ISSN 1 746-7233, England, UK
World Journal of Modelling and Simulation
Vol. 5 (2009) No. 2, pp. 96-104

Optimal conductor selection in radial distribution system using discrete particle swarm optimization

S. Sivanagaraju[1] , J. Viswanatha Rao[2]*

[1] Department of EEE, J. N. T. U. College of Engineering, Anantapur, A. P, 515001, India
[2] Department of EEE, Swarnandhra College of Engineering, Narsapur, A. P, 534275, India

(*Received May 10 2008, Accepted April 6 2009*)

Abstract. This paper presents optimal branch conductor selection of radial distribution systems using particle swarm optimization. The problem is posed as an optimization problem with an objective to minimize the overall cost of annual energy losses and depreciation on the cost of conductors. The conductor, which is determined by this method will satisfy the maximum current carrying capacity and maintain acceptable voltage levels of the radial distribution system. Besides, it gives maximum saving in the capital cost of conducting material and cost of energy losses. The effectiveness of the proposed method is demonstrated through different examples.

Keywords: conductor selection, Discrete Particle Swarm Optimization (DPSO), radial distribution systems.

1 Introduction

Distribution system is one from which the power is distributed to various users through feeders, distributors and service mains. Feeders are conductors of large current carrying capacity, carrying the current in bulk to the feeding points. Conductor is often the biggest contributor to distribution system losses. Economic conductor sizing is therefore of major importance. If a conductor is loaded up to or near its thermal rating, the losses will be increased. Therefore, line conductors are loaded below their thermal limit. The power loss is significantly high in distribution systems because of lower voltages and higher currents, when compared to that in high voltage transmission systems. Studies have indicated that as much as 13% of total power generated is consumed as I^2R losses in distribution level. Reactive currents account for a portion of these losses. Reduction of total loss in distribution systems is very essential to improve the overall efficiency of power delivery. The pressure of improving the overall efficiency of power delivery has forced the power utilities to reduce the loss, especially at distribution level.

Selection of conductors for design and upgrading of distribution systems is an important part of the planning process. After taking all the factors into consideration, utilities select four or five conductors to meet their requirement[8]. This selection is done mainly based on engineering judgment. Historical factors also play role in the selection process, i.e., if a company has been using a particular size of conductor, they would like to continue to use that size unless there are compelling reasons not to do so. The available literature consists of work of only a few researchers on finding the best set of conductors in designing a distribution system. Funkhouser and Huber[2] worked on a method for determining economical aluminum conductor steel reinforced (ACSR) conductor sizes for distribution systems. They showed that three conductors could be standardized and used in combination for the most economical circuit design for the loads to be carried by a 13 kV distribution system. They also studied the effect of voltage regulation on the conductor selection

* Corresponding author. Tel.: +91-9866681972 *E-mail address*: viswanath_72@yahoo.com.

process. Wall et al.[7] have considered a few small systems to determine the best conductors for different feeder segments of these systems. The study done by Ponnavaikko and Rao[4] suggested a model to represent feeder cost, energy loss cost and voltage regulation as a function of conductor cross-section. The researchers proposed an objective function for optimizing the conductor cross section.

Tram and Wall[6] worked on similar grounds where again the authors took different examples of feeder systems and calculated the best conductor for each feeder segment based on specific requirements of voltage and losses.Anders et al.[1] analyzed the parameters that affect the economic selection of cable sizes. The authors also did a sensitivity analysis of the different parameters as to how they affect the overall economics of the system. Leppert and Allen[3] suggested that conductor selection is not only based on simple engineering considerations such as current capacity and voltage drop but also on various other considerations such as load growth and wholesale power cost increase.

In this paper, Discrete Particle Swarm Optimization (DPSO) algorithm is proposed for selecting the optimal type of conductor for radial distribution systems. The conductor, which is determined by this method, will satisfy the maximum current carrying capacity and maintain acceptable voltage levels of the radial distribution systems. In addition, it gives the maximum saving in capital cost of conducting material and cost of energy loss.

