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Voltage stability maximization based optimal network reconfiguration in distribution networks using integrated particle swarm optimization for marine power applications

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This paper addresses a novel method to optimize network reconfiguration problem in radial distribution network considering voltage stability maximization and power loss reduction without violating the system constraints. In nature inspired population based standard particle swarm optimization (PSO) technique, the flight path of current particle depends upon global best and particle best position. However, if the particle flies nearby to either of these positions, the guiding rule highly decreases and even vanishes. To resolve this problem and to find the global best position, integrated particle swarm optimization (IPSO) is utilized for finding the optimal reconfiguration in the radial distribution network. The performance and effectiveness of the method are validated through IEEE 33 and 69 buses distribution networks and is compared with other optimization techniques published in recent literature for optimizing network reconfiguration problem. The simulated results simulate the fact that to attain the global optima, IPSO requires less numbers of iterations as compared to the simple PSO. The present method facilitates the optimization of modern electric power systems by empowering them with voltage stability.

[Keywords: Distribution network; Integrated particle swarm optimization; Marine electric power system; Network reconfiguration; Voltage stability]

Introduction

Ship electric power system, offshore oil and gas vessel operating in ultra-deep water requires large independent electric power system. Because of electric propulsion technology adopted by modern marines, the voltage stability becomes an important issue for proper operation of electric system[1-2]. Ship electric system is analogous to the electrical distribution system where one large power source is connected to different types of loads. Due to stressed system operations and rapid expansion of the radial distribution network (RDN), the network voltage stability has become an important issue. To reduce the power losses and to improve the voltage stability various efforts have been taken by power engineers and researchers. A typical electrical distribution network consists of two types of feeder switches. The one, which are normally open, and others are normally closed. By changing the status of these switches (i.e. Open to close and vice-versa), the topology of the network can be changed and also called feeder reconfiguration operation. The network reconfiguration is considered as non-linear, mixed integer, non-differentiable, multi objective constraint optimization problem. The network reconfiguration with the objective of power loss minimization was first proposed by Marlin and back in 1975. The knowledge based heuristic approach was applied in system reconfiguration problem for transformer overload reductions and feeder constraint problems in distribution network[3]. Artificial neural network (ANN) strategies were developed to solve feeder reconfiguration problem with an objective to reduce power losses in the RDN[4]. In recent years, various nature inspired population-based optimization methods are applied to obtain optimal reconfiguration in the distribution network. The metaheuristic global optimization methods such as simulated annealing (SA)[5] and genetic algorithm (GA)[6-7] are applied to optimize the reconfiguration in the distribution network. Recently developed optimization technique, e.g. enhanced gravitational search algorithm (EGSA)[8] is applied in reconfiguration problem with simultaneous consideration of reliability, operating cost and power losses. Honeybee mating optimization (HBMO) algorithm[9-10] is applied to optimize network reconfiguration in order to reduce the power losses and voltage deviation at nodes. The algorithms based on PSO and its alternatives are applied to feeder reconfiguration and marine applications[11-16]. Power loss minimization is achieved in reconfiguration with ant colony optimization (ACO)[17-19]. Hybrid optimization based on ACO-PSO[20] is applied to feeder reconfiguration to improve the voltage profile and power loss minimization. A new hybrid optimization based on fuzzy adaptive PSO and Nelder-Mead (NM) simplex search method is applied to network reconfiguration problem[21]. Hybrid optimization based on fuzzy-firefly algorithm[22] is applied to feeder reconfiguration and compared with GA, artificial bee colony (ABC) algorithm, GA-PSO. Other optimization techniques such as modified bacterial foraging optimization algorithm (BFOA)[23], runner root algorithm[24] are used for feeder reconfiguration problem. Kennedy and Eberhart[25] proposed PSO in 1995. In standard PSO technique, the flight path of current particle depends upon global best and particle best position. However, if the particle flies nearby to either of these positions, the guiding rule highly decreases and even vanishes. To overcome this condition and finding the global best reconfiguration, integrated particle swarm optimization (IPSO)[26] is utilized in this paper to feeder reconfiguration problem with objectives to minimize power loss and voltage stability enhancement. The simulated results are compared with optimization techniques i.e., Simple PSO, adaptive cuckoo search algorithm (ACSA)[27], harmony search algorithm (HSA)[28] and Fireworks algorithm (FWA)[29].

