to escape from local minima. q is a randomly chosen index $\in \{1, \cdots, D\}$, which is used to ensure that the trial vector gets at least one parameter from the mutant vector.

3.4 Selection

The selection operator forms the population by choosing between the trial vectors and their predecessors (target vectors) those individuals that present a better fitness or are more optimal according to Eq. (7).

$$X_i^{(G+1)} = \begin{cases} X_i^{''(G)}, & \text{if } f(X_i^{''(G)}) \leq f(X_i^{(G)}), \\ X_i^{(G)}, & \text{otherwise}, \end{cases} \qquad i = 1, \cdots, N_p. \tag{7}$$

3.5 Other modification to DE: migration if necessary

In order to effectively enhance the investigation to the search spaces and reduce the choice pressure to a small population, a migration operation is introduced to regenerate a new diverse population of individuals. The new populations are yielded based on the best individual X_h^{G+1}. The h^{th} gene of the i^{th} individual is as follows:

$$X_{hi}^{(G+1)} = \begin{cases} \text{round}\left(X_{hi}^{(G+1)} + \rho_1(X_{h\min} - X_{hb}^{(G+1)})\right), & \text{if } \rho_2 < \frac{X_{hi}^{(G+1)} - X_{h\min}}{X_{h\max} - X_{h\min}}, \\ \text{round}\left(X_{hi}^{(G+1)} + \rho_2(X_{h\min} - X_{hb}^{(G+1)})\right), & \text{otherwise}, \end{cases} \tag{8}$$

where ρ_1,ρ_2 are randomly generated numbers uniformly distributed in the range of $[0, 1]$; $i = l, \cdots, N_p$; $h = l, \cdots, n_c$. The migration in MDE is executed only if a measure fails to match the desired tolerance of population diversity. The measure is defined as follows:

$$\rho = \sum_{i=1, i\neq b}^{N_p} \sum_{j=1}^{n_c} \frac{X_{ji}}{n_c(N_p - 1)} < \varepsilon_1, \tag{9}$$

where

$$X_{ji} = \begin{cases} 1, & \text{if} \left| \frac{X_{ji}^{G+1} - X_{jb}^{G+1}}{X_{jb}^{G+1}} \right| > \varepsilon_2, \\ 0, & \text{otherwise}. \end{cases} \tag{10}$$

Parameter $\varepsilon_1 \in [0, 1]$ and $\varepsilon_2 \in [0, 1]$ respectively express the desired tolerance for the population diversity and the gene diversity with respect to the best individual. Here X_{ji} is defined as an index of gene diversity. A value of zero of X_{ji} denotes that the j^{th} gene of the i^{th} individual is very close to the j^{th} gene of the best individual. From Eqs. (9) and (10), it can be seen that the value of ρ is in the range of $[0, 1]$. If ρ is smaller than ε_1, then the MDE performs the migration to generate a new population to escape the local point; otherwise, the MDE breaks off the migration which keeps an ordinary search direction.

3.6 Termination criteria

After the fitness has been calculated, it has to be determined if the termination criterion has been met. This can be done in several ways. The algorithm used here stops when a finite generation number has been reached and the best fit among the population is declared the winner and solution to the problem.

4 Problem formulation

The problem is to select conductor cross-section from a set of inventory available such that the total cost consisting of the cost of the conductor and the cost of losses is minimized while satisfying the constraints on voltage drop at far end nodes and maximum current carrying capacity of conductor. The problem may be stated as a minimization of an objective function representing the fixed costs correspondent to the investment in lines and the variable costs associated to the operation of the system, subject to voltage and current constraints, expressed by the following equation:

$$\begin{aligned} J &= \min(F1 + F2), \\ F1 &= \sum_{k=1}^{n-1} [\alpha \times A_{(k)} \times cost_{(k)} \times Len_{(i)}], \\ F2 &= \sum_{i=1}^{n-1} Ploss_{(i,k)} \times (K_P + K_E \times 8760 \times LSF). \end{aligned} \tag{11}$$

$J =$ the cost function to be minimized and consists of: fixed cost (F_1) which caused by installation and maintenance cost of feeders and variable cost ($F2$) associated with power and energy loss cost;

$Ploss(j,k)$	:	real power loss of branch i with k type of conductor in kW;
K_P	:	Annual demand cost of power loss in Rs/kW;
K_E	:	Annual demand cost of energy loss in Rs/kWh;
Lsf	:	loss factor;
α	:	interest and depreciation factor;
$A_{(k)}$	:	cross sectional area of k type of conductor in mm^2;
$Cost_k$	:	cost of k type conductor in $Rs/mm^2/km$;
Len_i	:	length of branch i in km.

