Third International Conference on
Advances in Control and Optimization of Dynamical Systems
March 13-15, 2014. Kanpur, India

Application of Firefly Algorithm for Radial Distribution Network Reconfiguration Using Different Loads

Y.LakshmiReddy*, Sathiyanarayanan.T **,Dr.M.Sydulu *.**

**Student (lakshmireddy217@gmail.com), Department of Electrical Engineering, National Institute of Technology-Warangal Andhra Pradesh-India.*

***Student (sathyaee@gmail.com), Department of Electrical Engineering National Institute of Technology- Warangal Andhra Pradesh-India.*

****Professor (sydulumaheswarapu@gmail.com), Department of Electrical Engineering National Institute of Technology- Warangal Andhra Pradesh-India.*

Abstract— This paper proposes a Bio-inspired heuristic algorithm to solve the power distribution network reconfiguration problem for loss minimization. The proposed method is based on the social behaviour of firefly insects and their shining phenomenon. During the optimization process, several equality and inequality constraints are to be taken in account for network reconfiguration. The objective function is to improve the voltage of the each bus and reduce the power losses of reconfigured network. Implementing this method is a more robust and easier and it is simulated for IEEE33 and IEEE69 standard distribution test systems with different load levels.

Keywords: Firefly Algorithm, Distribution networks, reconfiguration, Loss minimization, Power loss.

I.INTRODUCTION

Distribution Network Reconfiguration is the process of changing the topology of distribution systems by altering the open/closed status of switches to transfer loads among the feeders. Two types of switches are used in primary distribution systems. There are normally closed switches (sectionalizing switches) and normally opened switches (tie switches). Those two types of switches are designed for both protection and configuration management.

In early seventies, the network reconfiguration for loss reduction concept was first introduced by A. Merlin and H. Back[1] by applying the Branch and Bound heuristic technique. Later several reconfiguration techniques have been proposed which can be grouped into 3 main categories: i)Those based upon a blend of Heuristics and Optimization techniques which proved to be very time consuming for large distribution systems therefore not practical for real time implementation, ii)Those based upon purely heuristic techniques[2] where the optimality is not guaranteed and the algorithms are more likely to fall into local optimum, and iii)Finally, techniques based on Artificial Intelligence and modern heuristics such as: Genetic Algorithms[3],Particle Swarm Optimization[4], Tabu Search[5], Simulated Annealing[6], Hybrid Algorithms etc. These AI based algorithms overcome the shortcoming of the conventional methods in saving the computation time, ensuring accuracy and optimality and thus suitable for real time application.

In this paper meta-heuristic algorithm is employed to solve the network reconfiguration problem. The algorithm is based on social behaviour of fireflies and their shining phenomenon. Some of the main benefits of network reconfiguration can be summarized as

1. Minimization of system active power losses,
2. Deviation of nodes voltage,
3. Branch current constraint violation,
4. Load balancing among various feeders [7].

In recent years, a wide range of techniques have been proposed to solve network reconfiguration problem which can be divided into four main categories: analytical based methods and heuristic search methods numerical programming methods and Artificial Intelligence based methods. The Genetic Algorithm (GA) as a successful optimization tool is employed to find the optimal solution of network reconfiguration problem. The Particle Swarm Optimization (PSO) algorithm is utilized to investigate network reconfiguration problem at multi-level load model in radial distribution systems. When both of GA and PSO algorithms have gained suitable results in different optimization problems, the main deficiency with both of them is dependency on the initial adjusting parameters. This aspect will increase the probability of trapping in local optima or premature convergence in the case of the distribution networks with different sizes.

According to the above discussion, the main purpose of this paper is to propose a new powerful optimization algorithm to investigate the network reconfiguration problem in detail. In this regard, Firefly Algorithm (FA)[8] as a successful evolutionary-based optimization algorithm is utilized. During the optimization process, several equality and inequality constraints should be satisfied while solving the network reconfiguration problem. The feasibility and superiority of

978-3-902823-60-1 © 2014 IFAC

10.3182/20140313-3-IN-3024.00052

the proposed method is examined on two standard distribution test systems.

