24th International Conference & Exhibition on Electricity Distribution (CIRED)

12-15 June 2017

Session 5: Planning of power distribution systems

Radial distribution network reconfiguration for power losses reduction using a modified particle swarm optimisation

ISSN 2515-0855
doi: 10.1049/oap-cired.2017.1286
www.ietdl.org

Inji Ibrahim Atteya[1] ✉, Hamdy Ashour[1], Nagi Fahmi[2], Danielle Strickland[2]

[1]*Arab Academy for Science, Technology and Maritime transport, Basic and Applied Science department, Electrical and control department, Alexandria, Egypt*
[2]*Aston University, Electrical department, Birmingham, UK*
✉ *E-mail: Eng_inji@yahoo.com*

Abstract: Recently, losses reduction gained a great deal of attention in distribution system due to low-voltage level and the high-current passing through the lines, pushing the distribution utilities to improve their profit margins on one hand by reducing the unnecessary operational cost, and improving their delivered power quality on the other hand by maintaining the system reliability, and the continuity of supply for varying load demand. Load balancing, voltage regulation, network reconfiguration and others are different techniques used to reduce the losses. This study addresses the distribution network reconfiguration to minimise the network losses. A new modified form of particle swarm optimisation (PSO) is used to identify the optimal configuration of distribution network effectively. The difference between the modified PSO (MPSO) algorithms and the typical one is the filtered random selective search space for initial position, which is proposed to accelerate the algorithm for reaching the optimum solution. The suggested MPSO is tested via 33 and 69 IEEE networks. A benchmark comparison has been conducted to prove the effectiveness of MPSO compared with previous optimisation techniques.

1 Introduction

Distribution system consists of many interconnected mesh circuits, operated as radial and linked by switches. There are two types of switches: sectionalising switches which are normally closed and tie line switches which are normally open. Distributed network reconfiguration (DNR) is the process of changing the structure of the distribution network by changing the status of the sectionalising and tie switches to maintain the radial topology [1]. DNR is considered highly complex, non-linear, discrete, combinatorial and stochastic optimisation problem [2, 3]. Heuristic, metaheuristic, mathematical and hybrid techniques are introduced for solving the complexity of DNR optimisation problem. Heuristic techniques are knowledge-based approaches, not suitable for large networks as they give local minimum solution in a very large processing time. Metaheuristic methods are probabilistic algorithms based on artificial intelligent methods. They achieve global optimum solution in a high computational time due to their probabilistic nature and their random selection which makes their convergence speed slower. Metaheuristic techniques include simulating annealing algorithm, artificial neural network, music-based harmony search, genetic algorithm (GA) and swarm intelligent algorithms. Many researchers worked on improving them by integrating them with each other's or with other optimisation algorithms to solve their computational time problem. In this research paper, the DNR problem is briefly defined. The optimisation algorithms suggested for solving DNR are stated. Particle swarm optimisation (PSO) algorithm is selected for active losses reduction. PSO is also reviewed and the modified PSO (MPSO) suggested in this paper is deeply explained and verified through the 33 and 69 IEEE test networks. A benchmark comparison is conducted. Finally, the results are discussed in the last section.

2 PSO review

PSA is one of the swarm intelligence optimisation techniques based on social behaviour of swarming animals, introduced by Kennedy and Eberhart in 1995 [4], when they mathematically imitate the social behaviour of bird flock and fish schools searching for corn, introducing this metaheuristic optimisation method. Particles 'birds' move through the search space adjusting their positions and their velocities with respect to their own experience and to their neighbouring particles experience to find the optimal solution. Typical swarm has been modified many times through many researchers improving the technique. Binary PSO (BPSO) was introduced in 1997, applying a sigmoid function for velocity and position equation to limit their values [0,1] to deal with discrete functions [5]. Multi-objective PSO was developed in 2004 by CoelloCoello [6]. More versions of swarm were introduced by hybridising two or more intelligent techniques together to improve the computational time and the convergence of the algorithm such as rank evolutionary PSO, the integration between the GA and PSO and others. In this research paper, a modification was added to the technique by controlling the initial position generation via tree diagram algorithm, which in turn improves the searching capability of the particles in less computational time by neglecting the infeasible particles based on the given constraints, accelerating the algorithm.

3 Networks description

3.1 33-Bus test distribution system

The 33 IEEE network, 12.6 kV, as shown in Fig. 1, consists of 37 branches, 32 normally closed switches (sectionalising switches) and 5 normally open switches (tie line switches). Interactive power

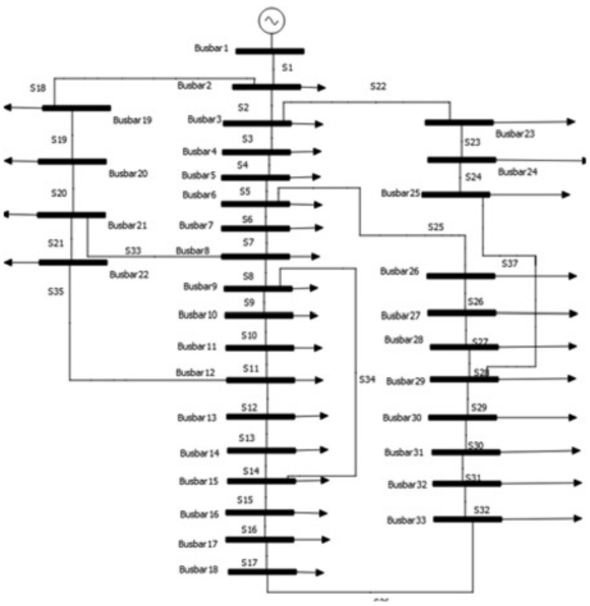

Fig. 1 *33 IEEE network (IPSA simulation window)*

system analysis (IPSA) tool is used for distribution network simulation and load flow calculations using Python programming language. The initial tie lines switches of the network are from bus 33 to bus 37 before any reconfiguration. The total number of loops that should be formed by closing the tie switches is five loops. The system load is 3715 kW and 2300 kVAr. The network line data are given in [7].

3.2 69-Bus test distribution system

The single line diagram of 69 IEEE network, 12.6 kV, 10 MVA, as shown in Fig. 2, consists of 73 branches, 68 normally closed switches. The network line data are given in [8]. The total active losses calculated before reconfiguration is 226 kW. The minimum voltage value occurs at bus 65, 0.909 pu. The initial ties are from 69 to 73. Five loops are formed by closing the initial five ties.

3.3 General problem formulation

In this research, line losses minimisation during operation is the objective function used for DNR optimisation problem and could be described as

$$\text{Min Power}_{\text{losses}} = \sum_{j=1}^{n} \left(I_j^2\right) R_j \tag{1}$$

where j is the branch number, N is the total number of branches, I_j is the current at branch j andR_j is the resistance at branch j

3.4 General constraints

Three constraints are considered for losses reduction:

(i) *Node voltage limit*

The bus voltage magnitude should be within the permissible limits to maintain power quality

$$V_{\min} \le V_{\text{bus}} \le V_{\max} \tag{2}$$

(ii) *Feeder capacity limit*

The magnitude of the feeder's branch current (I_j) should not exceed the maximum value of the allowed current passing in the branch ($I_{\max}$) eliminating the insulation failures assuming thermal limits are achieved

$$I_j \le I_{\max} \tag{3}$$

(iii) *Maintain the radial topology*

For a simple, inexpensive operation and protection of distribution power grid, radial configuration is preferred. It is stated that each loop should contain a tie line and a corresponding sectionalising switches. Thus, to retain a radial network structure, when a tie is closed in a loop, only one switch should be open in the same loop. To maintain this topology, the following criteria should be considered:

- The total number of main loops obtained by closing all the ties

$$N_{\text{main loops}} = \left(N_{\text{br}} - N_{\text{bus}}\right) + 1 \tag{4}$$

where N_{br} is the total number of branches and N_{bus} is the total number of buses.

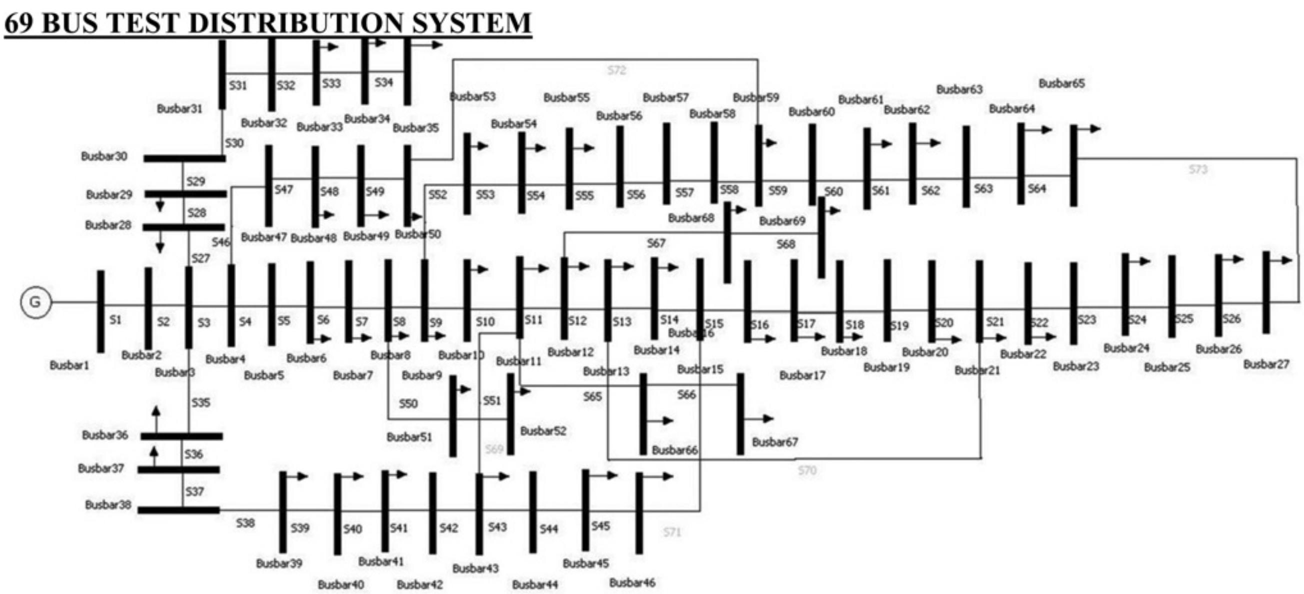

Fig. 2 *69 IEEE distribution network (IPSA simulation window)*

• The total number of sectionalising switches

$$N_{\text{br}} = N_{\text{bus}} - 1 \tag{5}$$

• The total number of tie switches should be the same as the number of main loops.

4 Modified PSO

In this research, the individual particle (i) is composed of a set of the tie switches ($S_1, \ldots, S_n$) that are to be opened in a radial system, where (n) is the size of the particle, in a swarm of (S) particles. It should be noted that the particle's size is the same size of tie switches in a system. The position of the particle (X_i) is the index of the tie switch per loop. $P_{\text{best } i}$ is the configuration realising best fitness function (losses reduction) for the same particle, whereas $G_{\text{best } i}$ is the configuration achieving best losses reduction for all the particles for one iteration. The modifications accelerate the convergence rate and the computational time. These modifications are:

- the random selective search space and
- the position control algorithm.

4.1 Random selective search space

The main difference between the typical PSO and the suggested MPSO is the filtered random selective search space in the initial position based on tree diagram theory method which generates all the possible configurations including only one tie switch from each of the five loops composing the test network. The elements for each loop of the 69 network are illustrated in Table 1. In this research, the total search space for initial radial configurations for both 33 and 69 networks are 16,128 and 139,776 configurations, respectively, calculated based on the tree diagram probability. The search space for the 33 IEEE network is studied in [9, 10]. It should be noted that some switches should not be within the search space such as:

(i) S1, S2 link between the main supply and the overall system.
(ii) [S27–S34], [65–66] and [67–68] could not formulate any loops.

4.2 Position control

After updating the particles using (7), some positions could exceed the total number of switches in the existing network, ($S37$ and $S69$, in the 33 and the 69-bus system, respectively) or could be negative number, which is illogical. In the previous version of swarm, these infeasible positions are discarded, thus losing some probabilities. To maintain a feasible search space, a position control algorithm has been suggested in [11], and is applied in this paper. Although, this algorithm retains all the particles in the search space, it could duplicate some switches in the same particle position, and violate the tie switch number conditions, which are calculated to be 5, and only in this case the particle should be discarded.

4.3 MPSO solution steps

A designed software has been implemented following MPSO steps discussed below using Python language 2.7.8 to communicate with IPSA 2.4 on a 2.4 GHz, core™ i7-5500 central processing unit with 8.0 GB random access memory for losses reduction. MPSO flowchart is explained and presented in [9]:

(i) Enter the swarm parameters including the acceleration constants, the weighting factor and the swarm size (S).
(ii) Generate all possible configurations using tree diagram method based on Table 1.
(iii) Select several configurations equal to (S), having losses less than the initial losses using (1), and satisfying voltage and current constraints using (2) and (3), to represent the random initial positions for the particles P_{best}.
(iv) Set the configuration having the minimum losses to be G_{best}.
(v) Calculate the velocity and the position for each particle in the swarm size S using (6) and (7)

$$\begin{aligned} V_i^{K+1} &= w \times V_i^K + c_1 \times \text{rand}_1 \times \left(P_{\text{best}\,k} - X_{ik}\right) \\ &\quad + c_2 \times \text{rand}_2 \times \left(G_{\text{best}\,k} - X_{ik}\right) \end{aligned} \tag{6}$$

$$X_i^{k+1} = X_{ik} + V_i^{K+1} \tag{7}$$

W is the inertia weight, it is a decreasing function, calculated using (8), V_i^K is the velocity for the particle (i) for the iteration (k), C_1 and C_2 are acceleration variables usually set to 2.0, rand_1 and rand_2 random number from 0 to 1, P_{best}. Best position for particle (i) based on its own experience, G_{best} is the best position achieved by the entire particles in the swarm

$$w^k = \frac{\left(w_{\max} - w_{\min}\right)}{\text{iter}_{\max}} \times \text{iter} \tag{8}$$

$W_{\max}$ is 0.9, $W_{\min}$ is 0.4, $\text{iter}_{\max}$ is the total number of iterations and is the current iteration.
(vi) Increase the iteration by one
(vii) Calculate the fitness function using (1) for all the particles.
(viii) Apply the constraints using (2) and (3).
(ix) Update the p_{best} and the G_{best}.
(x) Apply the position control to maintain the particles within the feasible search space.
(xi) Repeat the steps from vi to x until a termination criteria are satisfied.

5 Simulations, results and discussion

The proposed MPSO algorithm is tested through the 33 and the 69 IEEE test systems for optimum losses.

5.1 Losses reduction

MPSO reduced the initial losses in the 33-bus system from 193 to 136.36 kW saving 56.7 kW. Similar trend is observed in the 69 IEEE network as the losses have been decreased from 226 to 100.3 kW saving 126 kW. Table 2 illustrates the performance of MPSO for losses reduction and voltage improvement for both the 33 and 69 IEEE networks, respectively. Fig. 3 shows the conversion characteristic for MPSO for both networks.

Table 1 Search space for 69 IEEE network

Loops	Elements
1	S11, S12, S13, S14, S43, S44, S45, S71
2	S4, S5, S6, S7, S8, S46, S47, S48, S49, S52, S53, S54, S55, S56, S57, S58
3	S3,S9,S10,S35,S36,S37,S38,S39,S40,S41,S42,S69
4	S21, S22, S23, S24, S25, S26, S59, S60, S61, S62, S63, S64, S73
5	S15, S16, S17, S18, S19, S20, S70

Table 2 MPSO performances for 33 and 69 bus networks

	Reconfiguration	Ties	Losses	Minimum voltage
33 IEEE network	before	33-34-35-36-37	193.3	0.918
	after	9-7-14-37-32	136.3	0.940
69 IEEE network	before	69-70-71-72-73	226	0.909
	after	14-55-69-61-70	100.3	0.942

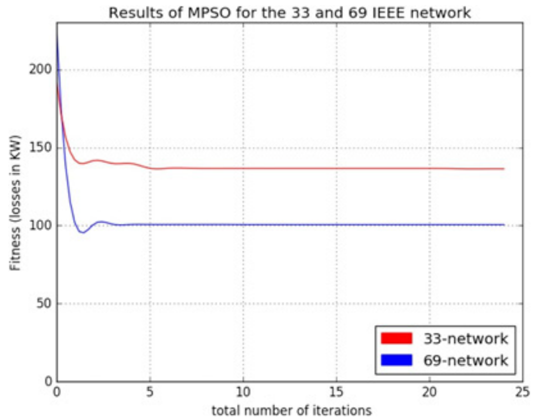

Fig. 3 *Fitness function for the best particle using MPSO*

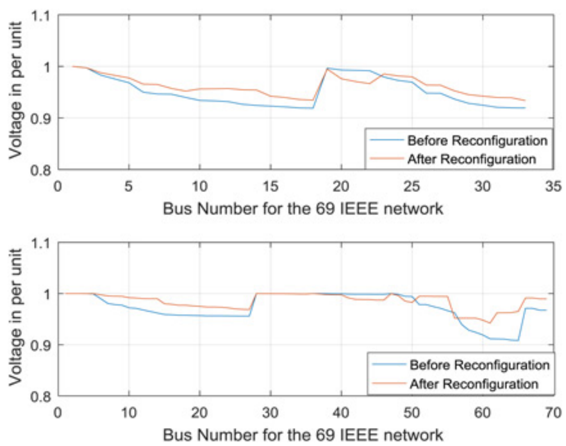

Fig. 4 *Voltage profile improvement*

5.2 Voltage improvement

MPSO has a significant effect on the busbar voltage as shown in Fig. 4. The minimum bus bar voltage rises after the reconfiguration from 0.918 to 0.94 at bus 18 in the 33 IEEE network and from 0.905 to 0.942 at bus 61 for the 69 IEEE network.

Owing to the stochastic nature of swarm algorithm, 50 runs are performed to select the swarm size and the maximum iterations required for reaching the optimum configuration. It was found that 50 particles are suitable for both test networks.

5.3 Benchmark comparison

Tables 3 and 4 compare between the performance of the proposed MPSO and other algorithms including the typical PSO [12], BPSO [10], multi-cooperative PSO (MCPSO) [13] and selective PSO for the 33 and the 69 test networks. The losses are recalculated using Python/IPSA software. It should be noted that MPSO suggests nearly the same configuration proposed by selective particle swarm (SPSO) for both networks. Both algorithms MCPSO and the proposed MPSO achieve the minimum losses for the 33 network but the proposed MPSO surpasses the losses reduction calculated by MCPSO for the 69 network.