2 Load flow method

In any radial distribution system, the electrical equivalent of a typical branch, which is connected between node 1 and 2 having a resistance $r_{(1)}$ and inductive reactance $x_{(1)}$ is shown in Fig. 1. From Fig. 1, current flowing branch-1is given by

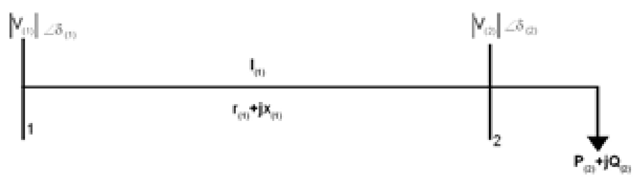

Fig. 1. Single line diagram of a typical branch

$$I_{(1)} = \left|V_{(1)}\right| \angle\delta_{(1)} - \left|V_{(2)}\right| \angle\delta_{(2)} / \left(r_{(1)} + jx_{(1)}\right) \tag{1}$$

$$I_{(1)} = \left(P_{(2)} - jQ_{(2)}\right) / V_{(2)} * \angle\delta_{(2)} \tag{2}$$

From eqns. (1) and (2)

$$\frac{P_{(2)} - jQ_{(2)}}{|V_{(2)}|\angle\delta_{(2)}} = \frac{|V_{(1)}|\angle - \delta_{(1)} - |V_{(2)}|\angle - \delta_{(2)}}{r(1) + jx_{(1)}}$$

Separating real and imaginary parts, the real part is

$$\left|V_{(1)}\right| \left|V_{(2)}\right| \cos\left(\delta_{(1)} - \delta_{(2)}\right) = \left|V_{(2)}\right|^2 + \left\{P_{(2)}r_{(1)} + Q_{(2)}x_{(1)}\right\} \tag{3}$$

and the imaginary part is

$$\left|V_{(1)}\right| \left|V_{(2)}\right| \sin\left(\delta_{(1)} - \delta_{(2)}\right) = \left\{P_{(2)}x_{(1)} - Q_{(2)}r_{(1)}\right\} \tag{4}$$

$$\begin{aligned} \Rightarrow \left|V_{(2)}\right|^4 + 2\left|V_{(2)}\right|^2 \left(r_{(1)}P_{(2)} + x_{(1)}Q_{(2)} - 0.5\left|V_{(1)}\right|^2\right) \\ + \left(r_{(1)}^2 + x_{(1)}^2\right)\left(P_{(2)}^2 + Q_{(2)}^2\right) = 0 \end{aligned} \tag{5}$$

Eq. (5) has a straightforward solution and does not depend on the phase angle, which simplifies the problem formulation. In a distribution system, the voltage angle is not so important because the variation of voltage angle from the substation to the tail end of the distribution feeder is only few degrees. Note that from the two solution of $|V_{(2)}|^2$ only the one considering the sign of the square root of the solution of the quadratic equation gives a realistic value. The same is applicable when solving for $|V_{(2)}|$. Therefore from Eq. (5), the solution of $|V_{(2)}|$ can be written as

$$\begin{aligned}|V_{(2)}| = \{\{(r_{(1)}\,P_{(2)} + x_{(1)}Q_{(2)} - 0.5\,|V_{(1)}|^2)^2 \\ -(r^2_{(1)} + x^2_{(1)})(P^2_{(2)} + Q^2_{(2)})\,\}^{1/2} \\ -(r_{(1)}P_{(2)} + x_{(1)}Q_{(2)} - 0.5\,|V_{(1)}|^2)\,\}^{1/2}\end{aligned} \tag{6}$$