Objective Function

The total active power loss (P_{Tloss}) could be calculated by adding the losses of all the feeders in the given distribution network (Fig. 1) and formulated as follows:

$$P_{T_{loss}} = \sum_{m=1}^{N_{br}} R_m \times \left(\frac{P_m^2 + Q_m^2}{V_m^2} \right) \quad \ldots (1)$$

Where, R_m is the resistance of feeder connected between node 'm' and 'm+1'. P_m, Q_m and Vm are the output active power and reactive power flows and voltage magnitude respectively at node 'm'. N_{br} represents the total number of feeders in the network.

In literature, many researchers have solved network reconfiguration problem with the objective to minimize power loss. Very few researchers have focused on voltage stability of distribution network while solving the reconfiguration problem. The power loss reduction in the distribution system can be calculated by Eq. (2).

$$\Delta P_{loss}^{R} = \frac{P_{loss}^{REC}}{P_{loss}^{0}} \quad \ldots (2)$$

Where, P_{loss}^{REC} and P_{loss}^{0} are active power loss with and without reconfiguration. In this paper, voltage stability index (VSI)[30] is used to represent the status of network voltage stability. Critical values of this index lie between 0 and 1. The node having a minimum value of VSI is the most vulnerable node from the stability point of view. Higher values of VSI indicate higher stability in the network. The formulation of considered VSI is given by Eq. (3).

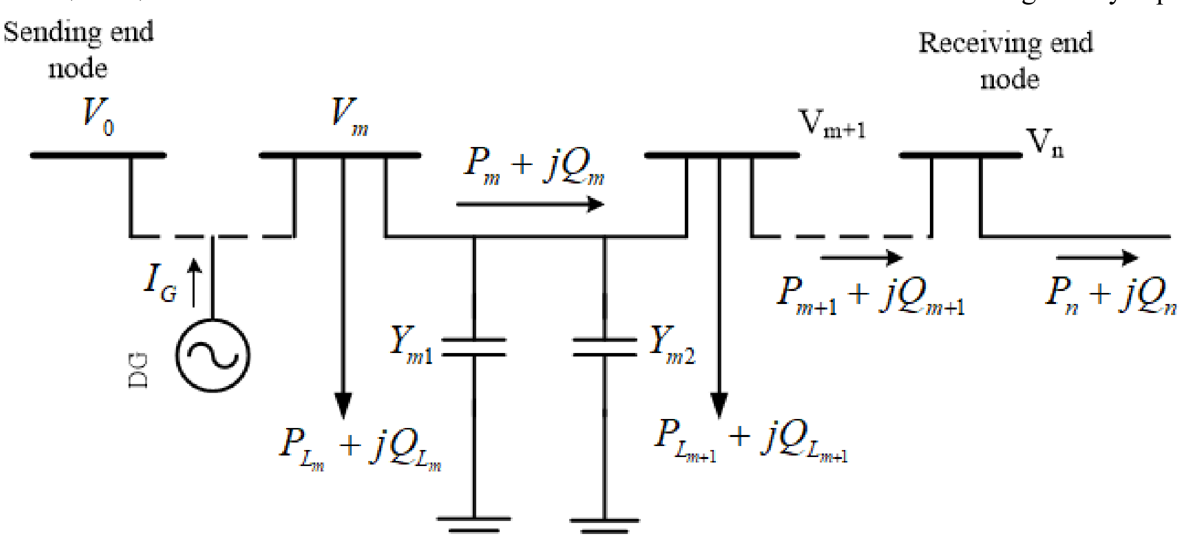


Fig. 1 — A schematic diagram of distribution network[28]

$$VSI_{m+1} = |V_m|^2 - 4\left(P_{m+1}X_m - Q_{m+1}R_m\right)^2 - 4\left(P_{m+1}R_m - Q_{m+1}X_m\right)|V_m|^2 \quad \dots (3)$$

