Journal of Engineering Science and Technology
Vol. 7, No. 4 (2012) 487 - 497

A HYBRID APPROACH FOR RURAL FEEDER DESIGN

DAMANJEET KAUR

University institute of Engineering and Technology, Panjab University,
Sector-25, Chandigarh, India
E-mail: damaneee@pu.ac.in

Abstract

In this paper, a population based approach for conductor size selection in rural radial distribution system is presented. The proposed hybrid approach implies a particle swarm optimization (PSO) approach in combination with mutant property of differential evolution (DE) for conductor size selection in radial distribution system. The conductor size for each feeder segment is selected such that the total cost of capital investment and capitalized cost of energy losses is minimized while constraints of voltage at each node and current carrying capacity of conductor is within the limits. The applicability and effectiveness of the proposed method is demonstrated with the help of 32-node test system.

Keywords: Radial, Feeder, PSO, DE, PSO-DV, Distribution system.

1. Introduction

In distribution system, consumers are supplied power with the help of conductors named as feeders. These conductors are lengthy in nature and carry bulk amount of power to service mains and consumers. Generally, distribution system is operated in radial configuration due to low cost and its ease of protection. Due to radial nature, current in feeders decreases from source to far end. Thus it proves economical to have multi-conductor in the radial distribution system. Although mesh type distribution systems proves more reliable, but due to economy of radial distribution system, multi-conductor selection for feeders is still in practice in developing countries like India. The concept of multi-conductor was first introduced by Funkhouser and Huber [1] considering uniform load on the distribution system. Later on practical model considering load growth rate, load factor and cost of energy and cost of power is developed [2-7].

Authors developed method based on local search [2], heuristic [3, 4], partial enumeration technique [5] and Evolutionary Algorithms [6, 7] to obtain optimal sizes of conductors in radial feeders.

Nomenclatures

A_t	Cross-section area of *t* type of conductor, mm^2
alpha	Carrying charge rate of feeder
Cap(t)	Maximum current carrying capacity of the *t* type of conductor
Cc	Constant associated with the variable installation cost of feeder, Rs./mm^2/km
C_e	Cost of energy, Rs./kWh
C_p	Cost of power, Rs./kW
Cr	Crossover probability
c_1 , c_2	Acceleration constants
F	Real valued weight factor to control the amplification of the differential variation between two chosen vectors.
gbest	Global best fitness function of swarm of PSO in a iteration
I(i,t)	Current flowing through each feeder segment *i* for *t* type conductor
int	Operator of rounding the variable to the nearest integer
k	Current number of iteration
$K_{1(i,t)}$	Cost of conductor, Rupees
$K_{2(i,t)}$	Cost of losses, Rupees
K_{Ti}	Total cost of the feeder, Rupees
k_{max}	Maximum number of iterations
L_i	Length of feeder segment *i*, km
Lsf	Load loss factor
Np	Random population vector
n	Total number of feeder segments
$P_{loss(i,t)}$	Power loss in kW in feeder segment *i* for *t* type of conductor
	Theoretical normal force slope parameter, 1/rad
pbest	Local best fitness function of particle *p* in PSO
rand1	Random number generated in [0, 1]
rand2	Random number generated in [0, 1]
T	Total number of hours in one year
U	Each individual of the population, $U \in Np$
V_{max}	Maximum value of voltage at each node *i*
V_{min}	Minimum value of voltage at each node *i.*
w	Inertia weight factor
x_{max}, x_{min}	Bounds on the variable i.e. sizes of conductors in the inventory
Z	Maximum number of successive iterations up to which change in position of particle is tolerated

Greek Symbols

β	Scalar factor between 0 and 1

Abbreviations

PSO	Particle swarm optimization
DE	Differential evolution

These days Evolutionary Algorithms inspired by biological and sociological motivations are most commonly used [6, 7]. But in most of implemented

Evolutionary Algorithms (EA) methods tuning of parameters is of prime importance and size of population affects the quality and convergence of solution.

In last decade, to overcome the problem of tuning of parameters and convergence criteria, a population based Particle Swarm Optimization (PSO) search algorithm is developed which has ability to ensure an optimal solution because of its implicit parallelism. It is observed that sometimes PSO traps in local minima. Now a day another population based Differential Evolution (DE) algorithm is also very common. DE has inherent feature of not trapping in local minima due to randomness in its search space. Hence in this paper, to enhance the search capability of PSO, PSO is applied in combination with Differential Evolution (DE) technique. In PSO, velocity vector is updated using cognitive and social term to find an optimal solution. In PSO-DV (Particle Swarm Optimization with Differentially Perturbed Velocity), PSO cognitive term in velocity vector is replaced with the DE mutant vector. The mutant vector is generated by weighted difference vector of randomly chosen two position vectors from the swarm. The purpose of applying this mutant vector is to increase the diversity of PSO which helps to escape it from the local minima.