In general

$$\begin{aligned}|V_{(i+1)}| = \left\{\left(r_{(j)}P_{(i+1)} + x_{(j)}Q_{(i+1)} - 0.5|V_{(i)}|^2\right)^2 - \left(r^2_{(j)} + x^2_{(j)}\right)\left(P^2_{(i+1)} + Q^2_{(i+1)}\right)\right\}^{1/2} \\ - \left(r_{(j)}P_{(i+1)} + x_{(j)}Q_{(i+1)} - 0.5|V_{(i)}|^2\right)\end{aligned} \tag{7}$$

where, node no., $i = 1, 2, \ldots, nd$
branch no., $j = 1, 2, \ldots, nd - 1$
$nd =$ total no. of nodes
The active and reactive power losses in branch 'j' are given by

$$Ploss[j] = \frac{r_{(j)}\left\{P^2_{(i+1)} + Q^2{}_{(i+1)}\right\}}{|V_{(i+1)}|^2} \tag{8}$$

$$Qloss[j] = \frac{x_{(j)}\left\{P^2_{(i+1)} + Q^2{}_{(i+1)}\right\}}{|V_{(i+1)}|^2} \tag{9}$$

The total active and reactive power losses of the system are

$$TPL = \sum_{j=1}^{nd-1} Ploss[j] \tag{10}$$

$$TQL = \sum_{j=1}^{nd-1} Qloss[j] \tag{11}$$

where

$Ploss[j], Qloss[j] =$ Active and reactive power losses of branch 'j'
$TPL, TQL =$ Total active and reactive power losses of the system

3 Development of discrete particle swarm optimization

Particle swarm optimization as developed by the authors comprises a very simple concept, and paradigms can be implemented in a few lines of computer code. It requires only primitive mathematical operators, and is computationally inexpensive in terms of both memory requirements and speed. Early testing has found the implementation to be effective with several kinds of problems. Discrete Particle swarm optimization has also been demonstrated to perform well on genetic algorithm test functions.

3.1 Simulating social behavior

One motive for developing the simulation was to model human social behavior, which is of course not identical to fish schooling or bird flocking. One important difference is its abstractness. Birds and fish adjust their physical movement to avoid predators, seek food and mates, optimize environmental parameters such as temperature, etc. Humans adjust not only physical movement but cognitive or experiential variables as well. We do not usually walk in step and turn in unison (though some fascinating research in human conformity shows that we are capable of it); rather, we tend to adjust our beliefs and attitudes to conform to those of our social peers.

3.2 Precursors: the etiology of particle swarm optimization

The discrete particle swarm optimization is probably best presented by explaining its conceptual development. As mentioned above, the algorithm began as a simulation of a simplified social milieu. Agents were thought of as collision-proof birds, and the original intent was to graphically simulate the graceful but unpredictable choreography of a bird flock.

3.3 Nearest neighbor velocity matching and craziness

A satisfying simulation was rather quickly written, which relied on two props nearest-neighbor velocity matching and "craziness." A population of birds was randomly initialized with a position for each on a torus pixel grid and with X and Y velocities. At each iteration a loop in the program determined, for each agent (a more appropriate term than bird), which other agent was its nearest neighbor, then assigned that agent's X and Y velocities to the agent in focus. Essentially this simple de created a synchrony of movement.

3.4 Acceleration by distance

Though the algorithm worked well, there was something aesthetically displeasing and hard to understand about it. Velocity adjustments were based on a crude inequality test: If $presentx > bestx$, make it smaller; if $presentx < bestx$, make it bigger. Some experimentation revealed that further revising the algorithm made it easier to understand and improved its performance. Rather than simply testing the sign of the inequality, velocities were adjusted according to their difference, per dimension, from best locations

$$vx\,[\,]\,[\,] = vx\,[\,]\,[\,] + rand() \times p\_increment \times (Pbestx\,[\,]\,[\,] - presentx\,[\,]\,[\,]) \tag{12}$$

(Note the parameters vx and $presentx$ have two sets of brackets because they are new matrices of agents by dimensions; increment and $bestx$ could also have a g instead of p at their beginnings.)

4 Implementation of pso for optimal conductor selection

In this section, the optimal size of the conductor in each branch of the radial distribution system is calculated using PSO. The different steps for implementation of PSO are explained in the following section.