Where, P_{m+1} and Q_{m+1} are the total real and reactive power fed from node 'm+1'. The deviation in VSI is given by Eq. (4)

$$\Delta VSI = \left(1 - VSI_m\right) \quad \text{for } m=1,2,3\ldots\ldots,N_{br} \quad \dots (4)$$

Where, N_{br} is the total number of feeders in the distribution network. The combined objective to power loss reduction and voltage stability enhancement can be formulated as follows:

$$F_{obj} = \min\left(\Delta P_{loss}^R + \Delta VSI\right) \quad \dots (5)$$

Integrated Particle Swarm Optimization

PSO is nature inspired population based optimization method invented by Eberhart and Kennedy in 1995. The algorithm simulates the social behavior of bird flock or fish school by taking initial solution candidates (called particles) which flight over a large search space. The flight path is governed by mathematical formulation over the particle's position and velocity. Each particle flight path depends upon local best known position (P_{best}), which is updated if better position is found by particle and best position in entire search space also called global best (G_{best}). However, the main drawback of the algorithm appears when the particles fly nearby to either of these positions and guiding path for flights decreases. Under this condition, there are chances to trap into local minima. To counter this problem, a third particle called weighted particle (X^w) was introduced into the velocity updating formulation[23]. The vector representation of the velocity and position updating of IPSO compared with PSO are shown in Figure 2[26].

Weighted particle (X^w) can be defined as follows:

$$X^w = \sum_{i=1}^{M} \hat{c}_i^w X_i^P \quad \dots (6)$$

$$\overline{c}_i^w = \left(\hat{c}_i^w \Big/ \sum_{i=1}^{M} \hat{c}_i^w\right) \quad \dots (7)$$

$$\hat{c}_i^w = \frac{\max\limits_{1\le k\le M}\left(f\left(X_k^P\right)\right) - f\left(X_i^P\right) + \varepsilon}{\max\limits_{1\le k\le M}\left(f\left(X_k^P\right)\right) - \min\limits_{1\le k\le M}\left(f\left(X_k^P\right)\right) + \varepsilon}$$

$$\text{for } i = 1,2,\ldots\ldots\ldots\ldots,N_P \quad \dots (8)$$

Where, N_P represents the population of particles; X^w is the position vector of weighted particles; $\hat{c}_i^w$ is the weighted constant of each particle. The function $f\,(.)$ represents the fitness of the particle, while $\max\limits_{1\le k\le M}\left(f\left(X_k^P\right)\right)$ and $\min\limits_{1\le k\le M}\left(f\left(X_k^P\right)\right)$ represents the maximum and minimum fitness values in the P_{best}. Finally, ϵ specifies a small positive number (0.0001) to prevent the condition of division by zero. In IPSO particle position vector with weighted particle are updated as follows

$$\text{If } rand_{0i} \le \alpha$$

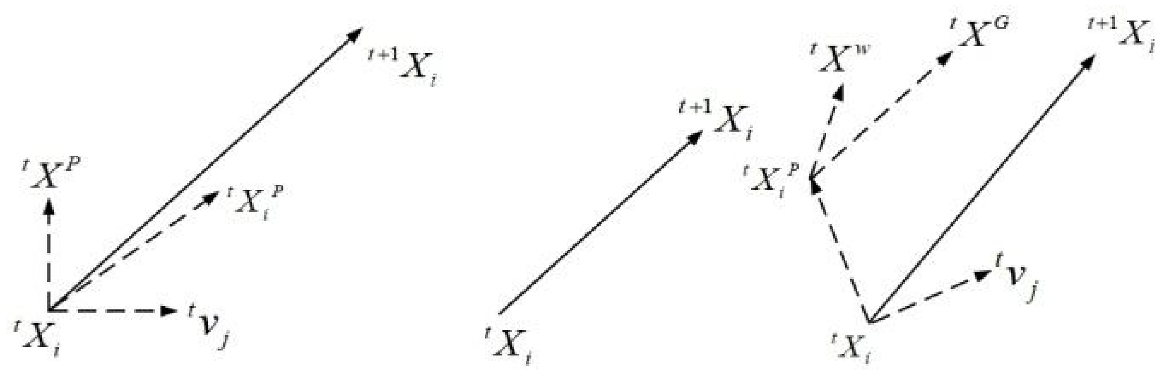
$${}^{t+1}v_i = 0 \quad \dots (9)$$

$${}^{t+1}X_i = {}^{t}X_i + \varphi_{4i}\left({}^{t}X^w - {}^{t}X_i\right) \quad \dots (10)$$