In this paper, a PSO-DV based algorithm is developed for conductor size selection in radial distribution systems. The conductor sizes are selected such that the total cost of conductor and cost of energy losses are minimized while the constraint of voltage at all nodes and current carrying capacity of each conductor is within limits. Although PSO was initially developed for continuous variables, but in this paper it is used for discrete sizes of conductors. The proposed approach is tested on 32 node test feeder. The results obtained using proposed approach is optimal one in small computational time. The results are also compared with the Particle Swarm Optimization approach and it is found that the proposed approach gives better results than PSO.

2. Problem Formulation

The problem of conductor size selection is to select conductor size for each feeder segment in a feeder such that the total cost of feeder, i.e. the cost of energy and power losses and cost of conductor is minimized while constraint of voltage on each node and current carrying capacity of each conductor is within permissible limits [6].

The objective function is given by Eqs. (1) to (3)

$$Min\,C = \sum_{i\in n} K_{Ti} = \sum_{i\in n} (K_{1(i,t)} + K_{2(i,t)}) \tag{1}$$

$$K_{1(i,t)} = alpha\ ccL_i A_t \tag{2}$$

$$K_{2(i,t)} = C_p\, P_{loss,(i,t)} + P_{loss,(i,t)} C_e\, T\, lsf \tag{3}$$

2.1. Voltage constraint

As in feeder design voltage constraint is the main factor. So, the voltage at each node *i* should be within the prescribed limit as:

$$V_{\min} < V_i < V_{\max} \tag{4}$$

2.2. Current carrying capacity constraint

The current flowing through each feeder segment *i* for *t* type conductor should be less than the maximum current carrying capacity (*Cap*) of the *t* type of conductor.

$$I(i,t) < Cap(t) \tag{5}$$

3. Solution Approach

In this section, a PSO-DV approach in combination is presented for optimal conductor sizing in radial distribution systems. Conductor size selection for feeder is solved as constrained optimization problem when voltage and current carrying capacity are constraint on the problem. In PSO-DV, the classical PSO algorithm is implemented except the velocity vector of PSO is modified using a differential random position vector (obtained by difference of two randomly chosen particles) in place of cognitive term in velocity vector. In this section, detail of proposed algorithm is discussed along with brief introduction of PSO and DE [8, 9].

3.1. Particle swarm optimization (PSO)

Particle Swarm Optimization is a population based evolutionary technique and it (PSO) was introduced by Kennedy and Eberhart [10] as an alternative to Genetic Algorithms. PSO has the flexibility to control the balance between the global and local exploration of the search space. This unique feature of a PSO overcomes the premature convergence problem and enhances the search capability and ensures the convergence to the optimal solution. It was originally proposed for continuous problems, and attempts have been made recently to extend it to discrete optimization problems [11, 12].

In PSO, initially a populations of individuals (particles) is generated randomly within the given search space of variables termed as swarm. Each particle p at iteration k has velocity (Vel_p^k) and position (pos_p^k) vector within n-dimensional search space. For each particle p at iteration k, fitness function corresponding to the objective function to be optimized is evaluated. Store best fitness value (*pbest)* for each particle p and the global best of swarm (*gbest*) respectively till k^{th} iteration. Store position vector of particle p ($pos_p^{best,k}$) and swarm (pos^{gbest}) which yields *pbest* and *gbest* respectively. Initially at iteration k, consider *gbest* is equal to *pbest*. Compare the fitness value of the particle p at $k+1$ with that of the previous best one and update velocity and position vector of particle p corresponding to *gbest* and *pbest* till iteration $k+1$ using Eqs. (6) and (7).

$$Vel_p^{k+1} = \mathrm{int}(wVel_p^k + c_1 rand_1(pos_p^{best,k} - Pos_p^k) + c_2\, rand_2(pos^{gbest} - Pos_p^k) \tag{6}$$

$$pos_p^{k+1} = pos_p^k + Vel_p^{k+1} \tag{7}$$

Equation (6) consists of three terms on RHS; first term is the velocity in k^{th} iteration; second term is the cognition-only model and the third term is the so-called social-only model, these terms are utilized to change the velocity of particle.

w provides balance between global and local explorations. w often decreases from 0.9 to 0.4 during the iterations. It is generally set using the following equation:

$$w = w_{\max} - ((w_{\max} - w_{\min}) / k_{\max}) * k \tag{8}$$

The above-mentioned procedure is repeated till the search satisfies the termination condition.