II. FORMULATION OF THE NETWORK RECONFIGURATION PROBLEM FOR LOSS REDUCTION

The reconfiguration problem can be formulated as follows:

$$\text{Min } f=\sum_{i=1}^{NR} R_i |i^2| \quad (1)$$

Subjected to the following constraints [9]:

1. The voltage magnitude

$$V_{min} \leq |V_i| \leq V_{max} \forall i \in Nb \quad (2)$$

2. The current limit of branches

$$|I_i| \leq I_{imax} \forall i \in Nr \quad (3)$$

3. Radial Topology: The distribution system should be radial without meshes. Normally all loads are served without disconnections.

Where *f* is the fitness function to be minimized corresponds to the total power loss in the system, *R,* is the resistance of the branch *i* and *Ii* is the magnitude of the current flowing through the branch *i,* V_i is the voltage on bus *i, Vmin* and *Vmax* are minimum and maximum bus voltage limits respectively, I_i and I_{imax} are current magnitude and maximum current limit of branch *i* respectively and *Nb* and *NR* are the total number of buses and branches in the system respectively. The objective Function is calculated starting from the solution of the power flow equations that can be solved using the Forward/Backward Sweep method which is very robust and proved to be efficient for solving radial distribution networks. To check the radiality constraints for a given configuration, a method based on the bus incidence matrix *A* is used in which a graph may be described in terms of a connection or incidence matrix. Of particular interest is the branch to node incidence matrix *A,* which has one row for each branch and one column for each node with a coefficient *aij* in row *i* and column *i.* The value of *aij*= 0 if branch i is not connected to node j, *aij*= 1 if branch *i* is directed away from node} and *aij*= -1 if branch *i* is directed towards node *i.* For a network calculation, a reference node must be chosen. The column corresponding to the reference node is omitted from *A* and the resultant matrix is denoted by *A.* If the number of branches is equal to the number of nodes then, a square branch-to-node matrix is obtained. The determinant of *A* is then calculated. If *det(A)* is equal to 1 or -1, then the system is radial. Else if the *det(A)* is equal to zero, this means that either the system is not radial or group of loads are disconnected from service.

III. FIREFLY ALGORITHM

The firefly algorithm has three particular idealized rules which are based on some of the major flashing characteristics of real fireflies. These are the following[10,11],

1) All fireflies are unisex, and they will move towards more attractive and brighter ones regardless their sex.

2) The degree of attractiveness of a firefly is proportional to its brightness which decreases as the distance from the other firefly increases due to the fact that the air absorbs light. Ifthere is not a brighter or more attractive firefly than a particular one, it will then move randomly.

3) The brightness or light intensity of a firefly is determined by the value of the objective function of a given problem. For maximization problems, the light intensity is proportional to the value of the objective function.

2.1. Attractiveness

In the firefly algorithm, the form of attractiveness function of a firefly is the following monotonically decreasing function:

$$\beta_r = \beta_o * \exp\left(-\gamma r_{ij}^m\right), with\ m \geq 1 \quad (4)$$

Where, r is the distance between any two fireflies, *β0* is the initial attractiveness at *r* = 0, and *γ* is an absorption coefficient which controls the decrease of the light intensity.

2.2. Distance

The distance between any two fireflies *i* and *j*, at positions *xi* and *xj*, respectively, can be defined as a Cartesian orEuclidean distance as follows:

$$r_{ij} = \|x_i - x_j\| = \sqrt[2]{\sum_{k=1}^{d}\left(x_{i,k} - x_{j,k}\right)^2} \quad (5)$$

Where $x_{i,k}$ is the kth component of the spatial coordinate xi of the ith firefly and d is the number of dimensions we have, for d = 2, we have rij as

$$r_{ij}=\sqrt{\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2} \quad (6)$$

However, the calculation of distance r can also be defined using other distance metrics, based on the nature of theproblem, such as Manhattan distance or Mahalanobis distance.

