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A new power system reconfiguration scheme for power loss minimization and voltage profile enhancement using Fireworks Algorithm

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A R T I C L E I N F O

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A B S T R A C T

In this paper, a new efficient method to solve the network reconfiguration with an objective of improving power loss minimization and voltage profile of the distribution system is presented. A new Meta-heuristics Fireworks Algorithm (FWA) is proposed to optimize the radial distribution network while satisfying the operating constraints. FWA is a recently developed swarm intelligence based optimization algorithm which is conceptualized using the fireworks explosion process of searching for a best location of sparks. Network reconfiguration is formulated as a complex combinatorial optimization problem. The radial nature of the system is secured by generating proper parent node–child node path of the network during power flow. To demonstrate the applicability of the proposed method, it is tested on a standard IEEE 33- and 119-bus system. The simulated results are compared with other methods available in the literature. It is observed that the performance of proposed method is better than the other methods in terms of quality of solutions. Different abnormal cases are also considered during reconfiguration of network to study the effectiveness of the proposed method and the results obtained are found to be encouraging.

Introduction

To satisfy the customer demands in a reliable and more economical manner is the main objective of a modern electric power system. The distribution system delivers power to a variety of loads, i.e. residential, industrial, commercial, etc., which are typically subjected to daily load variations over a wide range. With the increased loading and exploitation of the existing power structure, the probability of occurrence of voltage collapse is significantly increasing in the distribution system. Distribution system network reconfiguration is the process of changing the topology by altering the open/closed status of switches so as to find a radial operating structure that minimizes the loss and improves the voltage stability while satisfying the operating constraints. Under normal conditions, the DISCOs may expect to reduce the system power losses and balance the loading among transformers and feeders. On the other hand, the need of improving power quality has become progressively essential. More specifically, sensitive loads can only be subjected to less voltage drop and shorter interruption while abnormal conditions (faults) occur [1]. Even under faulted conditions, DISCOs or supply companies should ensure the quality of power supplied to the industries with the sensitive loads. Therefore, the feeder configuration problem becomes more complicated with the conflicting objectives of satisfying both normal and abnormal conditions.

In last two decades, many researchers had solved the network reconfiguration problem using different methods with the objective of power loss minimization and/or voltage profile improvement in power distribution networks. Authors in [2] were the first to solve the distribution system reconfiguration problem for loss reduction using a branch and bound-type optimization technique. The main disadvantage of this method was computation time taken for obtaining optimal configuration. Authors in [3] had solved the reconfiguration problem using two minimum-current neighbor-chain updating methods. Authors in [4] presented a new method for distribution network reconfiguration integrated with optimal power flow based on a benders decomposition approach for loss minimization and load balancing. Authors in [5] had implemented differential evolution algorithm to enhance power quality issues such as harmonics and voltage sags by optimizing the distribution network.

Later on, numerous optimization algorithms like fuzzy adaptation evolutionary programming [6], fuzzy mutated genetic algorithm [7], Refined Genetic Algorithm (RGA) [8], binary particle

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Nomenclature

P_{Lk}	real power load at bus k
P_k	real power flowing out of bus k
I_k	equivalent current injected at node k
V_k	voltage magnitude at bus k
R_k	resistance of the line section between buses k and $k+1$
$P_{Loss}(k, k+1)$	real power loss in the line connecting buses k and $k+1$
$P_{T,Loss}$	total power loss of the system (base case)
S_k	apparent power flowing in the line section between buses k and $k+1$
n_t	total number of buses in radial distribution system
Q_{Lk}	reactive power load at bus k
Q_k	reactive power flowing out of bus k
J_k	branch current in the line section between buses k and $k+1$
$\Delta V_{\max}$	maximum voltage deviation limit between buses 1(substation) and k
X_k	reactance of the line section between buses k and $k+1$
V_{worst}	worst voltage magnitude of the system
$P^R_{T,Loss}$	total power loss of the system after reconfiguration (optimum case)
$S_{k,\max}$	maximum power flow capacity limit of line section between buses k and $k+1$
n_b	total number of branches in radial distribution system

swarm optimization [9], plant growth simulation algorithm [10] and Harmonic Search Algorithm (HSA) [11,12] had been proposed to solve the reconfiguration problem with various objectives. In the very recent researches, discrete artificial bee colony [13] and particle swarm optimization [14] along with graph theory had been proposed to optimize the distribution network.

All the above researches [1–14] mentioned have gained encouraging results in solving the problem of distribution network optimization, but they also have some shortcoming in some respects such as computation time in solving large scale systems, inclusion of external parameters like crossover rate and mutation rate, convergence property and computing efficiency. Also the above researches are implemented only under normal condition (operation) of distributed systems.

Authors in [15] had optimized the radial distribution network assuming a series fault at a bus using Bacterial Foraging Optimization Algorithm (BFOA). But the optimal configuration obtained was not found to be in radial nature, and it is observed that it forms a mesh loop in the network. This would collapse and endanger the entire radial distribution network. Hence maintaining radial nature of distribution system becomes vital at all phases of reconfiguration.

In the present work, a new Fireworks Algorithm (FWA) is proposed for optimizing the radial distribution network. FWA is robust, stochastic and is one of the most efficient evolutionary algorithms. The main objective of this paper is to minimize the power loss and voltage deviation, and also to maintain the radial nature of the distribution system. The novelty of this article lies in the implementation of new swarm intelligence based global optimization process FWA, for solving the complex combinatorial reconfiguration problem. Also the novelty lies in implementing the proposed method under abnormal conditions. Under abnormal conditions, the proposed method will isolate the faulted areas and assures power supply to the non-faulted areas of the system with minimum voltage deviation and load shedding. The proposed method is tested on two standard IEEE test systems and the results obtained are very encouraging. Further, the simulated results are compared with other methods available in the literature to evaluate the performance of the proposed method.

Problem formulation

Radial nature of the distribution network

For reconfiguration problem, the radial nature of the network is considered as a very important constraint. To maintain the radial nature of the distribution network during reconfiguration, the nodes of the distribution system are optimally ordered in order to generate proper parent node–child node path as in [16]. This path generation will ensure the radial nature of the system, also prevents the creation of unconnected branches or nodes, and formation of mesh loops. Hence at each phase of distribution system reconfiguration, the power flow is carried out only after the generation of proper parent node–child node path of the network. For the sample distribution network shown in Fig. 1, the generation of parent node child node path is illustrated in Table 1.

Power flow equations

Distribution system power flow is calculated by the following set of basic recursive equations [17] derived from the single line diagram shown in Fig. 2.