The power losses in the grid are calculated from load-flow results for the maximum load condition. Then, the energy losses for the period of one year are calculated multiplying the power losses for the maximum load condition by the loss factor and by the number of hours in one year (8760 hr). The associated cost of the energy losses is calculated according to the costs of the energy in (\$/kW/year).

4.1 Constraints

The optimization problem of conductor size selection in planning radial distribution systems is to select the conductor sizes with the minimal total cost under the constraints of:

Voltage: The voltage amplitude at every node in the feeder must be higher than minimum acceptable value of voltage ($V_{\min}$), means:

$$|V_i| > V_{\min} \text{ for } i = 2, 3, \cdots, n. \tag{12}$$

Current: Current flowing through section j with a given type of conductor (K) should be less than the maximum allowable current carrying capacity of K conductor ($I_{\max(k)}$), i.e.

$$|I_{jj,k}| < I_{\max(k)} \text{ for } jj = 1, 2, \cdots, m. \tag{13}$$

For the sake of simplicity, the following conditions apply in this paper: 1- only a peak load for a planning period of one year is considered. And 2- the feeder configuration is known.

In each generation fitness value of J according to [10] will be calculated that must be minimized in the optimization process. To succeed this aim the constraints like maximum allowable voltage drop and maximum allowable current carrying capacity must be satisfied. The conductor selection problem in under study radial distribution system will be solved with MDE operator's implementation and considering termination criterion of problem.

5 Test results

The proposed method is implemented on 32- bus radial distribution system as Fig. 1. The line and load data, also four different types of conductors that are used for optimization is given in [15] .

The basic data are considered for the cases as: $K_E = 0.5Rs/kWh$; $LSF = 0.2$; $K_P = 2500Rs/kW$; $Cost_k = 500Rs/mm_2/km$; $\alpha = 0.1$; $T = 8760hour$;

A radial distribution system has several branches. When these branches are re-conductored, it changes the resulting power losses and voltage profile. The re-conductored branches require capital investment. The proposed algorithm to select the best conductor type for each branch of RDS, such that the resulting RDS requires the least re-conductoring costs, yields the minimum power losses and gives best voltage profile.

5.1 Without load growth

In base case, all lines conductor type are "Weasel" and minimum voltage and total real power loss are 0.9825 $p.u.$ and 25.4 kW respectively.

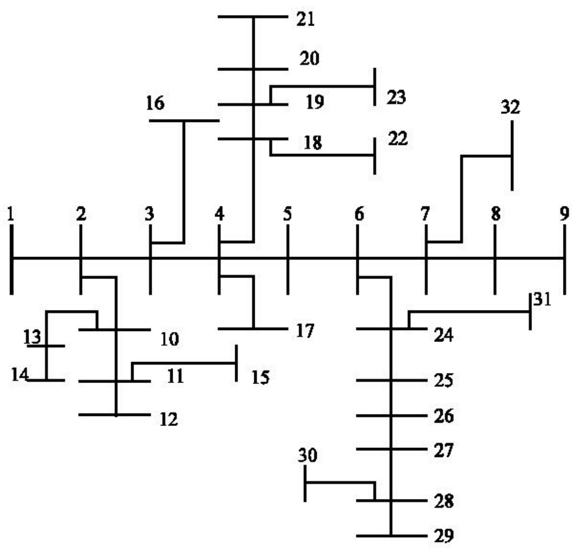

Fig. 1. Single line diagram of 32- bus RDS [12]

Table 1. Comparison of results before and after conductor grading

	Minimum voltage ($p.u.$)	Real power loss (kW)	Total cost (Rs)	Power loss reduction (kW)	Net saving (Rs)
Base case	0.9825	25.4	90598	-	-
Ref. [15]	0.9901	10.4	44004	15	46594
MDE	0.99036	10.376	42974	15	47624

The comparison of results for base case and after conductor grading are shown in Tab. 1. Based on algorithm, the results of conductor type selection are presented in Tab. 2.

From Tab. 1, it can be seen that real power loss reduced to 10.376 kW, minimum voltage improved to 0.9901 $p.u.$ and cost function reduced from 90598 (R_s) to 42974 (R_s) it means net saving of cost function in comparison with [15] has increased from 46594 (R_s) to 47624 (R_s). Fig. 2 represents the voltage profile before and after conductor optimization.

5.2 With future load growth

Load growth in future can be modeled as follows:

$$P_L = P_{L0} \times (1+g)^n, \qquad (14)$$
$$Q_L = Q_{L0} \times (1+g)^n,$$

where

P_L,Q_L	:	Real and reactive load for n years;
P_{L0},Q_{L0}	:	Real and reactive load at base condition;
n	:	number of years;
g	:	growth rate at 7%.