2.3. Movement

The movement of a firefly i which is attracted by a more attractive (brighter) firefly j is given by the following equation:

$$x_i = x_i + \beta_0 * \exp\left(-\gamma r_{ij}^2\right) * \left(x_j - x_i\right) + \alpha * \left(rand - \frac{1}{2}\right) \quad (7)$$

Where the first term is the current position of a firefly, the second term is used for considering a firefly's attractiveness to light intensity seen by adjacent fireflies, and the third term is used for the random movement of a firefly in case there are not any brighter ones. The coefficient α is a randomization parameter determined by the problem of interest, while rand is a random number generator uniformly distributed in the space [0, 1].we will use β0 =1.0, α ∈[0, 1] and the attractiveness or absorption coefficient γ =1.0, which guarantees a quick convergence of the algorithm to the optimal solution.

IV. APPLICATION OF FIREFLY FOR DISTRBUTION NETWORK RECONFIGURATION

The process of incorporating the firefly algorithm for solving the network reconfiguration is shown in algorithm and the test system for the case study is radial distribution system with IEEE 33 buses and IEEE 69 buses with different load sizes like normal load, light load and heavy loads as shown in Figure 2&3.

The network reconfiguration involves these steps:
Initialisation: The solution starts with encoding parameters by defining

- S: set of supply substations.
- N_B: set of buses.
- N_R: set of branches (switches), where each switch has two possible states either '0' for an opened switch (tie switch) or '1' for a closed switch (sectionalising switch).
- (P_{load}, Q_{load}): load data; (R_b, X_b): branch data.
- f(0): base configuration defined as a set of states (open/closed) assumed by the switches.

N: number of fireflies in each iteration and initially located on N randomly chosen open switches.

Once all fireflies' finish their tour, the configuration corresponding to each firefly is evaluated in three steps:

Step 1: Check the radiality constraints. If radial go to next step otherwise this trial configuration is discarded.

Step 2: Run the load flow and check for voltage and loading limits. If either limit is violated, the configuration is discarded; if no violations are there go to next step.

Step 3: Compute the objective function-minimisation of the line losses.
Termination of the algorithm: The solution process continues until maximum number of iterations reached or until no improvement of the objective function has been detected after specified number of iterations.
The firefly based network reconfiguration flow chart is as follows respectively shown in fig1.

The State Transition Rule: At first, each firefly is placed on a starting state. Each will build a full path from the beginning to the end state through the repetitive application of the state transition rule given in equation (8) which is also called the "random proportional rule".

$$P_k(i\,j) = \frac{[\tau(i,j)]^{\alpha}[\eta(i,j)]^{\beta}}{\sum_{m \in J_k(i)}[\tau(i,m)]^{\alpha}[\eta(i,m)]^{\beta}}, \forall j \in J_k(i) \qquad (8)$$

Where, Pk(i,j) is the probability with which firefly k in node i chooses to move to node j, τ(i,j) is the pheromone which is deposited on the edge between nodes i and j, η(i,j) is the visibility of the edge connecting nodes i and j which is problem specific, Jk(i) is the set of nodes that remain to be visited by firefly k positioned on node i. α and β are parameters that determine the relative importance of pheromone versus the path's visibility. The state transition rule favours transitions toward nodes connected by shorter edges with greater amount of pheromone.

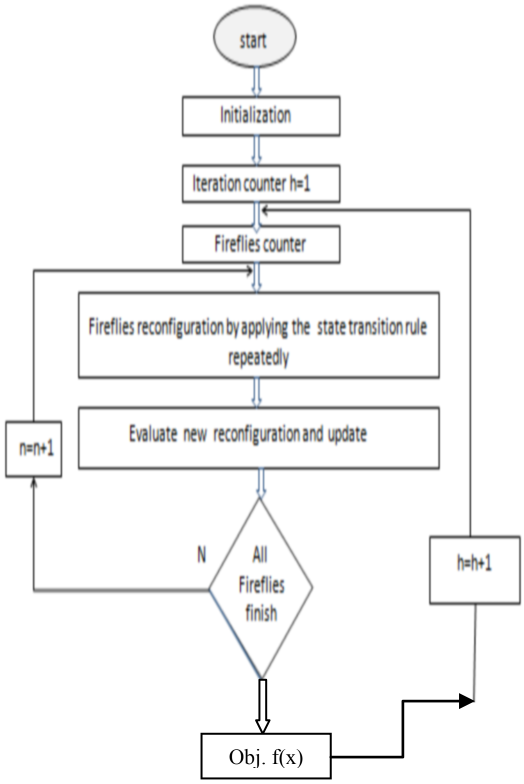

Fig1: Flow chart for firefly based network reconfiguration.