Table 3 MPSO results comparison for 33 network

Algorithms	Optimum ties	Losses	Minimum voltage
PSO [12]	33, 28, 34, 8, 17	149.8	0.931
BPSO [10]	7, 9, 14, 28, 32	139.8	0.941
MCPSO [13]	7, 9, 14, 32, 37	136.3	0.942
SPSO [10]			
MPSO			

Table 4 MPSO results comparison for 69 bus network

Algorithms	Optimum ties	Losses	Minimum voltage
BPSO [10]	13, 20, 55, 61, 69	107.05	0.942
MCPSO [13]	12, 18, 58, 61, 69	103.62	0.942
SPSO [10]	14, 56, 61, 69, 70	100.6	0.942
MPSO	14, 55, 61, 69, 70	100.6	0.942

6 Conclusion

In this research paper, the MPSO is proposed for network reconfiguration for losses reduction and in turn voltage improvement. The 33 and 69 IEEE test networks are used for validating the effectiveness of the suggested MPSO technique to deal with small and large networks. The modification added to the typical PSO accelerates the algorithm. IPSA software has been used for load flow calculations. A software program has been developed in Python language for MPSO implementation. MPSO did not only reduce the losses reduction for both networks saving 56.7 kW for the 33-test network while saving 126 kW for the 69-distribution system, but also improved the minimum voltage for both networks.

7 References

1 Tang, L., Yang, F., Ma, J.: 'A survey on distribution system feeder reconfiguration: objectives and solutions'. Proc. Innovative Smart Grid Technology Asia (ISGT), Kuala Lumpur, May 2014, pp. 62–67
2 Akduman, B., Turkay, B., Uyar, A.S.: 'Service restoration in distribution systems using an evolutionary algorithm'. Proc. Seventh Mediterranean Conference and Exhibition on Power Generation, Transmission, Distribution and Energy Conversion, November 2010, pp. 1–9
3 Esmailian, H., Fadaeinedjad, R.: 'Energy loss minimization in distribution systems utilizing an enhanced reconfiguration method integrating distributed generation', *IEEE Syst. J.*, 2014, **9**, pp. 1–10
4 Kennedy, J., Eberhart, R.: 'Particle swarm optimization'. Proc. Fourth Int. Conf. Neural Networks, Perth, November/December 1995, pp. 1942–1948
5 Kennedy, J., Eberhart, R.: 'A discrete binary version of the particle swarm optimization algorithm'. Proc. World Multi Conf. Systemic, Cybernetics and Informatics, Orlando, October 1997, pp. 4104–4109
6 CoelloCoello, C., Toscano Pulid, G., Lechuga, M.S.: 'Handling multi objectives with particle swarm optimization', *Congr. Evol. Comput.*, 2004, **8**, (3), pp. 256–279
7 Goswami, S.K., Basu, S.K.: 'A new algorithm for the reconfiguration of distribution feeders for loss minimization', *IEEE Trans. Power Deliv.*, 1992, **7**, (3), pp. 1484–1491
8 Savier, J.S., Das, D.: 'Impact of network reconfiguration on loss allocation of radial distribution systems', *IEEE Trans. Power Deliv.*, 2007, **22**, (4), pp. 2473–2480
9 Atteya, I., Ashour, H., Fahmi, N.,, *et al.*: 'Distribution network reconfiguration using modified particle swarm optimization'. Proc. Int. Conf. for Renewable Energy Research and Applications, November 2016
10 Tandon, A., Saxena, D.: 'A comparative analysis of SPSO and BPSO for power loss minimization in distribution system using network reconfiguration'. Proc. Int. Conf. Innovative Applications of Computational Intelligence on Power Energy and Controls with their Impact on Humanity, November 2014, pp. 226–232
11 Abdelaziz, A.Y., Mohamed, F.M., Mekhamer, S.F.,, *et al.*: 'Distribution systems reconfiguration using a modified particle swarm optimization', *Electr. Power Syst. Res. Elsevier*, 2009, **79**, (11), pp. 1521–1530
12 Dahalan, W., Mokhlis, H.: 'Network reconfiguration for loss reduction with distributed generations using PSO'. Proc. Int. Conf. Power and Energy, Kota Kinabalu, December 2012, pp. 823–828
13 Jena, S., Chauhan, S.: 'Solving distribution feeder reconfiguration and concurrent DG installation problems for power loss minimization by multi swarm cooperative PSO'. IEEE, 2016