3.2. Differential evolution (DE)

Differential Evolution (DE) is one of the recent developed population-based techniques which was invented by Price and Storn [13]. DE belongs to class of evolutionary algorithms that include Evolution Strategies (ES) and Genetic Algorithms (GA). DE differs from GA in its use of perturbing vectors, which are difference between two randomly chosen vectors. In DE, during optimization process four basic operations are carried: initialization, mutation, crossover and selection [8, 9].

3.2.1. Initialization

Initially at generation $Gen=1$, a random population vector (Np) of size n is generated. Each individual (U) of the population represents the solution vector of design variables of the problem in the given search space. Evaluate fitness function of each individual for the given objective function.

3.2.2. Mutation

In order to produce population for next iteration, $Gen=Gen+1$, a mutation operator is applied at the current population at $Gen=1$. The mutation operation produces mutant vectors by considering vector difference of randomly selected individual vectors from the population. In literature, different mutation mechanisms are available but the basic concept is difference of randomly selected two, three or more individuals are always considered [8] as given below

$$Mut_U = U_{3,Gen} + F(U_{1,Gen} - U_{2,Gen}) \qquad U \in Np \tag{9}$$

where Mut_U is the mutant vector obtained by random selection of individuals $U_{1,Gen}$, $U_{2,Gen}$ and $U_{3,Gen}$ as in Eq. (9). F has real value between 0 and 1.

3.2.3. Crossover

In order to extend further diversity in searching process, crossover operation is performed. Let $a_1....a_7$ and $b_1....b_7$ are values of design variables of target and mutant vector respectively. In crossover, target and mutant vectors are combined to produce trail vectors as shown in Fig. 1.

The j^{th} ($j \in n$) design variable in the trial vector is obtained by comparing the random number generated between 0 and 1 and crossover probability (Cr). If random number is greater than the Cr, j^{th} design variable of trial vector is chosen as in mutant vector otherwise as in target vector.

3.2.4. Selection

After generating trial vectors, next is to decide whether these trail vectors will be individuals of population at $Gen=Gen+1$ or not. To decide this, fitness of trial vector is compared with the target vector. If the value of fitness function of trial vector is better than target vector then trial vector will be considered as new individual otherwise the target vector will be taken in $Gen=Gen+1$. The above three steps: mutation, crossover and selection of DE are performed sequentially until the stopping criterion is met.

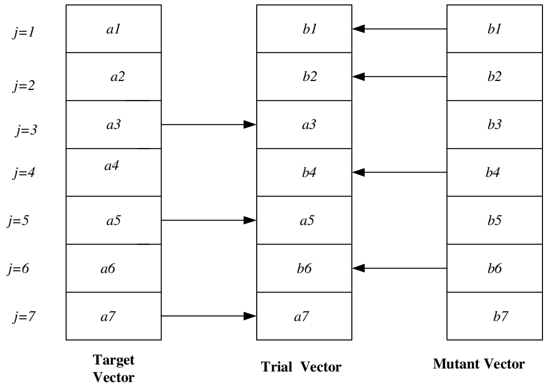

Fig. 1. Generation of Trial Vector by Mixing Mutant and Target Vectors.

3.2.5. Algorithm of PSO-DV for conductor size selection in radial distribution system

1. Generate randomly a swarm of integer particles. Each particle p has position and velocity vector in the given n-dimensional search space (n being feeder segments in a feeder) as in (6) and (7).

2. Evaluate fitness function for each particle using (1), (4) and (5) as:

$$Fitness = objective\ function + penalty\ for\ constraints\ violation \tag{10}$$

3. Update velocity of each particle p using PSO-DV in combination as given below:
   (i) Select two distinct particles q and s randomly from the swarm such that $p \neq q \neq s$.
   (ii) Obtain a difference vector by subtracting the position vectors of randomly selected particles q and s as:

$$delta = pos_q^k - pos_s^k \tag{11}$$

   (iii) Update velocity vector of u^{th} feeder segment ($u \in n$) of particle p using modified velocity vector of the classical PSO, in which cognitive part of the velocity update formula in (6) is replaced with the vector differential operator to produce some additional exploration capability as given below:

$$vel_{p,u}^{k+1} = \begin{cases} \text{int}\left(w\,vel_{p,u}^{k} + \beta\, delta_u + c_2\, rand_2 \left(pos_{p,u}^{gbest} - pos_{p,u}^{k} \right) \right) & \\ vel_{p,u}^{k} & if\ rand \le Cr \end{cases} \tag{12}$$

From Eq. (12) it is clear that size of conductor of some feeder segments are modified while for others it remains same as in earlier iteration. Repeat Step (iii) for all feeder segments (n) in a particle p.