V. SIMULATION RESULTS

The simulation results tested on standard IEEE 33 bus test system and IEEE 69 bus test systems. The original configuration of the 33 bus system is shown below in Fig. 2. The optimal configuration of the 33 bus system is shown in Fig. 4[12]. The voltage profile for 33 bus before reconfiguration and after reconfiguration shown in Fig3&5.

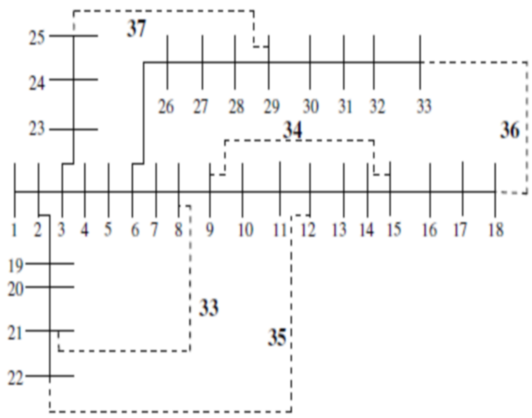

Fig2:IEEE33 bus system before reconfiguration.

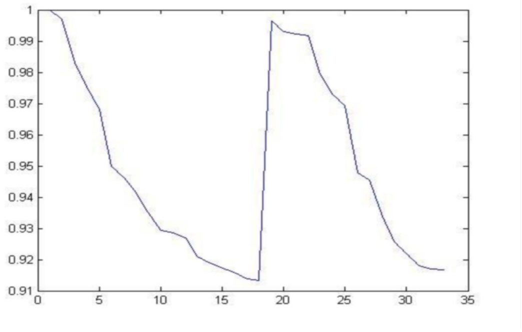

Fig3: voltage profile of 33 bus system before reconfiguration.

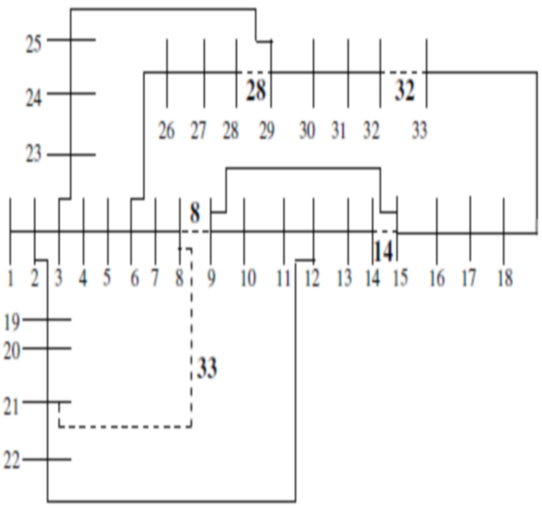

Fig4:IEEE33 bus system after reconfiguration

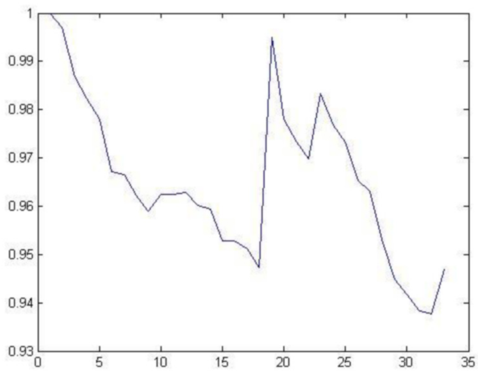

Fig5:Voltage profile of 33 bus system after reconfiguration.