From Fig. 2, the equivalent current injected at node k is calculated as

$$I_k = \left(\frac{P_{Lk} + jQ_{Lk}}{V_k}\right)^* \quad (1)$$

Branch current in the line section k is calculated by using Kirchhoff's Current law as

$$J_k = I_{k+1} + I_{k+2} \quad (2)$$

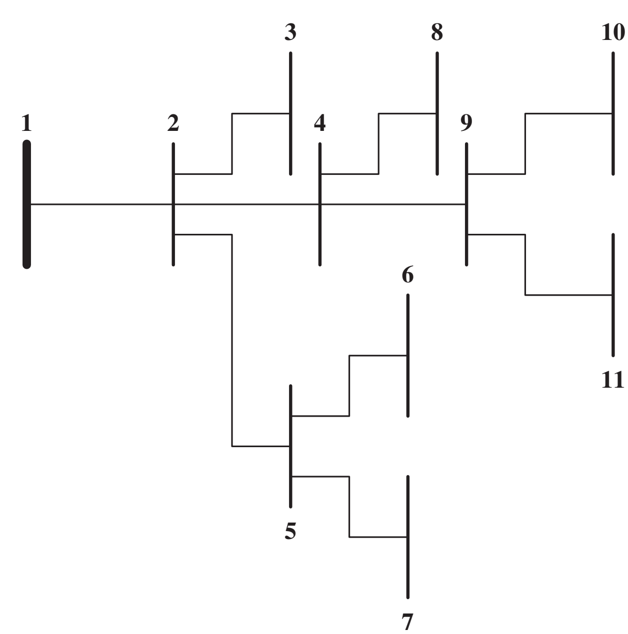

Fig. 1. Sample distribution system.

Table 1
Illustration of parent node child node path generation.

Parent node	1	2	2	2	5	5	4	4	9	9
Child node	2	3	4	5	6	7	8	9	10	11

The above equation (2) is generalized in a matrix form by using Bus current Injection to Branch Current matrix (BIBC) [17]. Now the branch current at each line can be calculated in a matrix form as follows

$$[J] = [BIBC] * [I] \tag{3}$$

By Kirchhoff's Voltage law, the voltage at the bus $k + 1$ can be calculated as

$$V_{k+1} = V_k - J_k * (R_k + jX_k) \tag{4}$$

The power loss in the line section k connecting buses k and $k + 1$ is computed as

$$P_{Loss}(k, k+1) = |J_k|^2 \cdot R_k = R_k \cdot \left(\frac{P_k^2 + Q_k^2}{|V_k|^2}\right) \tag{5}$$

The total power loss of the system is determined by the summation of losses in all line sections, which is given as

$$P_{T,Loss} = \sum_{k=1}^{n_b} P_{Loss}(k, k+1) \tag{6}$$

Power loss reduction using network reconfiguration

Radial distribution network is optimized mainly to minimize the system power losses. The net power loss reduced $\left(\Delta P_{TL}^R\right)$ by network reconfiguration is taken as the ratio of total power loss before and after reconfiguration of the system, and is given as

$$\Delta P_{TL}^R = \frac{P_{T,Loss}^R}{P_{T,Loss}} \tag{7}$$

Net power loss reduced by network reconfiguration in the system can be maximized by minimizing ΔP_{TL}^R.

Voltage deviation Index

One of the main advantages of the network reconfiguration in distribution system is the fall in voltage deviation. This index rebukes the configuration which gives the higher voltage deviation. The voltage deviation index (ΔV_D) can be defined as

$$\Delta V_D = \max\left(\frac{V_1 - V_k}{V_1}\right) \quad \forall\ k = 1, 2, \ldots, n_t \tag{8}$$

During network reconfiguration, if the state of the system has voltage limit violations, the proposed technique will try to minimize the ΔV_D closer to zero and thereby improves voltage stability and network performance.

Objective function of the problem

The objective function of the problem is formulated to minimize the power loss and voltage deviation of the distribution networks and is given as

$$\text{Minimize } F = \min\left(\Delta P_{TL}^R + \Delta V_D\right) \tag{9}$$

$$\text{Subjected to} |V_1 - V_K| \leqslant \Delta V_{\max} \tag{10}$$

$$|S_K| \leqslant |S_{k,\max}| \tag{11}$$

Furthermore, the radial nature of distribution network must be maintained, and all loads must be served. If any one of the above constraints is violated, then the resultant solution will be rejected.

Overview of Fireworks Optimization Algorithm (FWA)

Fireworks Algorithm (FWA) is a new swarm intelligence based stochastic search technique, developed by Tan and Zhu [18]. In recent years, FWA has been applied in solving number of optimization problems [19] due to its ability to search the promising areas of the solution space. In FWA, the explosion process of a firework is considered as a search in the local space around a specific point where the firework is set off through the sparks generated in the explosion. At each generation, FWA selects some quality points as fireworks, which generates a number of sparks to search the local space around them. The search process continues until at least one spark reaches a fairly desired optimum, or the stopping criterion is met.

In FWA presented in [18], the number of sparks (s_i) and the amplitude of explosion (A_i) for each firework x_i is defined as follows:

$$s_i = m \cdot \frac{y_{\max} - f(x_i) + \xi}{\sum_{i=1}^{n}(y_{\max} - f(x_i)) + \xi} \tag{12}$$

$$A_i = \widehat{A} \cdot \frac{f(x_i) - y_{\min} + \xi}{\sum_{i=1}^{n}(f(x_i) - y_{\min}) + \xi} \tag{13}$$

where m and $\widehat{A}$ are control parameters, $f(x_i)$ is the value of objective function (fireworks) at location x_i, $y_{\max}$ and $y_{\min}$ are the maximum (worst) and minimum (best) value of the objective function among the n fireworks, and ξ is a smallest constant in the computer to avoid zero-division-error.

To avoid overwhelming effects of splendid fireworks, bounds are defined for s_i, which is shown in Eq. (14).

$$S_i = \begin{cases} s_{\min} & \text{if } s_i < s_{\min} \\ s_{\max} & \text{if } s_i > s_{\max} \\ round(s_i) & \text{otherwise} \end{cases} \tag{14}$$

For a d-dimensional problem, the location of each spark x_j generated by x_i can be obtained by randomly setting z directions ($z < d$), and for each dimension k setting the component x_j^k ($1 \leqslant j \leqslant S_i$, $1 \leqslant k \leqslant z$).