4. Generate trial position vector (conductor sizes for feeder segments) for each particle p by updating the position vector as:

$$T_p^{k+1} = pos_p^k + vel_p^{k+1} \tag{13}$$

5. Evaluate fitness function for the trial position vector. If the fitness function is better than the earlier position. Then particle is placed at new location otherwise remains at the same old position as:

$$\begin{aligned} pos_p^{k+1} &= T_p^{k+1} \quad && if\ fitness(T_p^{k+1}) \le fitness(pos_p^k) \\ pos_p^{k+1} &= pos_p^k && otherwise \end{aligned} \tag{14}$$

6. If a p^{th} particle gets stagnated in local minima i.e. if the position is not changing for large number of successive iterations, then each u^{th} feeder segment of particle p is shifted to new position by random mutation after given number of successive generation as:

$$pos_{p,u}(k+z+1) = \text{int}(x_{\min} + rand(0,1)(x_{\max} - x_{\min}) \quad u \in n \tag{15}$$

7. Repeat the above steps 3 to 6 until stopping criterion of maximum number of iterations is achieved.

4. Computer Programme: Validation and Verification

The proposed approach is tested on large number of test feeders. In this paper, the proposed method is demonstrated with the help of 32 node test system [7]. The results of proposed approach are also compared with PSO approach.

A 32 node Indian rural distribution network is considered as shown in Appendix A, Fig A.1. The load data and line data is mentioned in Table 1 [11]. In this paper, the load data is taken after load growth period of eight year as mentioned in [11]. Four different types of conductors are considered in inventory and other basic data is tabulated in Tables 2 and 3 respectively. The minimum voltage at each node should be 0.98 pu. To optimize the size of conductor for each feeder segment, following parameters are set:

Size of swarm -20
Crossover rate (*Cr*)-0.3
Maximum number of iteration for PSO- 20
Maximum number of successive iterations up to which position vector does not change in PSO-DV- 5.

The results obtained using proposed approach is tabulated in Tables 4 and 5 respectively.

In the proposed approach, initially a random set of particles in the given search space is generated. Then fitness function for each particle is calculated as in (10). Next *pbest* and *gbest* are found out. To produce new population, velocity and position vectors are updated as explained in 3.2.5. This procedure is repeated until maximum number of iterations is achieved. The optimal sizes of conductors for feeder segments obtained using proposed approach are tabulated in Table 4.

As it is clear from the 3rd column of Table 4, the feeder segments near the far end has smaller size of conductor as compared to the feeder segments near the source end. The obtained results are also compared with the base case i.e. when all feeder segments have minimum size of conductor. The comparative results are tabulated in Table 5. It is clear from 2nd column of Table 5 that there is reduction in power losses from 117.81 kW to 30.081 kW, i.e. with reduction of 87.73 kW. In addition this, there is also reduction in total investment cost from Rs. 59373000 to Rs. 58763000 as tabulated in 2nd column of Table 6.

The conductor sizes obtained using proposed approach are also compared with conductor sizes obtained using PSO as shown in Table 4. It is clear from 2nd and 3rd column of Table 4 that proposed approach selects conductor sizes better than PSO. It is clear from Table 4 that PSO cause selection of higher sizes conductors for feeder segments 7, 20 and 21, etc., as compared to proposed approach. It requires investment of Rs. 58766000 which is less than the base case but more than the proposed approach as given in 2nd column of Table 6. From these results it is clear that the proposed approach gives better results than PSO.

Table 1. Line and Load Data of 32-node Radial Feeder [11].