The results after modification of the conductors for $n = 8^{th}$ and $n = 9^{th}$ year are shown in Tabs. 3and 4. From Tabs. 3 and 4, it can be seen that in case of MDE algorithm results re-conductoring isn't necessary for the branches from 8^{th} year to 9^{th} year, but in results of [15] some modification is necessary in the selection of conductors. This result is an important advantage that there is no need to change conductors cross section from a year to next year.

The results of modification in branch conductors for future load expansion for 32- bus network is shown in Tab. 5. It is observed that, the optimal conductor selection is obtained by the MDE algorithm is sufficient

Table 2. Results of MDE for conductor type without load growth

From bus	To bus	Conductor type using MDE	From bus	To bus	Conductor type using MDE
1	2	4	4	18	4
2	3	4	18	19	3
3	4	4	19	20	2
4	5	4	20	21	1
5	6	4	18	22	1
6	7	3	19	23	1
7	8	2	6	24	4
8	9	1	24	25	4
2	10	4	25	26	4
10	11	2	26	27	3
11	12	1	27	28	2
10	13	2	28	29	1
13	14	1	28	30	1
11	15	1	24	31	1
3	16	1	7	32	1
4	17	1			

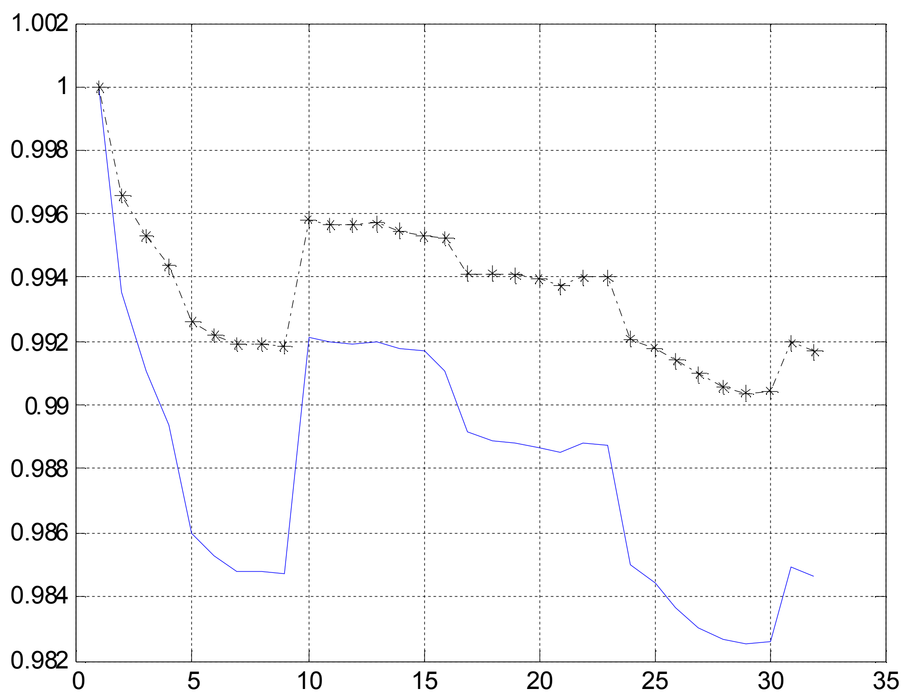

Fig. 2. voltage profile before and after conductor optimization without load growth case

to maintain voltage profile and reduction in power loss up to 8 years. From 9^{th} year the obtained optimal selection is not suitable to obtain maximum net savings, so, it is need to change some of the conductors by other type of conductors corresponding to Tabs. 3 and 4.

It is observed from Tab. 5, the power loss is reduced from 76.5 kW to 30.35 kW and net saving is increased to 151337 (R_S) using MDE algorithm instead of 149290 R_S for the 8th year in [15] . Similarly for the 9th year the power loss is reduced from 87.8 kW to 34.81 kW and net saving is increased to174710 (R_S)

Table 3. Results after modification of the conductors for $n = 8^{th}$ year

From bus	To bus	Conductor type [15]	Conductor type using MDE	From bus	To bus	Conductor type [15]	Conductor type using MDE
1	2	2	4	4	18	2	4
2	3	2	4	18	19	2	4
3	4	2	4	19	20	2	3
4	5	2	4	20	21	2	2
5	6	2	4	18	22	2	2
6	7	2	4	19	23	2	2
7	8	2	3	6	24	2	4
8	9	2	2	24	25	2	4
2	10	2	4	25	26	2	4
10	11	3	3	26	27	2	4
11	12	2	2	27	28	2	3
10	13	2	3	28	29	1	2
13	14	3	2	28	30	1	2
11	15	2	2	24	31	2	2
3	16	3	2	7	32	3	2
4	17	2	2				