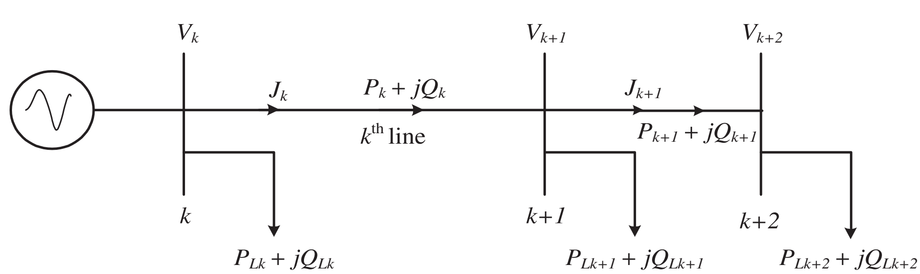

Fig. 2. Simple distribution Feeder.

There are two ways for setting x_j^k. For most sparks, a displacement $h = A_i * \text{rand}(-1, 1)$ is added to x_j^k as

$$x_j^k = x_j^k + h \tag{15}$$

To keep the diversity, for a few specific sparks, an explosion coefficient based on Gaussian distribution is applied to x_j^k and is given as:

$$x_j^k = x_j^k \cdot Gaussian(1, 1) \tag{16}$$

In both the ways, if the obtained new location falls out of the search space, it is mapped to the search space according to Eq. (17),

$$x_j^k = x_{\min}^k + \left| x_j^k \right| \% (x_{\max}^k - x_{\min}^k) \tag{17}$$

At each iteration of FWA, among all the current sparks and fireworks, the best location is always kept for the next explosion generation. Then $n - 1$ locations are selected with some probabilities proportional to their distances to other locations. The selection probability of a location is defined by the following equations.

$$R(x_i) = \sum_{j \in K} d(x_i, x_j) = \sum_{j \in K} \| x_i - x_j \| \tag{18}$$

$$p(x_i) = \frac{R(x_i)}{\sum_{j \in K} R(x_j)} \tag{19}$$

where K is the set of all current locations of both fireworks and sparks.

It is observed that, the spark search process of FWA naturally incorporates the structure of existing heuristics method. It preserves the best location that is fairly near the desired optimum and selects $n - 1$ locations from the two types of sparks generated with some probability for the next explosion generation. This is found to be the uniqueness of FWA with other optimization algorithms like Genetic Algorithm (GA). In GA, the new locations are selected only from two of the existing locations (the parents). In addition, FWA considers each dimension of a location independently while generating a new location of sparks, whereas GA cannot because it has to maintain the gene structure. These properties of FWA increase accuracy and convergence in solving the complex conventional problem.

Application of FWA for power loss minimization and voltage profile enhancement

The algorithmic framework of FWA to optimize the distribution network are presented as follows.

Step 1: Initialization of the FWA parameters.

N: number of iterations (50 for 33 bus system, and 100 for 119 bus system).

d: dimension of search space, i.e. number of open or tie switches in the system (5 in 33 bus system, and 15 in 119 bus system).

n: number of locations (20 for 33 bus system, and 30 for 119 bus system).

m: parameter controlling total number of sparks (25).

$\hat{A}$: maximum explosion amplitude (20).

Constants $s_{\min} = 2$, $s_{\max} = 20$ and $\check{n} = 5$.

Step 2: Randomly select n locations of sparks for fireworks as follows.

$$x = \begin{bmatrix} x_1^1 & x_2^1 & x_3^1 & \cdot & \cdot & x_d^1 \\ x_1^2 & x_2^2 & x_3^2 & \cdot & \cdot & x_d^2 \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ x_1^n & x_2^n & x_3^n & \cdot & \cdot & x_d^n \end{bmatrix} \tag{20}$$

The structure of the above solution vector x for radial distribution network optimization is expressed by "*Arc No.* (t)" and "*SW. No.* (t)" for each switch t. "*Arc No.* (t)" means the arc (loop) number which contains the tth open switch, and "*SW. No.* (t)" means the switch which is normally open on the *Arc No.* (t). For large distribution networks, it is not efficient to represent every branch in the string, as its length will be very long. Therefore, to memorize the radial configuration, it is enough to number only the open switch positions [20]. Thus the solution vector for network reconfiguration is formed as follows:

$$x = \begin{bmatrix} \overbrace{SW_1^1 \quad SW_2^1 \quad \cdot \quad SW_{d-1}^1 \quad SW_d^1}^{\text{Open Switches}} \\ SW_1^2 \quad SW_2^2 \quad \cdot \quad SW_{d-1}^2 \quad SW_d^2 \\ \cdot \quad \cdot \quad \cdot \quad \cdot \quad \cdot \\ \cdot \quad \cdot \quad \cdot \quad \cdot \quad \cdot \\ SW_1^n \quad SW_2^n \quad \cdot \quad SW_{d-1}^n \quad SW_d^n \end{bmatrix} \tag{21}$$

where SW_1, SW_2, SW_{d-1} and SW_d are the open switches in the loops formed corresponding to the tie switches respectively. The solution vector formation for network optimization is illustrated well with the help of standard 33-bus radial test system. In 33-bus system, there are five open tie switches 33, 34, 35, 36 and 37 respectively, which forms five loops L_{P1} to L_{P5} as shown in Fig. 3. In order to rep-

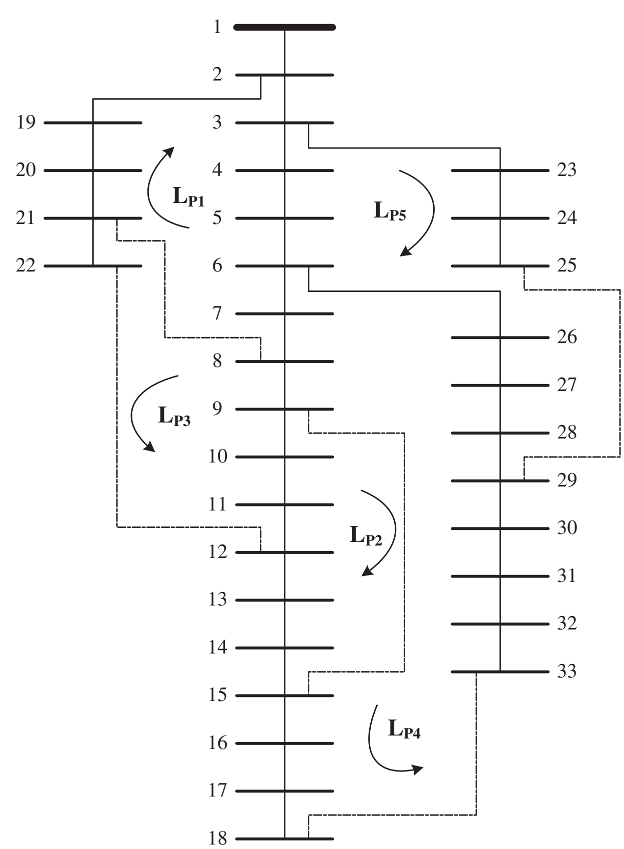

Fig. 3. Base configuration of 33-bus radial distribution system.

