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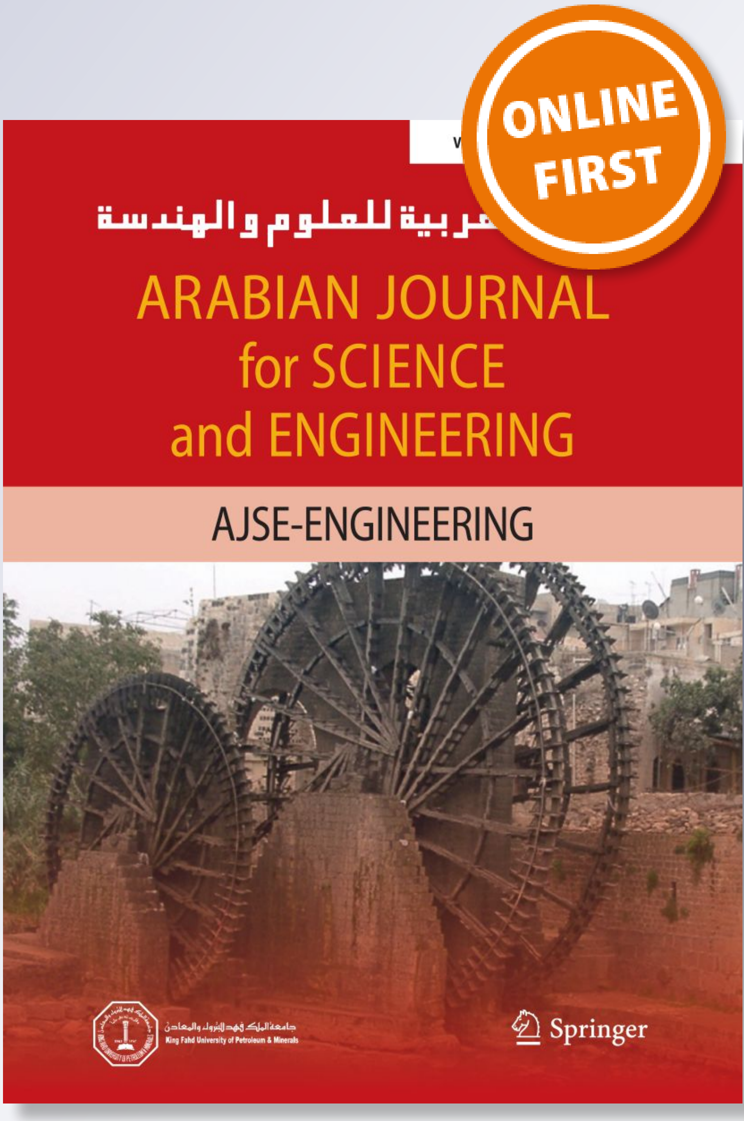
Arabian Journal for Science and Engineering

ISSN 2193-567X

Arab J Sci Eng
DOI 10.1007/s13369-017-2714-9



Springer

Arab J Sci Eng
DOI 10.1007/s13369-017-2714-9

RESEARCH ARTICLE - ELECTRICAL ENGINEERING

Multi-Objective Network Reconfiguration with Optimal DG Output Using Meta-Heuristic Search Algorithms

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Received: 21 February 2017 / Accepted: 13 July 2017

Abstract Network reconfiguration is a well-known technique for the distribution system to reduce power losses. However, the reconfiguration technique, by itself, could only minimize power losses up to a certain point. Further power losses reduction could be realized via the application of distributed generation (DG). However, the integration of DG to the distribution system at a non-optimal value could instead increase power losses and voltage fluctuation. Therefore, it is vital to develop an effective optimization strategy to determine the optimal output of the DG and simultaneously ensure optimal configuration. This paper presents a simultaneous optimal network reconfiguration with optimal DG output to minimize power losses and improve the voltage profile. Different objectives are discussed in this paper: (1) to minimize power losses, (2) to improve voltage profile index, (3) to maximize DG output. Evolutionary programming, particle swarm optimization, firefly, and gravitational search algorithm methods have been applied for optimal distribution network reconfiguration with optimal DG output. To evaluate the possibilities of the suggested method, simulations using MATLAB software are carried out on an IEEE 33-bus radial distribution system. The obtained outcomes prove the efficiency of the proposed strategy to find an optimal network configuration and optimal output of DG units.

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Keywords Distribution network reconfiguration · Distributed generation output · Meta-heuristic algorithm · Optimal solution · Voltage profile

List of symbols

F	Objective function
w_1 and w_2	Weighting factors
P_{loss}^{R}	Net power loss
IVD	Voltage profile index
$\text{DG}_{\text{output}}$	Distributed generation output
$P_{\text{loss}}^{\text{rec}}$	Active power loss after reconfiguration process
P_{loss}^{0}	Active power loss before reconfiguration process
P_{loss}	Total active losses power in the network distribution
M	Branch number
R_N	Resistance in the branch N
I_N	Current in the branch N
V_i	Voltage at base i; $i = 2, 3, \ldots$, nbus
K	Number of DG
$P_I^{\max}$, $P_I^{\min}$	Upper and the lower bound of DG output
P_{Load}	Total load of the network
β_0	Attractiveness at $r = 0$
γ	Coefficient of the light absorption
r	Distance between any two fireflies
$x_{l,k}$, $x_{j,k}$	A k_{th} component of the Cartesian coordinate x_l and x_j of fireflies l and j
m	Population size
n	Number of the switches
d	Number of the parameters that need to be optimized
α	A randomization parameter