Table 4. Results after modification of the conductors for $n = 9^{th}$ year

From bus	To bus	Conductor type [15]	Conductor type using MDE	From bus	To bus	Conductor type [15]	Conductor type using MDE
1	2	2	4	4	18	2	4
2	3	2	4	18	19	2	4
3	4	2	4	19	20	3	3
4	5	2	4	20	21	3	2
5	6	2	4	18	22	2	2
6	7	2	4	19	23	3	2
7	8	2	3	6	24	2	4
8	9	2	2	24	25	2	4
2	10	2	4	25	26	2	4
10	11	4	3	26	27	2	4
11	12	2	2	27	28	3	3
10	13	2	3	28	29	2	2
13	14	2	2	28	30	2	2
11	15	4	2	24	31	2	2
3	16	2	2	7	32	2	2
4	17	2	2				

in comparison with 172360 (R_S) without changes in the selection of conductors. Fig. 3 represents the voltage profile before and after conductor optimization.

Table 5. Comparison of results before and after conductor grading

	Scenario	Minimum voltage $(p.u.)$	Real power loss (kW)	Total cost (Rs)
	Base case	0.9696	76.5	263060
$N = 8_{th}$ year	Ref. [15]	0.9829	31.1	113770
	MDE	0.9838	30.35	111723
	Base case	0.9674	87.8	301490
$N = 9_{th}$ year	Ref. [15]	0.982	35.4	129130
	MDE	0.9827	34.81	126780

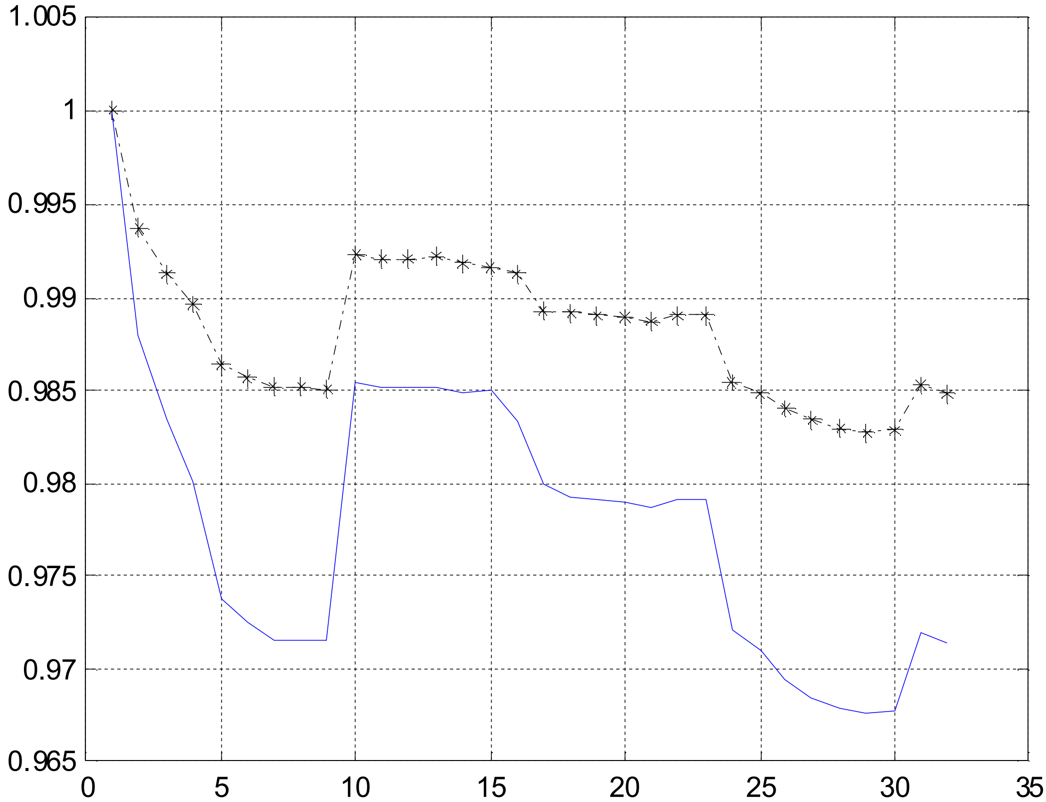

Fig. 3. voltage profile before and after conductor optimization with load growth case

6 Conclusion

This study has presented a robust and comprehensive approach to solve the optimal conductor selection problem in a RDS. The proposed algorithm can be used in conductor selection for planning and optimization of radial distribution networks. The objectives considered attempt to minimize of capital investment and power and energy loss, subject to voltage drop and current carrying capacity constraints. As two case studies, proposed algorithm is applied to 32- bus RDS with satisfactory and comparable results to other paper.

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