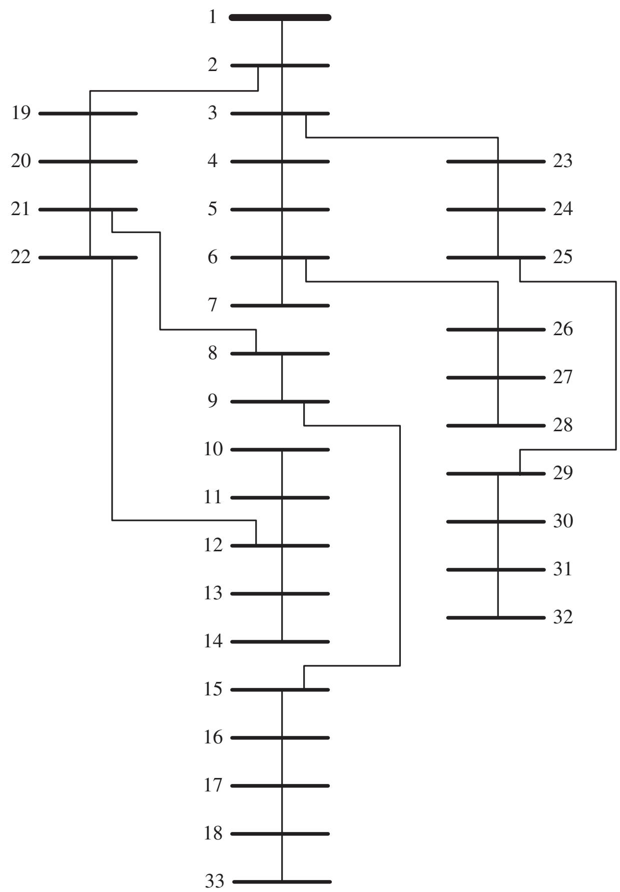

Fig. 4. Optimum configuration of 33-bus radial distribution system.

resent an optimum network topology, only positions of the open switches in the distribution network that satisfy the radial topology without any isolated node need to be known. Thus, the sample solution vector x of 33-bus system for network reconfiguration is shown below.

$$x = \begin{bmatrix} 33 & 34 & 35 & 36 & 37 \\ 07 & 13 & 10 & 36 & 26 \\ 06 & 13 & 10 & 30 & 25 \\ . & . & . & . & . \\ . & . & . & . & . \\ 07 & 14 & 09 & 32 & 28 \end{bmatrix} \tag{22}$$

Step 3: Fireworks loop $q = q + 1$.

Set off n fireworks at the selected n locations, i.e. for the selected n locations, objective function ($F(x_i)$) is calculated by the power flow.

$$\text{Let } F_{i,last} = F(x_i) \quad \forall\ i = 1, 2, \ldots, n \tag{23}$$

Step 4: For each firework $F(x_i)$.

Calculate the number of sparks that the firework yields, i.e. number of feasible solutions with minimum $F(x_i)$: S_i, according to Eq. (14). Unfeasible solution that violates the operating constraints will not be considered further.

Obtain the new location of S_i sparks of the firework x_i using displacement as in Eq. (15) and (17).

Step 5: Generation of specific sparks loop. For $i = 1, 2, \ldots, S_i$, while $p \leqslant \check{n}$,

(i) Let $p = p + 1$.
(ii) Randomly select a firework x_i and generate a specific spark for the firework using Gaussian explosion method as in Eq. (16) and (17).
(iii) Set off firework $F(x_i)$ for all the generated specific spark.
(iv) If $F(x_i) < F_{i,last}$, let $F_{i,last} = F(x_i)$ and then go to step (i). Else, let $p = \check{n}$. This is the end of while statement.

Step 7: Evaluate the quality of all the above locations and select the best location that gives minimum F and keep it for the next explosion generation.

Step 8: Randomly select $n - 1$ locations from the two types of sparks generated and the current fireworks according to the probability given in Eq. (19).

Step 9: if $q \leqslant N$, go to step 3. Otherwise end and display the results of best location.

These are the prime steps of FWA employed to reconfigure the distribution network for power loss minimization and voltage profile enhancement.

Numerical results and discussions

To demonstrate the performance and effectiveness of the proposed method using FWA, it is applied to two standard IEEE test systems consisting of 33 and 119 buses. For both the test systems, the substation voltage is considered as 1 p.u., and all the tie and sectionalizing switches are considered as candidate switches for solving reconfiguration problem. The FWA parameters initialized in the above section is common for both the test system. In the

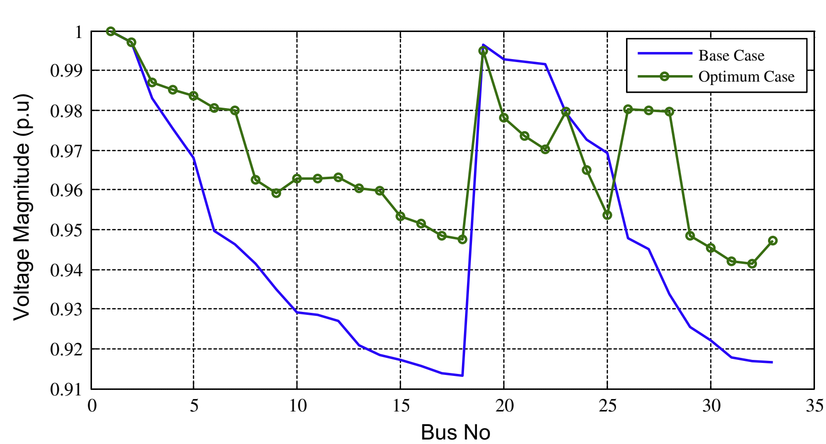

Fig. 5. Comparison of voltage magnitude of 33-bus system.