$$\varphi_{4i} = C_4 \times rand_{4i} \quad \dots (11)$$

$$\text{If } rand_{0i} > \alpha$$

$${}^{t+1}v_i = w_i \times {}^{t}v_i + \left(\varphi_{1i} + \varphi_{2i} + \varphi_{3i}\right)\left({}^{t}X_j^P - {}^{t}X_i\right) + \varphi_{2i}\left({}^{t}X^G - {}^{t}X_j^P\right) + \varphi_{3i}\left({}^{t}X^w - {}^{t}X_j^P\right) \quad \dots (12)$$



(i) **(ii)** **(ii)**

Fig. 2 — **(i)** Simple PSO **(ii)** IPSO for $rand_{0i} \le \alpha$ **(ii)** IPSO for $rand_{0i} > \alpha$

$$^{t+1}X_i = {}^{t}X_i + {}^{t+1}v_i \qquad \ldots (13)$$

$$\varphi_{1i} = C_1 \times rand_{1i} \qquad \ldots (14)$$

$$\varphi_{2i} = C_2 \times rand_{2i} \qquad \ldots (15)$$

$$\varphi_{3i} = C_3 \times rand_{3i} \qquad \ldots (16)$$

Where, superscripts 't' and 't+1' denotes present and next iteration respectively; ${}^{t}v_i$ and ${}^{t+1}v_i$ are the present and updated velocity of particles; w_i represents an inertia factor for present velocity, which is a random number chosen from [0.5, 0.55] in each iteration.

IPSO Implementation in Reconfiguration Problem

Determine primary loops in the distribution network using the algorithm given in Figure 3.

Determine the lower and upper limits of each tie line depending upon fundamental loop.

Set population size of particles and generate the initial particle represented by X_i.

X_i= [Tsw_1, Tsw_2,………,Tsw_{NO}]

```
Input: Incident matrix A for given radial distribution network
Output: Primary loop
FOR (k=1: Number of normally open branches)
   Add normal open branch k to incident matrix A
   Take absolute value of each element of each column in matrix A.
   Take summation column wise and store it in vector sum_column.
  FOR   sum_column (j^th)=1 {j=1:N  where N is no of nodes}
    FOR    i=1:Nbr  {Nbr- Number of branches}
       IF element (i, j)=1 or -1
           Remove the branch i^th from matrix A
       END IF
    END FOR
    Update sum of absolute elements of each column in matrix A
  END FOR
  Save the remaining branchs of matrix A to the k^th Primary loop
END FOR
```

Fig. 3 — Pseudocode for finding fundamental loop

Where, Tsw_1, Tsw_2,………,Tsw_{NO} are tie switches in primary loops PL_1 to PL_{NO}. NO is the number of tie lines in given distribution network.

Calculate the fitness function value for each particle and obtain global best (G_{best}) and personal best (P_{best}) positions of particles.

Set maximum number of iterations and start the counter (Iter=1).

Calculate weighted particle X^w using Eq. (6)-(8).

If $rand_{0i}$ > =0.4, update velocity (${}^{t+1}v_i$) vector and X_i using Eq. (9) - (11).

Else $rand_{0i}$ < 0.4, update velocity vector (${}^{t+1}v_i$) and X_i using Eq. (12)- (16). Where, $rand_{0i}$ is random number selected from interval [0 1].

Evaluate the fitness function for current particle *f(X_i)* and also for weighted particle *f(X^w)*

IF (min(f(X_i), f(X_w)) < f(X_{Pbest})

Update Pbest

IF (min(f(X_i), f(X_w)) < f(X_{Gbest})

SET G_{best}=X_i or X_w

End IF

Where, X_{Pbest} is the previous best position of the current particle. Replace X_{Pbest} and X_{Gbest} with X_i or X_w whichever has better fitness value.

Increment iteration number [Iter=Iter+1]

Stop the process when a termination criterion reaches.