4.1 Performance of discrete particle swarm optimization using inertia weights

The following describes the position and velocity update equations with weight factors included.

$$V_{id} = W \times V_{id} + C_1 \times rand() \times (P_{id} - X_{id}) + C_2 \times Rand() \times (P_{gd} - X_{id}) \tag{13}$$

$$X_{id} \rightarrow X_{id} + V_{id} \tag{14}$$

where C_1, C_2 are positive constants and called cognitive and social parameters.

Eq. (13) calculates a new velocity for each particle (potential solution) based on its previous velocity, the particle's location at which the best fitness so far has been achieved, and the population global (or local neighborhood, in the neighborhood version of the algorithm) location at which the best fitness so far has been achieved. Eq. (14) updates each particle's position in solution hyperspace. The two random numbers are independently generated. The use of the inertia weight, which typically decreases linearly from about 0.9 to 0.4 during a run, has provided improved performance in a number of applications.

4.1.1 Parameter selection in particle swarm optimization

Unlike many other computational intelligence techniques, the particle swarm optimizer has few parameters to tune. Many attempts have been made to improve the performance of originally developed PSO. Many parameters have been added to the originally developed PSO to modify or to improve the performance of the technique. A quick statistical experiment is used to fine tune these parameters for the class of constrained optimization problem considered.

Before going to the actual steps, various parameters of PSO with respect to the case are to be selected. In this case, types of conductors are selected as parameters. These values are system dependent. Hence, the PSO parameter values will vary from system to system. These parameters are encoded using suitable techniques. There are various encoding techniques. The decimal encoding technique is chosen, because of its simplicity for encoding and decoding. The other encoding techniques are binary, weighted sum, etc.

4.1.2 Swarm size, P

The swarm size or the number of individuals inside the population is determined by the integer parameter 'P'. For very small values of P the possibility of being trapped in local optima is very likely. Larger population will increase the computation time requirements.

4.1.3 Number of iterations

It is also a user defined parameter that determines the number of iterations for which algorithm has to run. Based upon computational experience a few hundred of iterations are usually sufficient to observe significant improvement in the solution providing that the initial solutions are feasible.

4.1.4 Velocity of particle

One of the important factors that affect performance of the PSO, Specifically the speed of the convergence is the particle's velocity of 'flying' inside the problem space. This parameter limits the steps taken by particles at every iteration. A small value can cause the particle to get trapped in local optima; on the other hand, a too large value can cause oscillation around a certain position. This problem of proper selection of velocity can be eliminated by using adaptive velocity to PSO's position updating. The following equation represents the velocity update equation.

$$V_{id} = W \times V_{id} + C_1 \times rand() \times (P_{id} - X_{id}) + C_2 \times Rand() \times (P_{gd} - X_{id}) \tag{15}$$

Where C_1 and C_2 are positive constants, called cognitive and social parameters respectively, both are equal to 2 in general cases. 'W' is inertia weight factor; a large weight factor facilitates a global search while a small inertia weight facilitates a local search.

4.2 Objective function

In any radial distribution system, the optimal choice of the size of conductor in each branch of the system, which minimizes the sum of depreciation on capital investment and cost of energy losses, is important. The problem of choice of the optimal size of conductor for each feeder segment is presented as an optimization problem using discrete particle swarm optimization technique.

The objective is to select optimal size of the conductor in each branch of the system, which minimizes the sum of depreciation on capital investment and cost of energy losses. In detail, the objective function for optimal selection of conductor for branch j with k type conductor is

$$\min F(j,k) = CL(j,k) + CC(j,k) \tag{16}$$

(i) Cost of energy losses (CL):
The annual cost for the loss in branch j with k type conductor is,

$$CL(j,k) = \text{Peak loss}(j,k)[Kp + Ke \times Lsf \times 8760] \tag{17}$$

where

$Kp =$ Annual demand cost due to power loss$(Rs./kW)$
$Ke =$ Annual cost due to energy loss$(Rs./kWh)$
$Lsf =$ Loss factor
Peak loss$(j,k) =$ Real power loss of branch j under peak load conditions with k type conductor