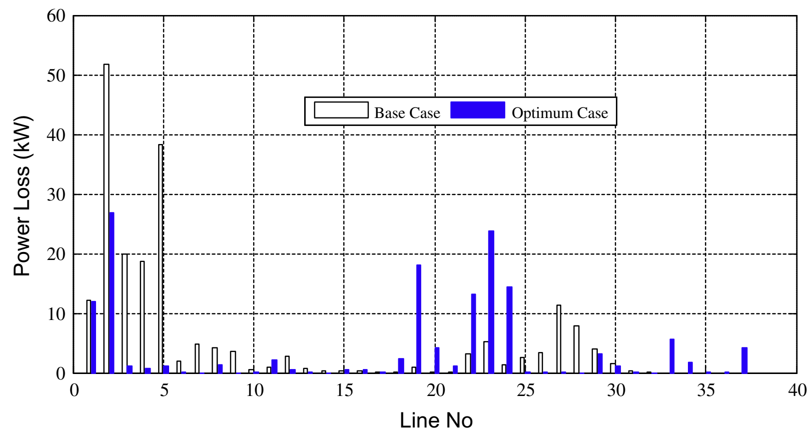

Fig. 6. Comparison of power loss at each line of 33-bus system.

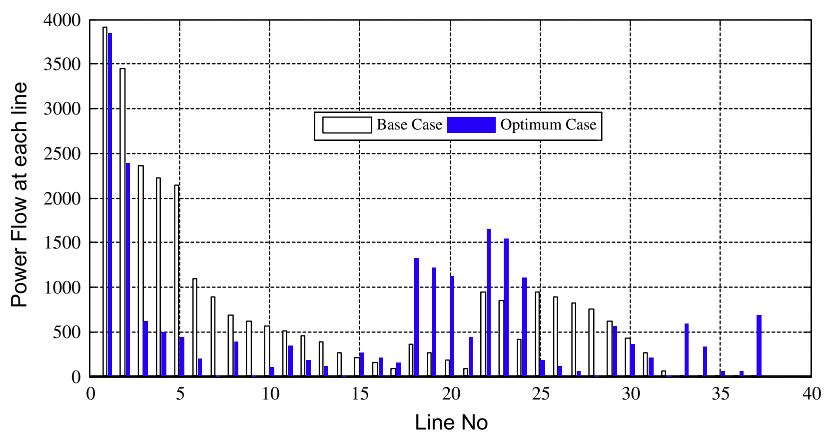

Fig. 7. Comparison power flow at each line of 33-bus system.

simulation of the test systems, three different abnormal cases are also considered to analyze the superiority of the proposed method.

Case I: The system is reconfigured assuming a series fault at a bus (i.e. the system will be reconfigured by isolating the faulted bus).

Case II: The system is reconfigured assuming a series fault at a line (i.e. the system will be reconfigured by switching out the faulted line).

Case III: The system is reconfigured assuming a series fault at both a bus and a line (i.e. the system will be reconfigured by isolating the faulted bus and by switching out the faulted line).

An analytical software tool has been developed in MATLAB environment for generating parent node child node path, to carry out power flow, calculate voltages and power losses.

5.1. 33-Bus test system

This is a medium scale, 12.66 kV, radial distribution system with 33 buses. The line, load and tie line data of this test system are taken from [21]. It consists of five tie lines and 32 sectionalize switches. The normally open tie switches are 33–37, and the normally closed sectionalize switches are 1–32. The single line diagram of 33-bus system with the loops (L_{P1} to L_{P5}) formed corresponding to each tie switch is shown in Fig. 3. The dotted lines

Table 2
Performance analysis of FWA for 33-bus test system. The bold values define the significance of proposed method over other methods in terms of power loss minimization and voltage profile improvement.

Item	Base case	Optimum case				
		GA [11]	RGA [11]	ITS [11]	HSA [11]	FWA
Lines switched out	33, 34, 35, 36, 37	07,14, 09, 32, 37	07,14, 09, 32, 37	07, 14, 09, 36, 37	07, 14, 10, 36, 37	07, 14, 09, 32, 28
$P_{T,Loss}$ (kW) (200 runs)						
Best	**202.67**	**139.55**	**139.55**	**145.11**	**146.39**	**139.98**
Worst		202.67	198.4	196.3	195.10	155.75
Average		166.2	164.9	163.5	152.33	145.63
STD		14.53	13.34	12.11	11.28	5.49
Average % loss reduced	–	18.01	18.65	19.34	24.85	28.14
Best % loss reduced	–	31.14	31.14	28.40	27.77	30.93
V_{Worst} (p.u.)	**0.9131**	**0.9378**	**0.9378**	**0.9336**	**0.9336**	**0.9413**
ΔV_D	0.0869	0.0622	0.0622	0.0664	0.0664	0.0587
Average computation time (s)	–	19.1	13.8	8.1	7.2	6.4

represent the tie lines. The total real and reactive power loads of the system are 3.72 MW and 2.3 MVAr, respectively. The total real and reactive power losses for the base case calculated from power flow are 202.67 kW and 135.14 kVAr respectively. The minimum voltage magnitude of the system is 0.9131 occurs at bus no. 18.

When the simulated results are compared with other methods published in the literature, it is observed that there are some incongruities in the total power loss value for the same 33-bus test system. Authors in [6,9,13] have obtained the real and reactive power loss for the base case as 210.98 kW and 145.32 kVAr, while others in [4,8,10,11,15,20,21] have obtained it as 202.67 kW and 135.14 kVAr respectively. In view of these incongruities, the line and load data was investigated, which were found to be exactly coincident with the original data of [6,21] except the line data of 7th line. In [6], the resistance and reactance value of 7th line is 1.7114 Ω and 1.2351 Ω, whereas in [21], it is found to be 0.7114 Ω and 0.2351 Ω. As 7th line is opened in most of the published literature during reconfiguration of this system, the oddness in total power losses after reconfiguration was absent. Even if there are any incongruities in reference to the total power loss for the same opened tie lines after reconfiguration, it may be due to the power flow techniques employed by the respective authors. This is investigated to avoid unnecessary confusion and to provide proper guidance to the future researchers.

The optimal configuration of this system obtained by the proposed method is 07–14–09–32–28. The total power loss and

Table 3
Performance analysis of parameters of FWA for 33-bus system. The bold values define the significance of optimal parameter selection in terms of power loss minimization, convergence and computation ability.