The IEEE Distribution systems for 69 bus before reconfiguration and after reconfiguration shown in Fig6&7.The voltage profile for normal load bus before reconfiguration and after reconfiguration shown in Fig8. The voltage profile for heavy load bus before reconfiguration and after reconfiguration shown in Fig9. The voltage profile for light load bus before reconfiguration and after reconfiguration shown in Fig10.

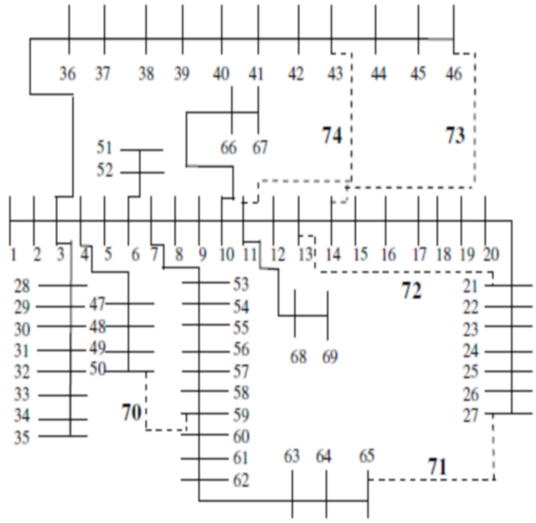

Fig6: IEEE69 bus system before reconfiguration

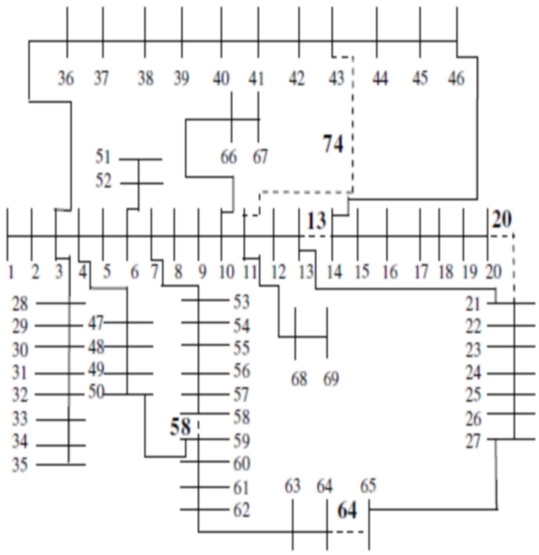

Fig7: IEEE69 bus system after reconfiguration

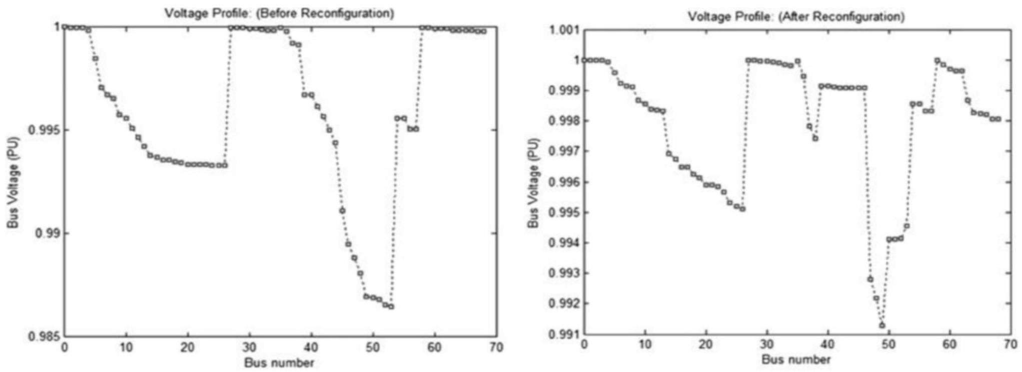

Fig8: voltage profile of69 bus system before and after reconfiguration (normal load)