(ii) Depreciation on capital investment (CC):
The annual capital cost for branch j with k type conductor is,

$$CC(j,k) = \text{á} \times [cost(k) \times len(j)] \tag{18}$$

where

á $=$ Interest and depreciation factor
$Cost(k) =$ Cost of$k$type conductor$(Rs./km)$
$Len(j) =$ Length of branch$j(km)$

Loss factor is defined as ratio of energy loss in the system during a given time period to the energy loss that could result if the system peak loss had persisted throughout that period. In British experience, loss factor is expressed in terms of the load factor (Lf) as

$$Lsf = 0.2Lf + 0.8Lf^2 \tag{19}$$

4.3 Evaluation of fitness function

The evaluation of fitness function is a procedure to determine the fitness of each string in the population. Since the DPSO proceeds in the direction of evolving best-fit strings and the fitness value is the only information available to the DPSO, the performance of the algorithm is highly sensitive to the fitness values. The fitness function f, which has been chosen in this problem, is

$$f = \frac{1}{F(j,k)} \tag{20}$$

4.4 Algorithm for optimal type of conductor selection

The detailed algorithm to determine optimal size of the conductor is given below
Step 1. Read the system data.
Step 2. Perform load flow.
Step 3. Initialize population.
Step 4. Set the iteration count to '1'.
Step 5. Calculate the objective function using Eq. (16).
Step 6. Calculate the fitness value using Eq. (20).
Step 7. Sort data in the ascending order of fitness.
Step 8. Now copy the best string of chromosomes of old population to new population.
Step 9. Now perform crossover and mutation operations respectively for generating remaining chromosomes.
Step 10. Now, replace old population with new population.
Step 11. Increment iteration count. If iteration count <max. count, goto Step 4. Else go to Step12.
Step 12. Print the total real power loss, reactive power loss, and voltages.

5 Results and analysis

In this section, the effectiveness of the proposed algorithm is demonstrated through two examples, consisting of 26-node and 32-node radial distribution systems.

5.1 Example-1

Before analyzing the results, it is worth mentioning that presently in India, utilities are using three or four different types of conductors for distribution feeders. This type of conductor data is given in appendix The single line diagram for practical 26-node, practical radial distribution systems in India is shown in Fig. 2. The line and load data are given in [5]. Based on algorithm, the results of conductor type selection are presented