Segment /Node Number	From	To	Length (km)	Real Power Demand (kW)	Real Power Demand (kVar)
1	1	2	0.3837	0	0
2	2	3	0.1936	137.45	103.09
3	3	4	0.1428	0	0
4	4	5	0.4231	0	0
5	5	6	0.0968	137.45	103.09
6	6	7	0.1944	0	0
7	7	8	0.0133	0	0
8	8	9	0.0511	137.45	103.09
9	2	10	0.4477	137.45	103.09
10	10	11	0.108	0	0
11	11	12	0.0222	0	0
12	10	13	0.0802	137.45	103.09
13	13	14	0.2262	137.45	103.09
14	11	15	0.3379	137.45	103.09
15	3	16	0.014	137.45	103.09
16	4	17	0.2065	137.45	103.09
17	4	18	0.1396	137.45	103.09
18	18	19	0.045	0	0
19	19	20	0.0866	0	0
20	20	21	0.1761	137.45	103.09
21	18	22	0.1322	137.45	103.09
22	19	23	0.0265	137.45	103.09
23	6	24	0.0514	137.45	103.09
24	24	25	0.1392	0	0
25	25	26	0.2538	137.45	103.09
26	26	27	0.2426	137.45	103.09
27	27	28	0.2443	137.45	103.09
28	28	29	0.1979	0	0
29	28	30	0.1006	137.45	103.09
30	24	31	0.0964	137.45	103.09
31	7	32	0.2045	137.45	103.09
32				137.45	103.09

Table 2.Type of Conductors Available in Inventory [7].

Type of Conductor	Squirrel	Weasel	Rabbit	Raccoon
Area of Cross Section (mm^2)	12.90	19.35	32.26	48.39
Resistance (ohm/km)	1.3760	0.9108	0.5441	0.3657
Reactance (ohm/km)	0.3896	0.3797	0.3673	0.3579
Maximum Current Carrying Capacity (A)	115.0	150.0	208.0	270.0

Table 3. Other Data Used in the Example.

cc	=	Rs. 500/mm^2
C_e	=	0.50 Rs./kWh
Cp	=	Rs. 2500/kW
lsf	=	0.2
alpha	=	0.1

Table 4. Optimal Conductors Sizes Using Proposed Approach.

Segment Number	Conductor Size Selected using PSO	Final Conductor Sizes Selected
1	Raccoon	Raccoon
2	Raccoon	Raccoon
3	Raccoon	Raccoon
4	Raccoon	Raccoon
5	Raccoon	Raccoon
6	Raccoon	Raccoon
7	Raccoon	Weasel
8	Rabbit	Squirrel
9	Raccoon	Raccoon
10	Raccoon	Raccoon
11	Raccoon	Raccoon
12	Raccoon	Raccoon
13	Raccoon	Raccoon
14	Raccoon	Raccoon
15	Raccoon	Raccoon
16	Rabbit	Rabbit
17	Raccoon	Raccoon
18	Raccoon	Raccoon
19	Raccoon	Raccoon
20	Rabbit	Raccoon
21	Raccoon	Weasel
22	Rabbit	Raccoon
23	Raccoon	Raccoon
24	Raccoon	Raccoon
25	Raccoon	Raccoon
26	Raccoon	Raccoon
27	Raccoon	Raccoon
28	Raccoon	Raccoon
29	Raccoon	Raccoon
30	Raccoon	Squirrel
31	Raccoon	Raccoon

The performance of proposed approach in terms of convergence criteria is also shown in Fig. 2. From this figure it is clear that for a small size of swarm, the proposed approach converges to global solution in few numbers of iterations due to PSO ability to search best solution of the problem.

Hence it can be concluded that the PSO-DV approach gives better results than the solution obtained using PSO. The DV of PSO-DV enhances PSO search capability while solution quality is also improved. The other advantage of proposed approach is that the tuning of parameters is quite less as compared to other evolutionary techniques and easy to implement.

Table 5. Comparison of Base Case and Proposed Approach.

Case	Voltage (pu)	Real Power Losses (kW)
Base Case	0.957	117.8
After Conductor Size Selection	0.9841	30.081

Table 6. Comparison of Objective Function for Base Case, PSO and Proposed Approach.

	Objective Function
Base Case	59373000
Using PSO	58766000
Using Proposed Approach	58763000

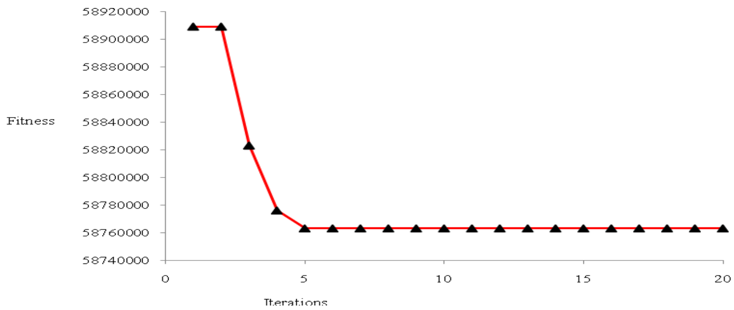

Fig. 2. Variation of Fitness Function with Number of Iterations.

5. Conclusions

In this paper a population based approach for conductor size selection in radial distribution system is presented. In the proposed approach DV increases the search capability of PSO while PSO ability of giving global solution is not affected. The conductor sizes are selected for each feeder segment such that total cost of investment of conductor and cost of losses is minimized while constraints of voltage and current are satisfied. The proposed approach produces global solution even for large size of network. The proposed approach is applicable to design a new radial distribution system or reconductoring of an existing one.

References

1. Funkhouser, A.W.; and Huber, R.P. (1955). A method for determining economical ACSR conductor sizes for distribution systems. *Transactions of the AIEE on Power Apparatus and Systems*, 74(3), Part III, 479-483.
2. Ponnavaikko, M; and Prakasa Rao, K.S. (1982). An approach to optimal distribution system planning through conductor gradation. *IEEE Transactions on Power Apparatus and Systems*, PAS-101(6), 1735-1741.
3. Wang, Z.; Liu, H.; Yu, D.C.; Xiaohui, W.; and Song, H. (2000). A practical approach to the conductor size selection in planning radial distribution systems. *IEEE Transactions on Power Delivery*, 15(1), 350-354.

4. Nagendra Rao, P.N. (1985). An extremely simple method of determining optimal conductor selections for radial distribution feeders. *IEEE Transactions on Power Apparatus and Systems*, PAS-104(6), 1439-1442.
5. Kaur, D.; and Sharma, J. (2008). Optimal feeder design in planning radial distribution systems. *International Journal of Electrical Power and Energy Systems*, 30(4), 261-271.
6. Sivanagaraju, S.; Sreenivasulu, N.; Vijayakumar, M.; and Ramana, T. (2002). Optimal conductor selection for radial distribution systems. *Electric Power Systems Research*, 63(2), 95-103.
7. Sreedhar, M.; Visali, N.; Sivanagaraju, S.; and Sankar, V. (2008). A novel method for optimal conductor selection of radial distribution feeders using fuzzy evolutionary programming. *International Journal of Electrical and Power Engineering*, 2(1), 6-10.
8. Kaur, D. (2011). A PSO-DV Based Approach for Capacitor Placement in Radial Distribution Systems. *IEEE 24th Canadian Conference of Electrical and Computer Engineering held at Ontario, Canada*, 400-405.
9. Das, S.; Abraham, A.; and Konar, A. (2008). Particle swarm optimization and differential evolution algorithms: Technical analysis, applications and hybridization perspectives. *Advances of Computational Intelligence in Industrial Systems. Studies in Computational Intelligence*, 116, 1-38.
10. Kennedy, J.; and Eberhart, R. (1995). Particle swarm optimization. *IEEE Proceedings on 1st International Conference on Neural Networks*, 4, 1942-1948.
11. Kennedy, J.; and Eberhart, R.C. (1997). A discrete binary version of the particle swarm algorithm. *IEEE International Conference on Systems*, *Man*, *and Cybernetics*, 5, 4104-4109.
12. Al-Kazemi, B.S.N.; and Mohan, C.K. (2000). Multi-phase discrete particle swarm optimization. *Electrical Engineering and Computer Science.* Paper 54.
13. Price, K.; Storn, R.M.; and Lampinen, J.A. (2005). *Differential evolution - A practical approach to global optimization*. Springer.

Appendix A

Figure of the Given Data

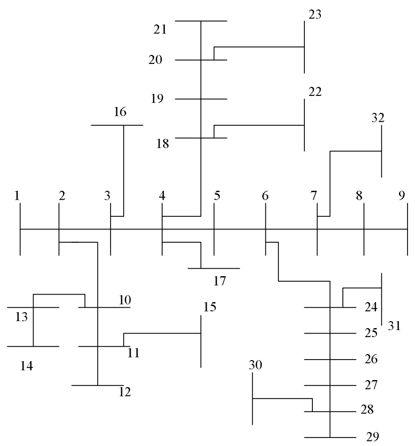

Fig. A.1. Single Line Diagram of 32 Bus Radial Distribution System [7].