Case	Parameter setting			$P_{T,Loss}$ (kW)	No of iterations	CPU time (s)
	n	m	$\hat{A}$			
1	20	25	10	146.78	27	12.3
	20	25	15	142.21	25	11.5
	20	**25**	**20**	**139.98**	**12**	**6.1**
	20	25	30	141.33	19	8.7
	20	25	40	148.24	29	12.9
2	20	10	20	148.63	27	12.2
	20	15	20	147.96	23	10.2
	20	20	20	143.21	18	8.6
	20	30	20	145.47	25	11.7
	20	40	20	153.33	29	13.2
3	10	25	20	139.98	31	7.8
	15	25	20	139.98	22	7.1
	25	25	20	139.98	12	7.6
	30	25	20	139.98	10	8.6
	40	25	20	139.98	09	8.9

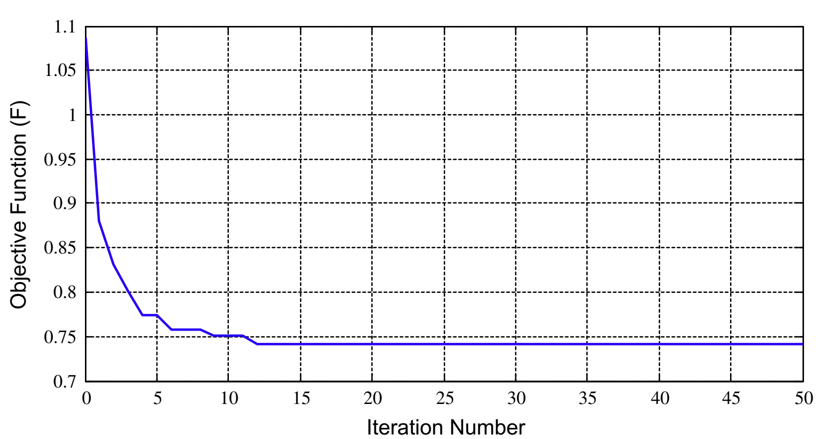

Fig. 8. Convergence characteristics of FWA for 33-bus system.

Table 4
Simulation results of 33 bus system for different cases.

Items	Case I	Case II	Case III
Lines switched out	07–14–09–13–32–28	07–14–09–17–28	07–14–09–13–17–28
Faulted bus	14	–	14
Faulted line	–	17	17
$P_{T,Loss}$ (kW)	131.58	146.29	138.72
% Loss reduced	35.08	27.82	31.55
V_{Worst} (p.u.)	0.9414	0.9327	0.9328
(node)	(32)	(18)	(18)
ΔV_D	0.0586	0.0673	0.0672

minimum voltage magnitude of the system for the optimum case is 139.98 kW and 0.9413 p.u. It is observed that nearly 31% of total power loss has been reduced in the optimum case. Also the minimum voltage magnitude has been improved from 0.9131 to 0.9413 p.u. after reconfiguration by FWA. The optimal configuration of this test system is shown in Fig. 4.

The voltage profiles of the system for base case and optimum case are compared and shown in Fig. 5. From the figure, it is observed that the voltage profile at all buses has been improved significantly after reconfiguration.

The real power loss in each line for base case and optimum case are compared and shown in Fig. 6. It is observed that the losses in almost every line is reduced, except at some lines (19, 22, 23, 24, 33, 34, and 37), where the losses are increased due to shifting of loads onto these feeders.

The comparison of real power flow in each branch for base case and optimum case is shown in Fig. 7. It is observed that the optimal reconfiguration reduces the real power flow in each branch, which will relieve the distribution feeders from overloading and makes it possible to load the feeders further.

In order to analyze the performance of the proposed algorithm, the simulated results are compared with the results of other classical algorithms like GA [20], RGA [8], Improved Tabu Search (ITS) [22] and HSA [11] available in the literature. To avoid unnecessary incongruities, the results of other algorithms compared are executed by the proposed power flow for the configuration obtained by their methodology and presented in Table 2. It can be noticed that the results obtained by [11] are slightly different from the values presented in Table 2, despite having the same solution of the opened tie lines, and the load remains unchanged. For effective comparison of performance of FWA, reconfiguration problem is solved 200 times repeatedly. The best and the worst values among the best solutions as well as the average value and Standard Deviation (STD) for the best solutions of these 200 runs are compared and presented in Table 2. A smaller STD implies that most of the best solutions are close to the average value. From Table 2, it is observed that the STD of FWA is very smaller than the other classical algorithms compared, which elicits the superiority of FWA. Also from Table 2, it is very clear that FWA has outperformed classical GA, RGA, ITS and HSA in terms of power loss minimization, voltage profile enhancement and computation time.

To determine the impacts of different parameters of FWA on the solution quality, computation time and convergence behavior, an empirical study is performed. To show the effects of single parameter changes, 15 different cases are tested as shown in Table 3. In cases 1, 2, and 3, n, m and $\widehat{A}$ are varied respectively, and other two parameters are kept constant. The total power loss, no of iterations taken to converge and computation time, for this test system by varying the parameters are summarized in Table 3. The larger the number of locations (n), the number of iterations taken to converge reduces, but the computation time increases despite the same power loss. From Table 3, it is observed that large and