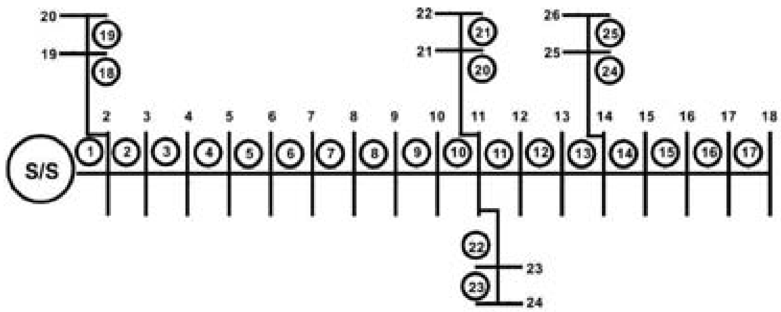

Fig. 2. Practical 26-node radial distribution system

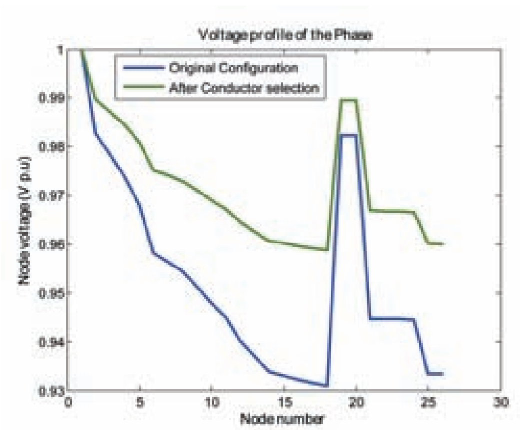

Fig. 3. Voltage profile of 26-node system before and after conductor selection

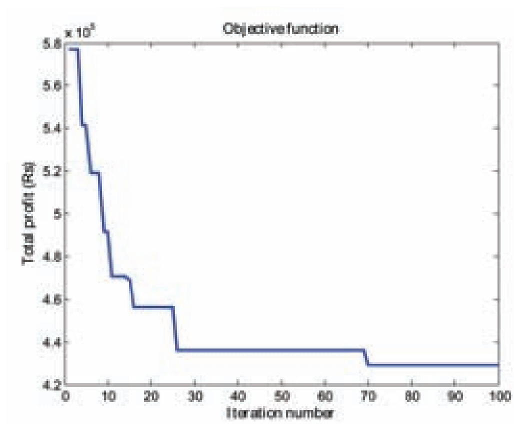

Fig. 4. Objective function of 26-node radial distribution system

in Tab. 1 From Tab. 1, it can be seen that reconductoring is necessary for all the branches except from 15 to 17. The minimum voltage is improved from 0.9309 p.u to 0.9572 p.u. The improvement in voltage regulation is 2.74%. Total real power loss reduction after conductor grading is 80.62 kW. Total power cost reduction after conductor grading is Rs. 4, 54, 579/-.

5.2 Example-2

The single line diagram of 32-node radial distribution system is shown in Fig. 5. Voltage profile of 32-node system before and after conductor selection is shown in Fig. 6. Objective function of 26-node radial distribution system is shown in Fig. 7.The line and load data of this system are also given in [5]. Based on the algorithm, the results of conductor type selection are presented in Tab. 3. From Tab. 3, it can be seen

Table 1. Modifications in the feeder conductor type after conductor selection of 26 node system

Branch Number	Existing Conductor (From)	Modified Conductor (To)
1 to 10	Weasel	Mink
11 to 14	Weasel	Rabbit
15 to 17	Weasel	Weasel
18t to 25	Weasel	Squirrel

Table 2. Summary of results of 26-node system

Description	Base Case	After Conductor Selection
Min.Voltage ($p.u$)	0.9309	0.9572
Real Power Loss (kW)	154.79	76.98
Total Cost ($Rs.$)	5,04,082/-	2,53,349/-

that reconductoring is necessary for all the branches except 21 to 23. It is seen that minimum voltage is improved from 0.9018 p.u to 0.9133 p.u. The improvement in voltage regulation is 1.25%. Total real power loss reduction after conductor grading is 56.92kW. Total power cost reduction after conductor grading is Rs 1,78,868/-.