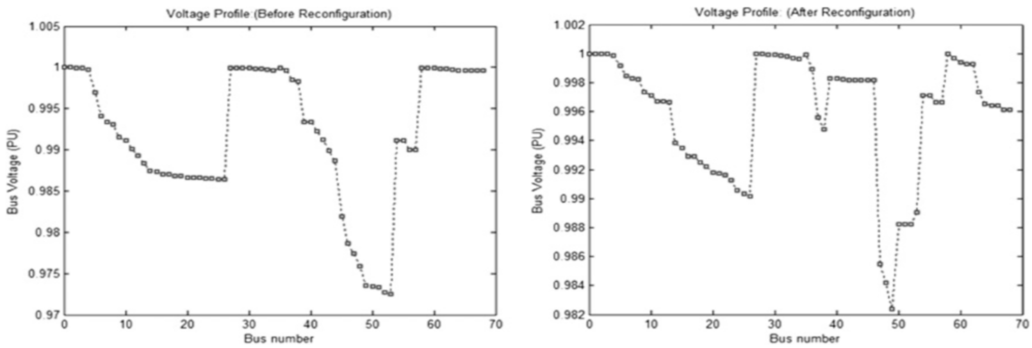

Fig.9 Voltage profile of the 69-bus system before and after reconfiguration (heavy load)

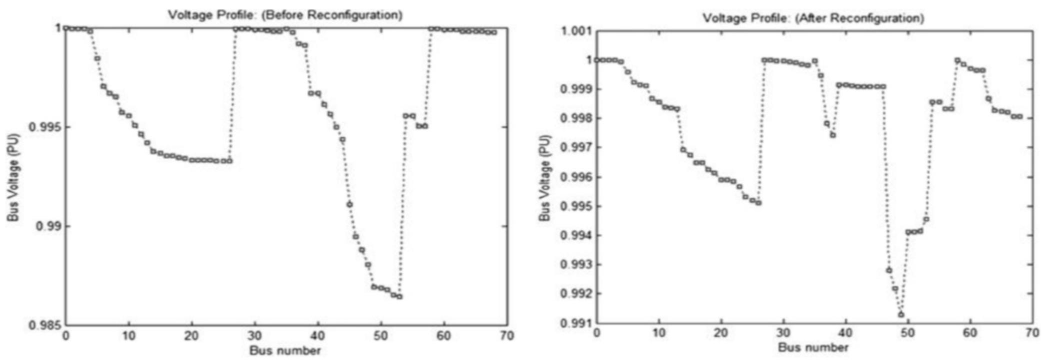

Fig.10 Voltage profile of the 69-bus system before and after reconfiguration (light load)

TABLE I
SIMULATION RESULTS OF RECONFIGURATION OF 33&69 BUS SYSTEMs

No of buses	Intial losses (kw)	FA evaluated reconfiguration losses (kw)	Tie switches open for optimal loss configuration	Loss reduction (kw)
33 bus	201.14	131.02	S33,S14,S18, S32,S28	70.12
69 bus	220.85	49.85	S58,S13,S64,S39,S74	171(normal load)

*** For 69 bus system light load is considered as multiplication of normal load with 0.5 and heavy load is considered as multiplication of normal load with 1.5.

V. CONCLUSION

In this paper, a novel heuristic approach is proposed to minimize the power loss and improve the voltage profile in the system by an efficient load flow method. The tie switches and its neighbouring switches are considered to generate the switching combination and the best combination among them is found with less computational effort. It is observed that the switching combinations in each loop of the network are very much nearer the lower potential of the tie switch. The algorithmgives the optimum solution with a few number of load flowiterations with less CPU time. Therefore, the proposed method can be effectively used in real time applications when largedistribution systems under widely loaded conditions are concerned with different load sizes.

REFERENCES

A. Merlinand H. Back, "Search *for a minimal loss Operating spanningtree configuration for an urban power distribution system*", *Proc. Of PSOC*, Cambridge, 1975, pp.1-18.

A.Augugliaro, L.Dusonchet and E.Riva Sanseverino: "*Genetic, Simulated Annealing and Tabu Search Algorithms: Three Heuristic Methods for Optimal Reconfiguration and Compensation of Distribution Networks*", *ETEP*.**9**, 1, 35-41 (1999).