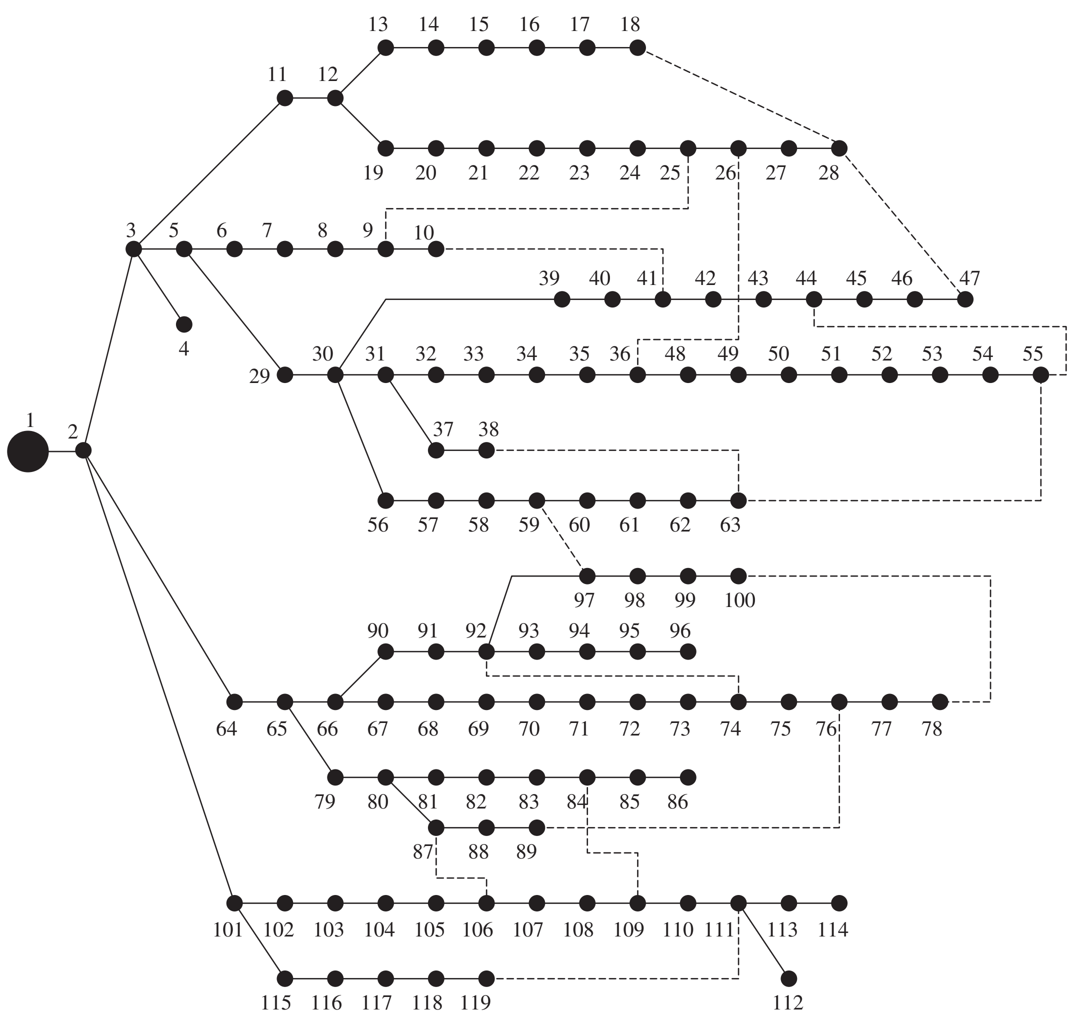

Fig. 9. Base configuration of 119-bus practical radial distribution system.

small values of m and $\widehat{A}$ values leads decrease in solution quality. Thus from Table 3, it is seen that FWA has small sensitivity to control parameters m and $\widehat{A}$.

In order to illustrate the convergence of FWA, the convergence characteristics of FWA for the best solution is shown in Fig. 8. It is observed that only twelve iteration are required to converge to the best solution, which takes less than 7 s. FWA shows a steady and rapid convergence with global searching ability in solving the reconfiguration problem.

For simulation of test system under abnormal conditions, the assumed faulted bus and line for this system are 14th bus and 17th line. For case I, the system is reconfigured by isolating the 14th bus, i.e. by switching out the lines (13 and 14) connecting the faulted 14th bus. With the lines (13 and 14) in open condition, the optimal configuration with minimum power loss and voltage deviation has been obtained by FWA is 7–9–13–14–32–28. The configuration (7–9–13–14–32) obtained by BFOA [15] for case I was not found to be radial in nature and forms a mesh loop (28–37–24–23–3–4–5–25–26–27–28) in the radial network. Also the total power loss for case I obtained by BFOA was 135.78 kW which is 4.2 kW higher than the proposed method. This proves the superiority of the proposed method in finding the optimal solution and maintaining the radial nature of the system at abnormal conditions. Similarly, the optimal configuration with minimum power loss and voltage deviation for case II (07–14–09–17–28) and case III (07–14–09–13–17–28) are obtained by the proposed method. The optimal configuration of this system for different abnormal cases is presented in Table 4.

The constraints have been checked for radiality, node voltages and branch security flows and found within an acceptable tolerance.

5.2. 119-Bus test system

To establish the applicability of the proposed algorithm in large-scale distribution systems, it is tested on this large scale, 11 kV practical radial distribution system with 118 sectionalizing switches (1–118) and fifteen tie switches (119–133). The initial configuration of 119-bus system with the open tie switches is shown in Fig. 9. The configuration, line, load and tie line data of this system are taken from [22]. The total real and reactive power loads of the system are 22.7097 MW and 17.0411 MVAr, respectively. The total real and reactive power losses for the base case calculated from power flow are 1298.09 kW and 978.84 kVAr respectively. The minimum voltage magnitude of the system is 0.8688 p.u. occurs at bus no. 78. The assumed faulted bus and line for this system are 50th bus and 31st line.

Similar to the 33 bus system, this test system is also simulated for optimum and other three abnormal cases. The optimal configuration of this system obtained by the proposed method is 43–26–24–122–51–59–40–96–72–75–98–130–131–110–35. The optimal configuration of this test system is shown in Fig. 10. The