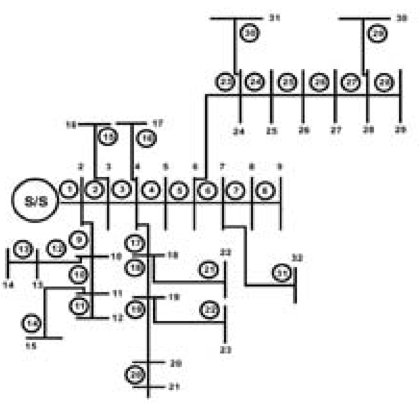

Fig. 5. 32-node Radial distribution system

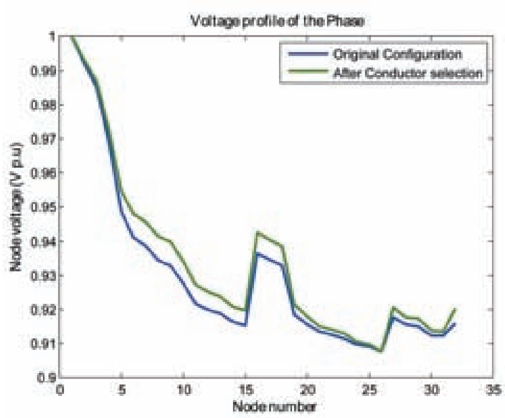

Fig. 6. Voltage profile of 32-node system before and after conductor selection

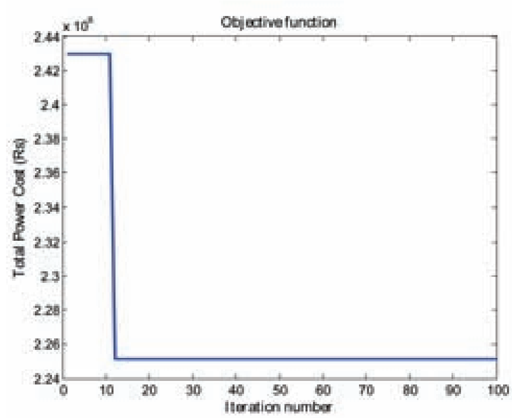

Fig. 7. Objective function of 32-node radial distribution system

Table 3. Modifications in the feeder conductor type after conductor selection of 32 node system

Branch Number	Existing Conductor (From)	Modified Conductor (To)
1 to 10	Weasel	Mink
11 to 20	Weasel	Ferret
21 to 23	Weasel	Weasel
24 to 31	Weasel	Squirrel

Table 4. Summary of results of 32-node system

Description	Before Conductor Selection	After Conductor Selection	Improvement
Min.Voltage (p.u)	0.9078	0.9133	0.0055
Real Power Losses (kW)	426.867	369.944	56.92
Total Power Cost (Rs.)	24,30,041/-	22,51,173/-	1,78,868/-

6 Conclusion

It is very challenging to select an optimal set of conductors for designing a distribution system. In this paper, an algorithm has been proposed for selecting the optimal branch conductor using discrete particle swarm optimization algorithm. The proposed method selects the optimal branch conductor by minimizing the sum of cost of energy losses and depreciation cost of feeder conductor. In addition the algorithm keeps the maximum current carrying capacity and minimum voltage within prescribed limit. The proposed algorithm has been implemented on 26-node and 32-node practical radial distribution systems in India.

References

[1] G. Anders, et al. Parameters affecting economic selection of cable sizes. *IEEE Trans. on Power Delivery*, 1993, **8**(3): 1661–1667.

[2] A. Funkhouser, R. Huber. A method for determining economical acsr conductor sizes for distribution system. *IEEE Trans. on Power Apparatus and Systems*, 1995, **74**: 479–484.

[3] S. Leppert, A. Allen. Conductor life cycle cost analysis. *Proc. Rural Electric Power Conf*, 1995, C2.1–2.8.

[4] M. Ponnavaikko, K. Rao. An approach to optimal distribution system planning through conductor gradation. *IEEE Trans. on Power Apparatus and Systems*, 1982, **101**(6): 1735–1742.

[5] S. Sivnagaraju, N. Sreenivasulu, et al. Optimal conductor selection for radial distribution system. *Electric Power Systems Research*, 2002, **63**: 95–103.

[6] H. Tram, Wall. Optimal conductor selection in radial distribution system. *IEEE Trans. on Power Systems*, 1988, **3**: 743–746.

[7] D. Wall, G. Thompson, J. Green. An optimization model for planning radial distribution network. *IEEE Trans. on Power Apparatus and Systems*, 1979, **98**: 1061–1065.

[8] H. Willis. *Power Distribution planning reference book*. Marcel Dekker, NewYork.

Appendix:

Table 5. Conductor Data

Type of Conductor	Area of cross Section (mm^2)	Resistance ohm/km	Reactance ohm/km	Maximum current carrying capacity CMAX (Amp.)	Rs/Km
Squirrel	12.90	1.3740	0.3915	115	1260
Weasel	19.35	0.9116	0.3820	150	1420
Ferret	32.26	0.6795	0.3760	181	1600
Rabbit	48.39	0.5449	0.3720	208	1785
Mink	50.00	0.4565	0.3660	234	1785