Results and Analysis

The proposed method is implemented on IEEE 33 and 69 bus radial distribution networks. The simulation is performed on MATLAB software in computer with Intel i7 processor (2.4 GHz) and 8GB RAM.

IEEE 33 bus test system

The 33-bus distribution test system includes 37 branches, 32 sectionalize switch and 5 tie switches[31]. Figure 4 shows the IEEE 33 bus test system. Total

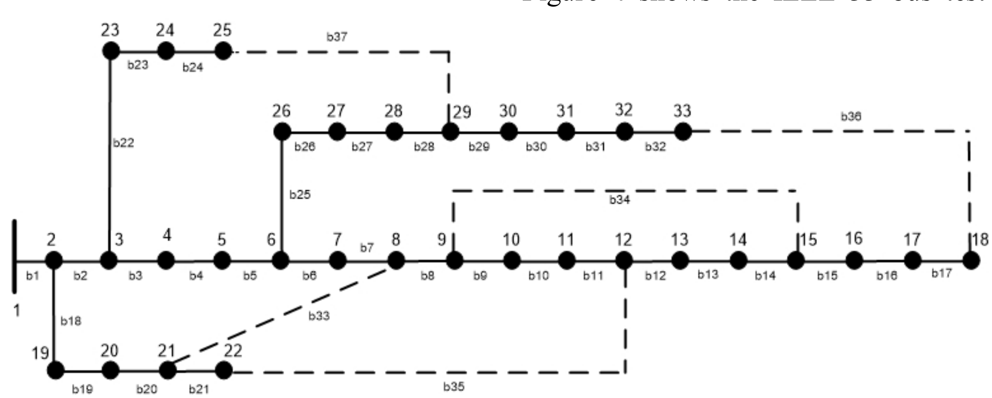


Fig. 4 — IEEE 33 bus test system

active and reactive load of test system are 3.72 MW and 2.3 MVAr respectively. Primary loops for 33-bus system are shown in Table 1, which are obtained by the algorithm given in Figure 3.

Two test cases are considered. No reconfiguration is taken in case –I. The system has total 202.77 kW active power loss whereas minimum voltage and VSI of the system are 0.9131 and 0.6951 respectively. In case-II, the feeder reconfiguration problem is solved using standard PSO and IPSO techniques and results are compared with ACSA[24], FWA[25] and HSA[26]. The parameters used in IPSO algorithm are population size N_{pop} =30, maximum iteration =500, w_i is considered as a random number selected from an interval of [0.5 0.55] in each iteration and α =0.4, The coefficient of acceleration factors considered are C1=-(φ_{2i}+φ_{3i}), C_2 =2, C_3=1 and C_4=2 are considered, $rand_{ki}$ is random number selected from an interval [0 1], where k=0, 1, 2, 3, 4. The tie switches [7, 14, 9, 32, 28] are considered as an optimal solution after 500 iterations. After reconfiguration, total power loss reduces to 139.98 kW whereas a minimum voltage and VSI value is improved to 0.9413 p.u. and 0.7850, respectively.

It is observed from Table 2 that the results obtained from PSO and IPSO are comparable with previously published optimization techniques. From Figure 5, it is observed that IPSO has converged to the optimal solution in 50 iterations, whereas standard PSO takes 240 iterations to converge. The voltage profile and VSI values have been improved after reconfiguration of the distribution network (Figs. 6 & 7).

Table 1 — Primary loops for 33 bus test system

Primary Loop	Tie Lines
PL -1	2, 3, 4, 5, 6, 7, 18, 19, 20, 33
PL- 2	9, 10, 11, 12, 13, 14, 15
PL- 3	2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 18, 19, 20, 21, 35
PL- 4	6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 25, 26, 27, 28, 29, 30, 31, 32, 36
PL-5	3, 4, 5, 22, 23, 24, 25, 26, 27, 28, 37

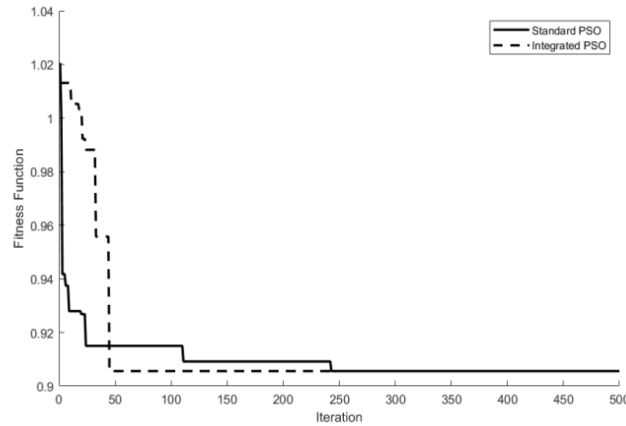


Fig. 5 — Fitness function vs iterations for 33 bus test system

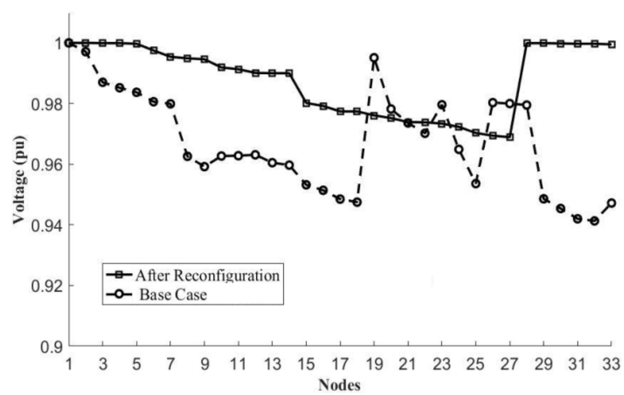


Fig. 6 — Voltage profile for 33 bus test system

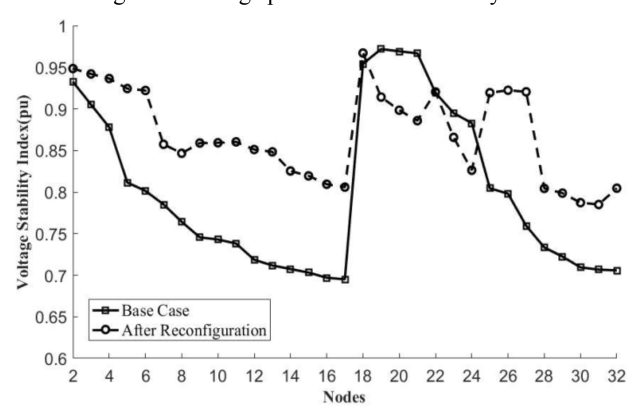


Fig. 7 — VSI values for 33 bus test system

Table 2 — Result analysis of IPSO with 33 bus distribution network

	Item	Integrated PSO	Standard PSO	ACSA[24]	FWA[25]	HSA[26]
Case I	Tie switch (Open)	33,34,35,36,37	33, 34,35,36,37	33,34,35,36,37	-	-
	Power loss (kW)	202.77	202.77	202.68	-	-
	Minimum voltage (p.u.)	0.9131	0.9131	0.9108	-	-
	Minimum VSI	0.6951	0.6951	0.6978	-	-
Case II	Tie switch (Open)	7,9,14,28,32	7,14,9,32,28	7,14,9,32,28	7,14,9,32,28	7,14,9,32,37
	Power loss (kW)	139.98	139.98	139.98	139.98	138.06
	% Loss reduction	30.93	30.93	30.93	30.93	31.88
	Minimum voltage (p.u.)	0.9413	0.9413	0.9413	0.9413	0.9342
	Minimum VSI	0.7850	0.7850	0.7878	-	-

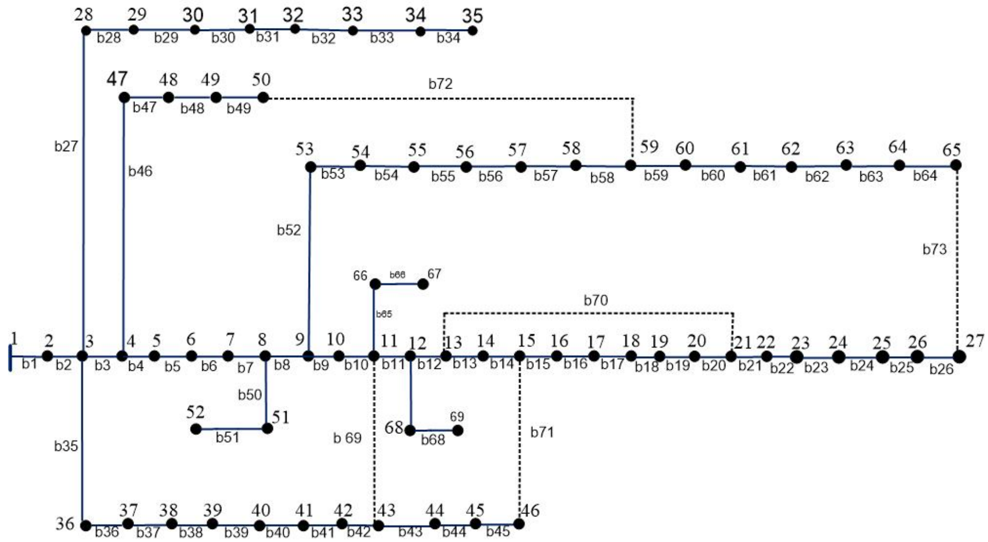


Fig. 8 — Single line diagram of IEEE 69 bus test system

Table 3 — Result analysis of IPSO with 69 bus distribution network

	Items	Integrated PSO	Standard PSO	ACSA[24]	FWA[25]	HSA[26]
Case I	Tie switch (Open)	69,70,71,72,73	69,70,71,72,73	69,70,71,72,73	-	-
	Power loss (kW)	224.99	224.99	224.89	-	-
	Minimum voltage (p.u.)	0.9092	0.9092	0.9092	-	-
	Minimum VSI	0.6833	0.6833	0.6859	-	-
Case II	Tie switch (Open)	69,70,14,55,61	69,70,14,56,61	69,70,14,57,61	69,70,14,56,61	69,18,13,56,61
	Power loss (kW)	99.59	99.59	98.59	98.59	99.35
	% Loss reduction	55.73	55.73	56.16	56.16	55.85
	Minimum voltage (p.u.)	0.9428	0.9428	0.9495	0.9495	0.9428
	Minimum VSI	0.7898	0.7898	0.8414	-	-

IEEE 69 bus test system

To examine the applicability of the method in the medium size distribution network, IEEE 69 bus test system has been considered for the study. Test system includes 73 branches, 68 sectionalize switches and 5 tie switches. The test system has 3.802 MW and 2.695 MVAr of active and reactive loads respectively. The test system is shown in Figure. 8.

Primary loops are obtained by the algorithm given in Figure 3 for 69 bus system and are shown in Table 3. Similar to 33 bus test system, two cases are considered. No reconfiguration is taken in case –I and is considered as the base case. The system has 224.99 kW active power loss. The minimum value of voltage and VSI are 0.9092 p.u. and 0.6833 respectively. In case-II, the feeder reconfiguration problem is solved using standard PSO and IPSO techniques and results are compared with ACSA, FWA and HSA.

The tie switches [69,70,14,55,61] are considered as an optimal solution after 1000 iterations. After the reconfiguration, total power loss is 99.59 kW, whereby the minimum voltage and VSI values are improved to 0.9428 p.u. and 0.7898 respectively. Simulation results are shown in Table 4. It is observed from Table 4 that the results obtained from PSO and IPSO are comparable with previously published optimization techniques. From Figure 9, it is observed that IPSO has converged to the optimal solution in 180 iterations, whereas standard PSO takes 238 iterations to converge. The voltage profile and VSI values have been improved after reconfiguration of the distribution network (Figs. 10 & 11). Power loss reduction after reconfiguration for IEEE 33 and 69 bus system is shown in Figure 12.

Table 4 — Primary loops for 69 bus test system

Primary Loop	Tie Lines
PL - 1	3, 4, 5, 6 ,7, 8, 9, 10, 35, 36, 37, 38, 39, 40, 41, 42, 69
PL- 2	13, 14, 15, 16, 17, 18, 19, 20, 70
PL- 3	3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 71
PL- 4	4, 5, 6,7, 8, 46, 47,48, 49, 52, 53, 54, 55, 56, 57, 58, 72
PL -5	9, 10, 11, 12, 13, 14, 15, 16 ,17, 18, 19 ,20, 21, 22, 23, 24, 25, 26, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 73

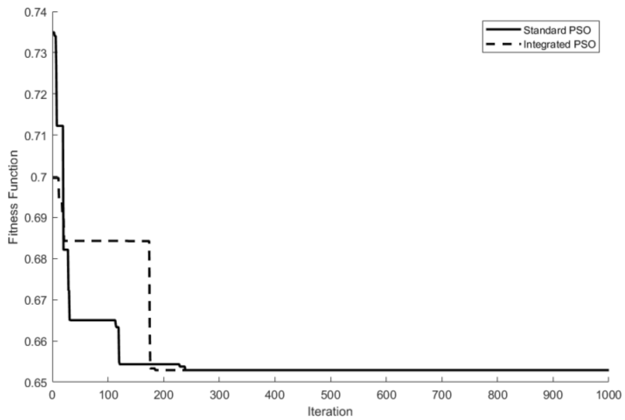


Fig. 9 — Fitness function vs iterations for 69 bus test system

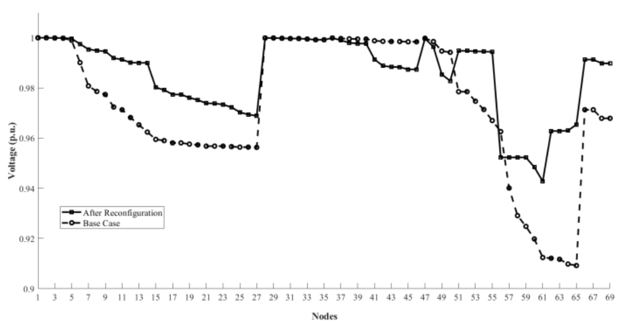


Fig. 10 — Bus voltages in 69 buses system

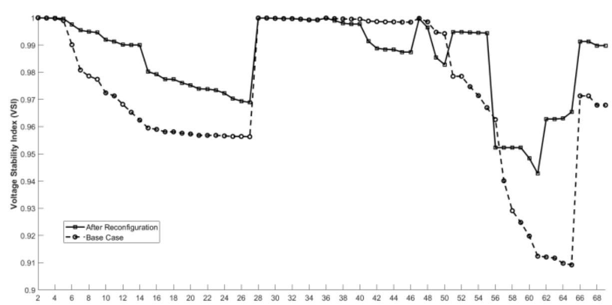


Fig. 11 — VSI values for 69 bus test system

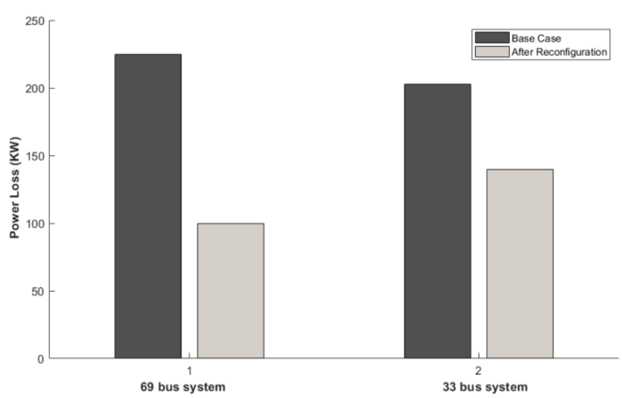


Fig. 12 — Comparision of power losses before and after reconfiguration

Conclusion

In this paper, IPSO technique is implemented in the feeder reconfiguration problem with an objective to minimize the power loss along with maximization of system voltage stability of the radial distribution network. The optimization method is implemented on IEEE 33 and 69 buses distribution test networks and compared with ACSA, FWA and HSA methods. From the results, it has been observed that the standard PSO and IPSO both converge to the same optimal solution. Howsoever, the convergence rate of IPSO algorithm is much faster than standard PSO method. In order to reduce the power losses and to improve the voltage stability in ship electric network, offshore oil and gas extraction area in deep water the proposed method is most suitable to the find optimal reconfiguration of the electric distribution network.

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