Published online: 20 July 2017

x_c^d	Position of c_{th} agent in the d_{th} dimensions
h	Apace dimension
S	Tie switch
P_{DG}	DG output
$m_o(t)$	Value of the fitness function of agent o at iteration t
M_{Ao}	Active gravitational mass
M_{Po}	Passive gravitational mass
M_{oo}	Computed using fitness evaluation
M_o	Inertial mass of mass o
$\text{fitness}_o(t)$	Agent o fitness value at time t
$G(t)$	Constant of gravitational at the time t
G_0	Initial value
$M_{\text{Ap}}(t)$, $M_{\text{Po}}(t)$	Active and the passive gravitational masses related to the agent o
ε	Constant term with a very small magnitude
$R_{op}(t)$	The Euclidian distance between o and p
rand_p	A random number between 0 and 1
$a_o^d(t)$	Acceleration of the agent o and at time t in the d_{th} direction
$v_o^d(t)$, $a_o^d(t)$	The current velocity and the acceleration of an agent o
rand_o	A random number between 0 and 1

1 Introduction

One of the important issues of power distribution companies is electrical power losses from their system. This problem is usually solved by reconfiguring the network [1]. Network reconfiguration is the process of changing the switch state of the network. This switch could be normally open, where it is called tie switches, or normally closed, where it is called sectionalizing switches. The topological structure of the network is changed by closing the open switches and opening the closed switches. This technique can reduce the power losses and improve the overall voltage profile, provided that the optimal reconfiguration could be determined. By doing this, the load will be transferred to relatively less heavily loaded feeders from the heavily loaded feeders; this leads to the minimization of power losses. The authors in [2], proposed multi-objective method to solve a reconfiguration problem for a radial system using adaptive genetic algorithm and fuzzy framework. The main objective function combines the objective of minimizing power losses, minimizing the number of node voltage that violate the constraints, and minimizing the number of branch current that violate the constraints. A heuristic method was used to generate the initial population of genetic algorithm (GA), and the genetic operator was used to create feasible individuals that achieved graph theory. The effectiveness of the presented method was demonstrated in 70-bus and 136-bus radial distribution network. The results obtained show that the presented method is promising and efficient for multi-objective reconfiguration of radial systems and takes less computational time compared with other published work.

Since distribution network has many candidate configurations and the switch status is regarded as discrete nature, the network reconfiguration method is considered as a discrete, non-differentiable optimization issue, and constrained combinatorial. Furthermore, it will become more serious when integrating with discrete size and location of DG. Thus, a robust approach is needed to solve such a complex issue in an efficient manner. The renowned methods used to treat reconfiguration problem are categorized as follows:

(a) Heuristic methods such as branch exchange [3], branch and bound [4], single-loop optimization [5], and loop cutting [6].
(b) Meta-heuristic algorithms such as simulated annealing (SA) [7], genetic algorithm (GA) [8], Evolutionary programming (EP) [9], ant colony optimization (ACO) [10], and harmony search algorithm (HSA) [11].

Heuristic methods are very fast, but it could find a local solution rather than global solutions. By contrary, Meta-heuristic algorithms could find a global solution than the local solution, but the computation time is greater than for heuristic due to the random selections and probabilistic nature.

Power losses could be also minimized by installing local generation, commonly referred to as the distributed generation (DG). A DG is a small generating unit installed at strategic location in the distribution system, and most of the time, it is based on renewable energy sources, such as mini-hydro, wind, solar, and biofuels [12]. The integration of DG to the distribution system leads to benefits such as the improvement of the voltage profile, deferral the expansion of the network, and improving the reliability of the system. In [13], an ordinal optimization (OO) methodology is presented for determining the size and the location of the DG. This method aims to a trade-off between both maximum capacity of the DG and minimum power losses, and it consists of three stages. In the beginning, the method presents a large space of the search for the potential combinations of the DG location as a relative sampling. Then, the objective function of each sample is evaluated by the efficient computation crude program. At the end, the maximum alternatives evaluated from the crude program are simulated to determine the capacity and the location of the DG via optimal power flow program. This methodology describes the sampling approaches problem, implementation of the crude model, and size selection of the substation. To validate the method efficiency, the results were compared with other published work and carried out on a 69-node system. The results were shown that OO satisfies more ability to reduce the computation effort for a hard problem. Moreover, the results prove that the optimal DG location minimizes the system power losses. Moreover, studies in [14] presented an optimization framework that optimizes the planning of distributed generation by leveraging different complementary resources, e.g., solar energy, wind energy, and energy storage. Studies in [15] analyzed realistic renewable energy data and developed a theoretic framework for the placing and sizing of distributed energy resources that improves the utilization of renewable energy and enhances the power supply reliability.

By combining both approaches, power losses could be further reduced. However, the network reconfiguration problem will be more challenging when accounting for DGs in the network. Thus, a robust approach is needed to solve such a complex issue efficiently. Many works have been conducted for optimal reconfiguration method and optimal DGs output. However, there are few works on network reconfiguration that studied optimal DGs output at the same time. Furthermore, the focus is to minimize power losses. Most of them are based on sequential or simultaneous techniques. In the former, the optimal size of the DG is determined first before conducting network reconfiguration. The work in [16] is an example of the sequential technique. The ACO was used in the proposed reconfiguration method with DG that aims to minimize power losses and improve the load balance factor of radial distribution networks. The effectiveness of the proposed method is validated using a 33-bus distribution network of the 11.4 kV system. The result showed that network reconfiguration with DG results in lower power losses and better load balance compared to a system without DG. