

Solving Reconfiguration Problem Using Multi Objective Particle Swarm Optimization for Power Distribution System

S Navya Lakshmi¹, M.C.V.Suresh² and Dr.Shaik Rafi Kiran³

¹ M.Tech Student, Department of EEE, SVCE, Tirupati, Email: navya.sanam@gmail.com

² M.Tech, Asst Prof, Department of EEE, SVCE, Tirupati, Email: mcvsuresh@gmail.com

³ Professor & HOD, Department of EEE, SVCE, Tirupati, Email: rafikiran@gmail.com

Abstract: This paper introduces a new Multi Objective Particle swarm Optimization algorithm (MOPSO) for the purpose of solving the DSR problem & optimal placement of DGs. The objectives of the problem are to minimize real power losses and improve the voltage profile with minimum switching operations. The best solution is determined by simply considering the sum of the normalized objective values. Radial system topology is satisfied using graph theory by formulating the branch bus incidence matrix (BBIM) and checking the rank of each topology. To test the algorithm, it was applied to widely studied test systems and a real one. The results show the efficiency of this algorithm as compared to other methods in terms of achieving all the goals simultaneously with reasonable population and generation sizes and without using a mutation rate, which is usually problem dependent.

Index Terms—Distribution system reconfiguration, Multi Objective Particle swarm Optimization algorithm (MOPSO), Distribution Generations (DG's).

I INTRODUCTION

The distribution system constitutes a significant part of a total power system. A 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 and carry the current in bulk to the feeding points. Power losses in the lines account for the major portion of the distribution system losses. These power losses mainly depend on the type of conductor and its resistance, size and length. To meet the present growing domestic, industrial and commercial load day by day, effective planning of the radial distribution network is required. Increasing costs of energy and costs of generating capacity are encouraging the electric

utility to spend capital to improve the efficiency of the distribution system. The objective of distribution system planning is to assure the growing demand for electricity, in terms of increasing growth rates and high load densities that can be satisfied in an optimum way by additional distribution systems. The single line diagram of a sample radial distribution feeder is shown in Figure 3.1 where the digits indicate branch and alphabets represent the node.

Proper selection of branch conductors for connecting the load point is required to reduce the planning cost. Although the uniform conductor can reduce the loss of the system, it increases the planning cost.

An electric distribution system is an electric power system interface between the power source and the consumer's service switches. The efficiency of a distribution system in fulfilling the functions is measured in terms of voltage regulation, service continuity, flexibility, efficiency and cost. The cost of distribution is a significant factor in the delivered cost of electric power. The power sources are located in the load area to be served by the distribution system that generates power substations supplied over transmission lines.

(a) Sub-Transmission Circuits

The sub-transmission circuits extend from the bulk power source or source to the various distribution substations located in the load area. They may be radial circuits connected to a bulk power source at only one end or loop and ring circuits connected to one or more bulk power sources at both ends. The sub-transmission circuits consist of underground cable, aerial cable or overhead open-wire conductors carried on poles or some combination of them. The sub-transmission voltage is usually between 11/33KV.

(b) Distribution Substation

Each distribution substation normally serves its

own load area, which is a sub division of the area served by the distribution system. At the distribution substation, the sub-transmission voltage is reduced for general distribution throughout the area. The substation consists of one or more power transformer banks together with the necessary voltage regulating equipment, buses and switchgear.

(c) Primary Feeders

The area served by the distribution substation is also sub-divided and each sub-division is supplied by a distribution or primary feeder. The three-phase primary feeder is usually run out from the low-voltage bus of the substation to its load centre, where it branches into three phase sub feeders and single-phase laterals.

(d) Distribution Transformers

Distribution transformers are ordinarily connected to each primary feeder and its sub feeders and laterals. These transformers serve to step down from the distribution voltage to the utilization voltage. Each transformer or banks of transformers supply a consumer or group of consumers over its secondary circuit. Each consumer is connected to the secondary circuit through his service leads and meter. The secondary and service connections may be either cable or open-wire circuits.

(e) Classification of Distribution Systems

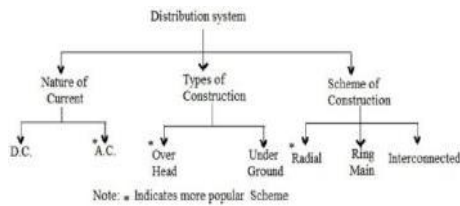


Fig1. Classifications of Distribution Schemes

Three different ways exist to lay out a power distribution system used by electric utilities, each of which has variations in its own design. A considerable amount of effort is necessary to maintain an electric power supply within the requirements of the various types of consumers.

The size of the conductor of a feeder is governed by the current carrying capacity, voltage drop and overall economy. The current carrying capacity of a conductor depends on the conductor losses and surrounding. For determining the voltage drop, it is necessary to calculate the inductive reactance of the feeder. After calculating the inductive reactance, the voltage drop of the conductor can be calculated. If the voltage drop is high, another conductor size is selected to reduce the voltage drop. The value of the conductor size obtained above should be checked for overall economy. By the application of Kelvin’s Law, the

most economical conductor size can be calculated. According to Kelvin’s law the most economical cross-section is that which makes the annual value of interest and depreciation of the conductor equal to the annual cost of the energy wasted in the conductor.

II SOLUTION METHOD

A. Problem Formulation

The DSR problem is to determine the optimum open/closed status of all the switches in the system. The problem is formulated as a multi-objective optimization problem to achieve the following four objectives, which lead to optimum system performance. These objectives are expressed as fitness functions to be implemented in the FNSGA.

- 1) Real power loss minimization, expressed as

$$\sum_{k=1}^{N_k} R_k \frac{P_k^2 + Q_k^2}{V_k^2} \dots \dots (1)$$

where

Nb number of branches;

Rk resistance of branch ;

Pk real power at sending end of th branch;

Qk reactive power at sending end of th branch'

Vk voltage at sending end of th branch.

- 2) Voltage profile optimization to enhance the system quality. This can be achieved by choosing the topology w

$$\max(\min\{V_j\}) \quad \forall \in N \quad (2)$$

Where N is the number of buses, and Vj is the voltage at bus.

- 3) Load balancing optimization to minimize the likelihood of system overloading which is achieved by transferring loads from heavily loaded feeders to less loaded ones. This requires a modification of the radial topology of the system, and it is characterized by minimizing the system load balancing index (SLBI) [7]. This objective is expressed as

$$\min SLBI = \min \left(\frac{1}{N_b} \sum_{j=1}^{N_b} \frac{S_j}{S_j^{max}} \right) \dots \dots (1)$$

Where Sj is the apparent power flow in branch j, and Sjmax is the maximum apparent power capacity of branch .

4) Minimization of the number of switching operations. We assume that there is a switch associated with each branch.

This number of operations should be minimized in order to reduce the switching transients and operating costs due to continuous change in the distribution system. This objective is expressed as

$$\min \sum_{i=1}^{aw} x_i \quad (2)$$

where s_w is the number of tie switches, and x_i is the status of the i th tie switch in the initial topology after reconfiguration (0 or 1).

These four objectives are subject to the following constraints:

- 1) The power flow equations must be satisfied. Thus

$$g(z) = 0$$

where (7) take into account the fundamental circuit laws, assume balanced conditions, and are based on the Newton-Raphson algorithm.

- 2) Voltage should be constrained within maximum and minimum allowable limits, i.e.,

$$V^{min} \leq V_j \leq V^{max} \quad \forall j \in N \quad (3)$$

- 2) In order to achieve the load balancing objective, branches should not exceed their current capacities, i.e.,

$$|i_k| \leq i_k^{max} \quad \forall k \in N_b \quad (4)$$

Where i_k is the k th branch current, and i_k^{max} is the current capacity of branch k .

- 4) The final system topology must be radial without isolating any load buses.

The four objectives are evaluated for a given system topology and sorted according to the above-described nondominated set concept, with real power loss minimization chosen as the principal objective. The new algorithm is illustrated by the flowchart shown in Fig. 1 and described in some detail in the following Sections III-B through III-H. It produces a list of the nondominated set of solutions satisfying these four objectives, and the operator has the option of selecting the topology that best fits his requirements.

III Conventional FNSGA Codification

The system topology refers to the state of the power system, including feeders, buses, loads, closed branches (sectionalizing switches), and open branches (tie switches). A chromosome is a description of which branches

are closed and which are open. Thus, every chromosome defines a unique system topology.

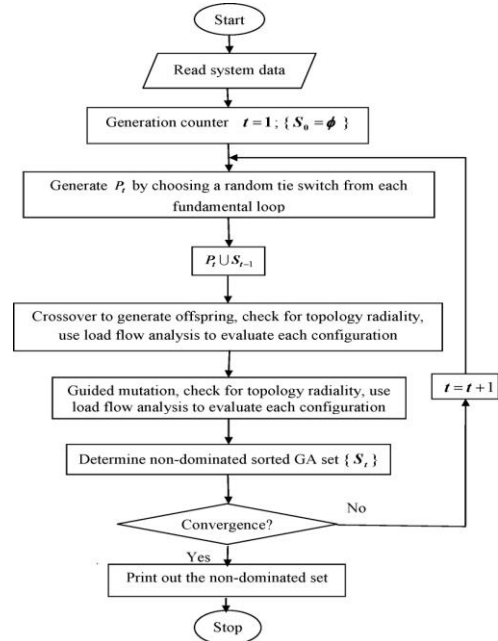


Fig. 2. Flowchart of the new FNSGA.

A valid or feasible chromosome is a chromosome that satisfies the above-described power flow, voltage, current and radiality constraints. Different methods for generating valid chromosomes for GA application to the DSR problem have been developed. The first one was introduced by Huang [13], who used binary coding of all closed branches in the system. Other researchers used each branch code plus its open/closed status. These codes suffer from three main issues: 1) "Hamming cliffs" such as the transition from 0111111 to 1000000, which requires alteration of many bits or genes; 2) long chromosomes, which consume excessive computing time; and 3) in order to deal with real optimization problems, coding and decoding processes are required, which are time consuming.

A second method for coding individual chromosomes uses floating point representation of real numbers. Carrano *et al.* [14] represented every switch in the system in each chromosome, which is very difficult to process, especially for large scale systems. Finally, Hong *et al.* [15] introduced prefer number encoding and decoding to the DSR problem. This method guarantees generation of a minimum number of spanning trees (feasible chromosomes), where a spanning tree is defined in graph theory as a tree that connects all vertices without forming any loops. The spanning tree with the minimum sum of edges weight

factors [16] is called the minimum spanning tree, and it is the optimum solution.

The disadvantage of this method is that it is excessively time consuming. In the current work, valid chromosomes are generated following the method described in [17] by first forming the fundamental loops matrix, where a fundamental loop is one that does not contain any loops within itself, and the number of fundamental loops L of the meshed system is equal to the number of tie (open) switches sw , and it is given by the following relation:

$$L = N_b - N + 1 \quad (5)$$

Where N_b and N are the respective numbers of branches and buses in the system, as defined above. Then, all possible chromosomes are generated by choosing a random branch from each fundamental loop to represent the switch to be opened in that loop, and without using that branch to represent a subsequent loop.

C. Crossover

In the present work, a uniform crossover is generally applied for each topology with a crossover rate of 1.0. However, for small number of fundamental loops, as in the case of the three fundamental loops 16-bus test system to be described, a one point crossover is sufficient for convergence.

D. Guided Mutation

Most GAs use random mutation with a very small mutation rate. A novel guided mutation process is introduced here, which depends on the results of load flow analysis of each chromosome-defined topology. The following steps describe this new guided mutation process:

- 1) Find the bus with the smallest voltage (the minimum voltage bus) ($N_{min} v$).
- 2) Find the branch b_1 that connects bus ($N_{min} v$) to the system.
- 3) Search b_1 for in the current chromosome.
- 4) If b_1 exists, search for another branch b_2 that connects bus ($N_{min} v$) to the system but is not present in the current chromosome.
- 5) If b_2 exists, mutate it with b_1 in the current chromosome.
- 6) If neither b_1 nor b_2 exist, mutation is skipped for this topology.

This procedure changes the mutation process in order to improve (raise) the minimum voltage and thereby improve system quality and reduce the power losses.

E. Radial Topology

In order to determine whether a given topology is radial, a novel approach based on the branch-bus incidence

matrix $BBIM$, is introduced here. A graph of $(N-1)$ buses (vertices), excluding the reference bus, and (N_b-L) branches (edges) is formulated as follows [40]. For each element b_{ij} in the $BBIM$

$$b_{ij} = \begin{cases} 1 & \text{if bus } i \text{ is at the sending end of branch } j. \\ -1 & \text{if bus } i \text{ is at the receiving end of branch } j. \\ 0 & \text{if branch } j \text{ is not connected to bus } i. \end{cases}$$

The dimensions of the $BBIM$ are the number of energized branches in the system and the number of buses. The number of energized branches is equal to the total number of branches in the system minus the number of fundamental loops, i.e., (N_b-L) . Thus, the $BBIM$ has dimension $((N_b-L)*N)$, or, if (10) is used, $((N_b-1)*N)$.

The column corresponding to the reference node is omitted from the $BBIM$, and a square matrix is obtained. The nonreference buses are called independent buses. Then the rank (the maximum number of independent rows or columns) of the new matrix is calculated, and if it is equal to (N_b-L) or, equivalently, $(N-1)$, the system is radial; otherwise it is not. In case of isolated buses or the system topology is not radial, and the rank will be smaller than $(N-1)$. This last step is a novel feature of the present work.

F. Selection and Elitism

Selection of the best solution is based on the nondominated set described above. Entering the nondominated set into the next generation to compete with the next populations and ensure conservation of the best solutions satisfies elitism.

G. Convergence and Stopping Criteria

The algorithm stopping criteria is that either:

- 1) The number of generations (iterations) exceeds its limit, which is set by the operator, or
- 2) No changes occur in the nondominated solution set for four successive iterations.

The second criterion here gives the algorithm some flexibility to search for other best solutions.

H. Evaluation of Equal Importance Objectives

After one of the above-mentioned convergence criteria is satisfied, and if there is a preference objective from the operational and practical points of view, the best solution is simply identified from the set of nondominated solutions. Otherwise, i.e., if there is no preferred objective, a simple approach to identifying the best solution is implemented by summing all the normalized values of the

objective functions. The minimized objective functions (power loss, number of switching operations, and SLBI) are normalized using [41].

$$obj_{min}(norm) = \frac{obj - obj_{min}}{obj_{max} - obj_{min}} \quad (6)$$

and the maximized objective function (voltage) is normalized using

$$obj_{max}(norm) = \frac{obj_{max} - obj}{obj_{max} - obj_{min}} \quad (7)$$

where obj_{min} and obj_{max} are the minimum and maximum values, for that objective function in the nondominated set, respectively. The optimum solution is defined as the one with the smallest sum of normalized objective functions. The application of (12) and (13) to the DSR problem is a novel feature of the present work.

PARTICLE SWARM OPTIMIZATION

There is no known single advancement strategy accessible for taking care of all enhancement issues. A ton of advancement routines have been produced for taking care of diverse sorts of enhancement issues lately. The present day streamlining techniques (some of the time called nontraditional enhancement strategies) is effective and famous systems for taking care of complex building issues. These strategies are molecule swarm improvement calculation, neural systems, hereditary calculations, subterranean insect province advancement, fake insusceptible frameworks, and fluffy streamlining. The Particle Swarm Optimization calculation (truncated as PSO) is a novel populace based stochastic hunt calculation and an option answer for the complex non-direct advancement issue. The PSO calculation was initially presented by Dr. Kennedy and Dr. Eberhart in 1995 and its essential thought was initially enlivened by reproduction of the social conduct of creatures, for example, flying creature running, fish educating et cetera. It is taking into account the common procedure of gathering correspondence to share singular information when a gathering of winged animals or creepy crawlies look sustenance or relocate et cetera in a seeking space, albeit all feathered creatures or bugs don't know where the best position is. In any case, from the way of the social conduct, if any part can figure out an alluring way to go, whatever remains of the individuals will take after rapidly.

The individual particle in this case is composed of set of tie switches that are to be opened in operating the

distribution system in radial configuration only. The size of the particle is equal to number of tie switches in a system. Therefore individual i 's position in 0^{th} iteration can be represented as a vector $X_{i0} = (TS_1, TS_2, TS_3, \dots, TS_n)$ where ' n ' is the number of tie switches for a given radial distribution system. The velocity of individual ' i ' i.e., $V_{i0} = (V_{i1}, \dots, V_{in})$ represents the switch number updating quantity covering all tie lines and maneuver lines. The position and velocity of each element of a particle in this case is mere integer number. Here it is very important to note that while creating the individual particles it is very much essential to check for the radial nature of the network. To do this the below procedure is used to generate the particles at random.

Steps involved in MOPSO Algorithm

Step1: Initialization-initialize all particles as per the above algorithm.

Step2: Set iteration count=0

Step3: Evaluate the fitness function i.e. the Load Balancing Index for the each particle and fix the individual LBI to Pbest and from LBI of all the particles find the minimum LBI the fix it as Gbest for this iteration

Step4: Evaluate the velocity of each population by using the equation

$$v_{id}^{k+1} = \omega v_{id}^k + c_1 \text{rand} * (Pbest_{id} - s_{id}^k) + c_2 \text{rand} * (gbest_{id} - s_{id}^k) \quad (8)$$

Step5: Update the position of each population by using the equation

$$X_i^{k+1} = X_i^k + V_i^{k+1} \quad (9)$$

Step6: Find the new values of fitness function (LBI) for all the population and replace it with Pbest if it less than the former value and also fix the least value of Pbest among all the population to Gbest

Step7: Increase the iteration count by 1

Step8: Check the stopping criterion, if not satisfied go to step3 Finally the optimum solution can be obtained through „Gbest“.

IV RESULTS AND DISCUSSION

The proposed algorithm was programmed using MATLAB7.12 and implemented on a 1.64-GHz Notebook PC with 4 GB of RAM. It was applied to two widely-studied test systems, a 16-bus system and a 69-bus system; and a real one consisting of 136 buses. In order to test the convergence performance of the new FNSGA, it was applied 100 times to each system and the most repeated solution set (the mode) was selected as the actual or representative solution set. The mode set represented 96% of all solution sets for the 16-bus system, 92% of all solution sets for the 69-bus system, and 95% of all solution sets for the real system. All three systems were assumed to be operated at balanced conditions, and each chromosome was evaluated according to (3)–(6) using a Newton-Raphson based load flow program. The results are presented in the following and compared with results from other work.

6.1 69-Buses Test System

The system data is given in [18]. As shown in Fig. 3, the system consists of 69 nodes, 73 branches, and five fundamental loops. The base MVA and kV are 10 and 12.66, respectively, and the total system loads are 3.80 MW and 2.70 MVAR. The current carrying capacity of branch Nos. 1–9 is 400 A, that of Nos. 46–49 and Nos. 52–64 is 300 A, and that of the remaining branches, including the tie lines, is 200 A. Initially, branches 69, 70, 71, 72, and 73 are open, as shown in Fig. 3, and the total system power loss is 224.93 kW. The new FNSGA produced a set of 34 nondominated solutions. Only the optimum topologies (from that set) according to the four objective functions are listed in Table I. The results shown in Table I were obtained after ten generations and with an initial population of 30 chromosomes, and it required 20.2 s of CPU time. Solution 1 in the first row of Table III is the optimum in terms of number of switching operations, since it is the initial topology.

If all objectives are of equal importance, the optimum solution is determined using (12) and (13) and the smallest sum of normalized objectives procedure described above. That would make Solution 10, in the fifth row of Table I, with a summation value of 0.748, the optimum solution as compared to four other methods, all of which satisfied only the power loss objective with nearly the same value.

TABLE I

OPTIMUM SOLUTIONS OF THE FOUR OBJECTIVES RESULTING FROM THE APPLICATION OF FNSGA TO THE 69-BUS SYSTEM

Methods	Power Losses In KW	Minimum Voltage in pu	Loss Improvement in %
Base Case	225.006	0.9092	0
FNSGA	99.625	0.9428	55.7212
FPSO	94.64	0.9521	5.01

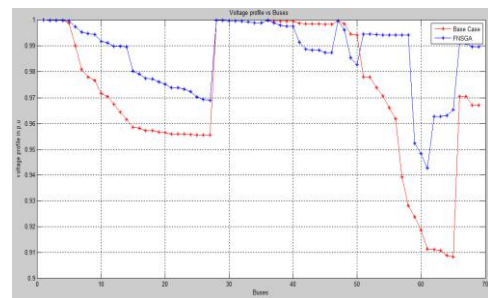


Fig3 Comparison of the Voltage profile in pu for base case & FNSGA Optimization

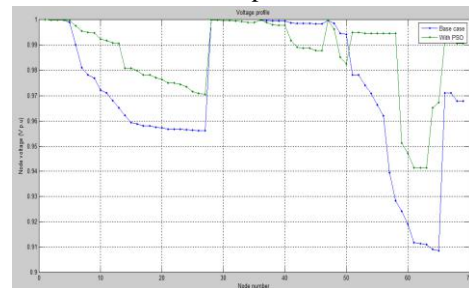


Fig 4 Comparison of the Voltage profile in pu for base case & PSO Optimization

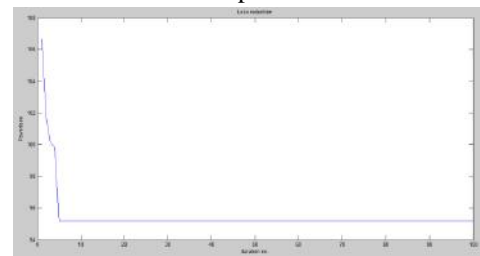


Fig5 Power Losses in KW using Particle Swarm Optimization

V CONCLUSION

An improved version of the PSO and its application, for the first time, to the multi-objective DSR problem are described. The main characteristic of the PSO is that it deals with only the random solution set and classifies it into only one rank, while other methods, such as the

FNSGA, search for all solutions and classify them into more than one rank, which is relatively time consuming. Power loss minimization is defined as the primary objective, while the other objectives are power quality improvement, defined by both the voltage profile and minimization of the number of switching operations. The set of non-dominated solutions provides the operator with alternatives, depending on needs. If there is (are) no preferred objective(s), the optimum solution is defined as that with the smallest sum of normalized objectives. Improvements to the PSO introduced here include a novel particles, which eliminates the need to choose or adapt mutation rates for each system; a novel approach to verifying system radiality, which eliminates the need to create infeasible solutions at each stage of the genetic evolution; and a novel approach to determining an optimum solution in the presence of equal importance objectives. Results of application of the revised PSO to two popular test systems and a real one are described and compared with results obtained with other algorithms.

The MATLAB results illustrate the ability of the algorithm to produce PSO solution sets in which all four objectives, rather than just one, are optimized simultaneously, and with relative smaller population sizes and/or numbers of generations, resulting in conveniently fast CPU times.

FUTURE SCOPE

This work is being extended to the case of service restoration, characteristic of system operation in the presence of fault or maintenance conditions.

REFERENCES

- [1] A. A. Zin, A. Ferdavani, A. Khairuddin, and M. Naeini, "Two circular updating hybrid heuristic methods for minimum-loss reconfiguration of electrical distribution network," *IEEE Trans. Power Syst.*, vol. 28, no. 2, pp. 1318–1323, May 2013.
- [2] T. Thakur and Jaswanti, "Study and characterization of power distribution network reconfiguration," in *Proc. 2006 IEEE Power and Energy Society Transmission and Distribution Conf.*, pp. 1–6.
- [3] D. Shirmohammadi and H. Wayne Hong, "Reconfiguration of electric distribution networks for resistive losses reduction," *IEEE Trans. Power Del.*, vol. 4, no. 2, pp. 1492–1498, Apr. 1989.
- [4] S. Civanlar, J. J. Grainger, H. Yin, and S. S. H. Lee, "Distribution feeder reconfiguration for loss reduction," *IEEE Trans. Power Del.*, vol. 3, no. 3, pp. 1217–1223, Jul. 1988.
- [5] M. E. Baran and F. F. Wu, "Network reconfiguration in distribution systems for loss reduction and load balancing," *IEEE Trans. Power Del.*, vol. 4, no. 2, pp. 1401–1407, Apr. 1989.
- [6] T. P. Wagner, A. Y. Chikhani, and R. Hackam, "Feeder configuration for loss reduction: An application of distribution automation," *IEEE Trans. Power Del.*, vol. 6, no. 4, pp. 1922–1931, Oct. 1991.
- [7] S. K. Goswami and S. K. Basu, "A new algorithm for the reconfiguration of distribution feeders for loss minimization," *IEEE Trans. Power Del.*, vol. 7, no. 3, pp. 1484–1491, Jul. 1992.
- [8] T. E. McDermott, I. Drezga, and R. P. Broadwater, "A heuristic nonlinear constructive method for distribution system reconfiguration," *IEEE Trans. Power Syst.*, vol. 14, no. 2, pp. 478–483, May 1999.
- [9] W. M. Lin and H. C. Chin, "A new approach for distribution feeder reconfiguration for loss reduction and service restoration," *IEEE Trans. Power Del.*, vol. 13, no. 3, pp. 870–875, Jul. 1998.
- [10] M. A. Kashem, G. B. Jasmon, A. Mohamed, and M. Moghavvemi, "Artificial neural network approach to network reconfiguration for loss minimization in distribution networks," *Int. J. Elect. Power Energy Syst.*, vol. 20, no. 4, pp. 247–258, May 1998.
- [11] A. Augugliaro, L. Dusonchet, M. G. Ippolito, and E. R. Sanseverino, "Minimum losses reconfiguration of MV distribution networks through local control of tie-switches," *IEEE Trans. Power Del.*, vol. 18, no. 3, pp. 762–771, Jul. 2003.
- [12] K. Nara, Y. Mishima, A. Gjiyo, T. Ito, and H. Kaneda, "Loss minimum reconfiguration of distribution system by tabu search," in *Proc. 2002 IEEE Conf. Transmission and Distribution, Asia*, pp. 232–236.
- [13] Y. Jeon and J. Kim, "Network reconfiguration in radial distribution system using simulated annealing and tabu search," in *Proc. 2000 IEEE Power Engineering Society Winter Meeting*, pp. 2329–2333.
- [14] A. Skoonpong and S. Sirisumrannukul, "Network reconfiguration for reliability worth enhancement in distribution systems by simulated annealing," in *Proc. 2008 IEEE Int. Conf. Electronics, Computer Telecommunications, and Information*, pp. 937–940.
- [15] K. H. Jung, H. Kim, and Y. Ko, "Network reconfiguration algorithm for automated distribution systems based on artificial intelligence approach," *IEEE Trans. Power Del.*, vol. 8, no. 4, pp. 1933–1941, Oct. 1993.
- [16] S. H. K. Vuppapapati and A. K. Srivastava, "Application of ant colony optimization for reconfiguration of shipboard power system," *Int. J. Eng., Sci., Technol. (IJEST)*, vol. 2, no. 3, pp. 119–131, 2010.
- [17] A. Ahuja, S. Das, and A. Pahwa, "An AIS-ACO hybrid approach for multi-objective distribution system reconfiguration," *IEEE Trans. Power Syst.*, vol. 22, no. 3, pp. 1101–1111, Aug. 2007.
- [18] Y. T. Hsiao, "Multi-objective evolution programming method for feeder reconfiguration," *IEEE Trans. Power Syst.*, vol. 19, no. 1, pp. 594–599, Feb. 2004.
- [19] M. Assadian, M. M. Farsangi, and H. Nezamabadi-Pour, "Optimal reconfiguration of distribution system by PSO and GA using graph theory," in *Proc. 6th WSEAS Int. Conf.*, Istanbul, Turkey, May 2007, pp. 83–88.
- [20] A. Swarnkar, N. Gupta, and K. R. Niazi, "Reconfiguration of radial distribution systems with fuzzy multi-objective approach using adaptive particle swarm optimization," in *Proc. 2010 IEEE Power and Energy Society General Meeting*, pp. 1–8.



Mr. M.C.V. Suresh is currently working as an Assistant Professor in EEE department, SV College of Engineering, Tirupati. His areas of interest include Network Theory Electrical Machines and Power systems.

S. Navya Lakshmi was born in AP, India in 1993. Currently she is studying her Post graduate degree in Sri Venkateswara College of Engineering (SVC) affiliated to Jawaharlal Nehru Technological University Anantapur in Power Systems. Her areas of interest

include Power Systems and FACTS, Renewable Energy Resources and Power Quality. Email Id: navya.sanam@gmail.com



Dr. Shaik Rafi Kiran a PhD from Jawaharlal Nehru Technological University Anantapur, Ananthapuramu, A.P, India. He has 17 years of teaching experience. At Present Dr. Shaik Rafi Kiran serving as a Professor and Head of

the department of Electrical and Electronics Engineering in Sri Venkateswara college of Engineering (SVCE), Tirupathi, Andhra Pradesh. He is a Life Member of ISTE. He has presented 25 research papers in reputed International Journals and Conferences. His research areas includes System Identification, Control Systems, Optimization Techniques and Power Systems. At present he is guiding two PhD scholars.