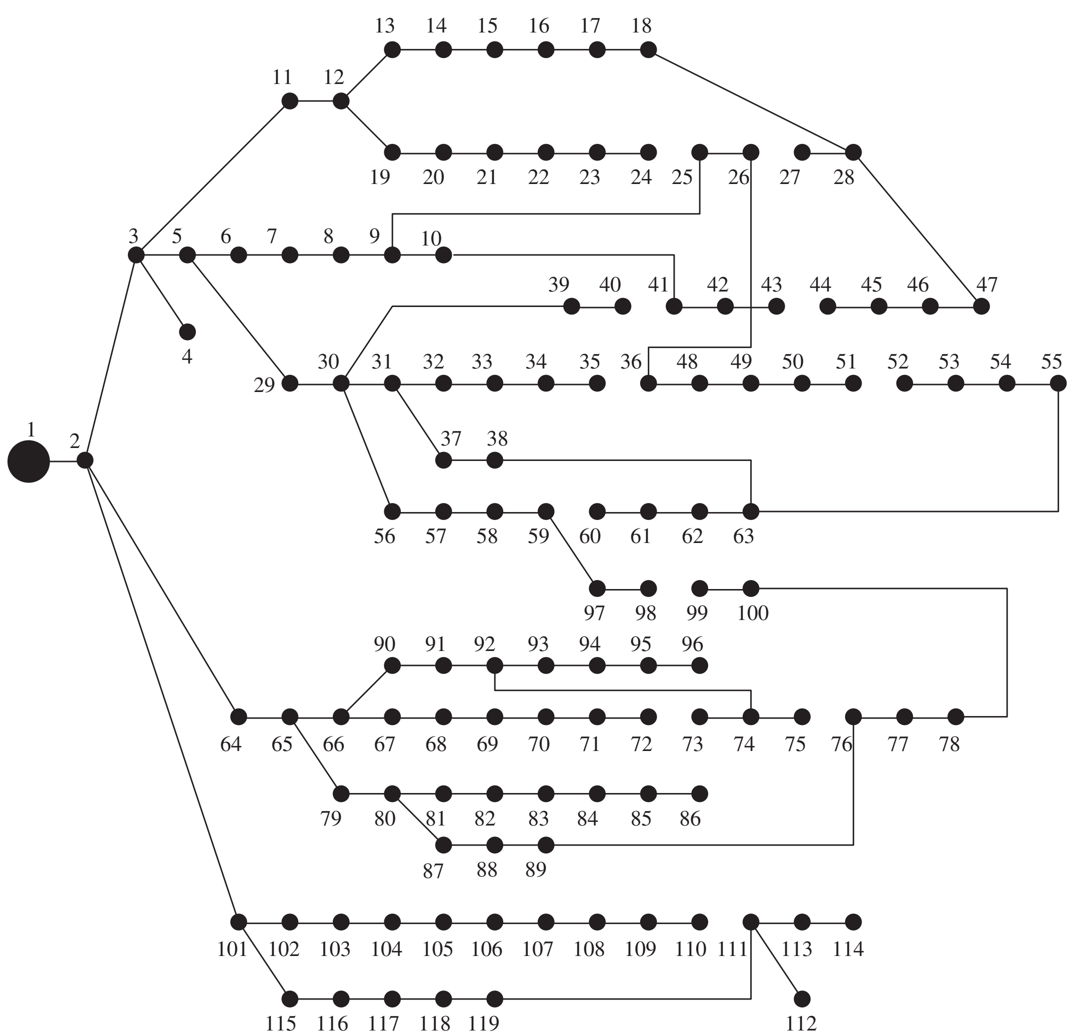

Fig. 10. Optimum configuration of 119-bus practical radial distribution system.

Table 5
Performance analysis of FWA for 33-bus test system. The bold values define the significance of proposed method over other methods in terms of power loss minimization and voltage profile improvement.

Item	Base case	Optimum case				
		GA [11]	RGA [11]	ITS [11]	HSA [11]	FWA
Lines switched out	119, 120, 121, 122, 123, 124, 125, 126, 127, 128, 129, 130, 131, 132, 133	43, 120, 24, 51, 49, 62, 40, 126, 74, 73, 77, 83, 31, 110, 35	43, 27, 23, 52, 49, 62, 40, 126, 74, 73, 77, 83, 131, 110, 33	43, 27, 24, 52, 120, 59, 40, 96, 75, 72, 98, 130, 131, 110, 35	43, 27, 23, 53, 123, 62, 125, 126, 75, 72, 129, 130, 131, 132, 33	43, 26, 24, 122, 51, 59, 40, 96, 72, 75, 98, 130, 131, 110, 35
$P_{T,Loss}$ *(kW) (200 runs)*						
Best	**1298.09**	**885.56**	**883.13**	**865.86**	**854.21**	**854.06**
Worst		1301.90	1297.34	1288.17	1282.73	942.34
Average		965.8	963.1	952.6	935.01	887.54
STD		78.5	77.4	73.2	69.3	29.58
Average % loss reduced	–	25.60	25.81	26.62	27.97	31.63
Best % loss reduced	–	31.78	31.97	33.30	34.19	34.21
V_{Worst} (p.u.)	**0.8688**	**0.9321**	**0.9321**	**0.9323**	**0.9323**	**0.9323**
ΔV_D	0.1312	0.0679	0.0679	0.0677	0.0677	0.0677
Average computation time (s)	–	24.45	17.53	9.038	8.61	7.72

Table 6
Simulation results of 119-bus system for different cases.

Items	Case I	Case II	Case III
Lines switched out	43, 26, 24, 122, 49,50, 59, 40, 96, 72, 75, 98, 130, 131, 110, 35	43, 26, 24, 122, 51, 59, 40, 96, 72, 75, 98, 130, 131, 110, 31	43, 26, 24, 122, 49, 50, 59, 40, 96, 72, 75, 98, 130, 131, 110, 31
Faulted bus	50	–	50
Faulted line	–	31	31
$P_{T,Loss}$ (kW)	929.02	954.69	957.07
% Loss reduced	28.64	26.67	26.49
V_{Worst} (p.u.)	0.9118	0.9302	0.9167
(node)	(51)	(32)	(51)
ΔV_D	0.0882	0.0698	0.0833

total power loss and minimum voltage magnitude of the system for the optimum case is 854.06 kW and 0.9323 p.u. It is observed that nearly 35% of total power loss has been reduced in the optimum case. Also the minimum voltage magnitude has been improved to 0.9323 p.u. (112) after reconfiguration by FWA.

The simulated results of this system is also compared with the results of GA, RGA, ITA and HSA available in the literature and presented in Table 5. From Table 5, it is observed that the results of the proposed method is encouraging and better than all other methods compared in terms of power loss minimization and voltage profile enhancement. The proposed method is solved repeatedly for 200 times. The best and the worst values among the best solutions as well as the average value and STD for the best solutions of these 200 runs are also compared and presented in Table 2. From the table, it is very clear that the performance of proposed FWA is better than GA, RGA, ITS and HSA methods. This demonstrate well the applicability of proposed method in a large scale radial distribution system.

The optimum results of three different cases obtained by the proposed method are presented in Table 6. From Table. 6, it is observed that the proposed method maintains the radial nature, guarantees power to the non-faulted areas with minimal power loss and voltage deviation even under abnormal condition. This demonstrates well the effectiveness of the proposed method. The constraints have been checked and found within acceptable limits.

Conclusion

In this paper, the application of recently developed global optimization process FWA for solving the problem of network reconfiguration with the objective of power loss minimization and voltage profile enhancement of power distribution systems has been presented. The radial nature of the network and proper current flow direction through-over all reconfiguration phases is maintained by generating proper parent node child node path and forming BIBC matrix during power flow. Three different abnormal cases are also considered during network reconfiguration. The proposed method has been tested on a medium and large scale radial test systems, and the results are compared with other classical methods GA, RGA, ITS, and HSA available in the literature. The computational results shows that the results obtained by proposed algorithm are encouraging and found to be better than the other methods compared. It is also observed that the performance of FWA has outperformed the other methods compared in terms of quality of solutions. For the large-scale system like 119-bus system, simulated results demonstrate that the applicability and advantage of FWA is more remarkable. The convergence rate curve presented confirms the global searching ability of FWA for the reconfiguration problem. An empirical study of different parameter setting of FWA has also been performed and demonstrated. The proposed method can be easily applied and adapted to any large scale practical radial distribution networks.

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