T. Apostolopoulosand A. Vlachos, *Application of the Firefly Algorithm for Solving the Economic Emissions Load Dispatch Problem*, International Journal of Combinatorics, 2011, Article ID 523806, 23 pages

M. E. Baran and F. F. Wu, "*Network reconfiguration in distribution systems for loss reduction and load balancing*," *IEEE Trans. PowerDel.*, vol. 4, no. 2, pp. 1401–1407, Apr. 1989.

Chis M, Salama M.M.A, Jayaram S, *Capacitor placement In distribution systems using heuristic search strategies*, lEEE Proc-Gener. Trunsm. Distrib., Vol. 144, No. 3, May 1997, pp.225-230

A. Coleho,A. B.Rodrigues andM. G. Da Silva, "*Distribution network reconfiguration with reliability constraints*," in *Proc. IEEE Power Con2004*, vol. 2, pp. 1600–06, 2004.

B. Enacheanu, B. Raison, R. Caire, O. Devaux, W. Bienia And N.HadjSaid, "*Radialnetwork reconfiguration using genetic algorithm based on the Matroid theory*," *IEEE Transactions on Power Systems*, vol. 23, no. 1, pp. 186 – 195, 2008.

V.Miranda and N.Fonseca, "*Evolutionary Particle Swarm Optimization, a new algorithm with applications in power system*", *Proc. IEEE/PESTransmission and Distribution Conference and Exhibition 2002: AsiaPacific* **2**, 745-750 (October 6-10, 2002).

K.Nara, Y.Mishima, A.Gjvo,T.Ito and H.Kaneda, "*Loss Minimum Re- Configuration of Distribution System by Tabu Search*", *Proc. Transm.andDistrib. Conference* **1**, 232-236 (2002).

P. Ravi Babu, M.P.R. Vanamali, M.P.V.V.R. Kumar, V. SaiHemachandra; "*A Novel Power Flow Methodology for Radial Distribution Systems*", Proceedings of 2nd IEEE International Conference on Compu -tational Technologies SIBIRCON-2010, Irkutsk Listvyanka, Russia, pp.507-512, 2010.

X. S. Yang, "*Firefly algorithms for multi modal optimization*," in Proceeding of the Stochastic Algorithms: Foundations and Applications(SAGA '09), vol. 5792 of Lecture Notes in Computing Sciences, pp. 178-178, Springer, Sapporo, Japan, October 2009.

X. S. Yang, "*Firefly algorithm, Levy flight sand global optimization*," in Research and Development in Intelligent Systems XXVI, pp. 209-218, Springer, London, UK, 2010.

BIOGRAPHIES

Y.LakshmiReddy received his B.Tech in Electrical & Electronics Engineering degree from KITS, Markapur Affiliated College of JNTU Kakinada University in 2012, and is currently pursuing Master of Technology in National Institute of Technology, Warangal. His current research interests are Distribution system studies, Distribution planning studies and management, optimization methods in Distribution systems, Distribution reconfiguration and smart grid.

Sathiyanarayanan.T received his B.E in Electric Engineering degree from Kongu Engineering College, Affiliated to Anna University, Chennai in 2012, and is currently pursuing Master of Technology in Power Systems from National Institute of Technology, Warangal. His current research interests are DG placement, Distribution load flow studies, Computer Methods In Power Systems and AI techniques in Power Systems.

Dr.Maheswarapu Sydulu received his B.Tech (Electrical Engineering, 1978), M.Tech (Power Systems, 1980), PhD (Electrical Engineering – Power Systems, 1993), all degrees from Regional Engineering College, Warangal, Andhra Pradesh, INDIA. His areas of interest include Real Time power system operation and control, ANN, fuzzy logic and Genetic Algorithm applications in Power Systems, Distribution system studies, Economic operation, Reactive power planning and management. Presently he is working as Professor and Head of Electrical Engineering Department, National Institute of Technology, Warangal (formerly RECW).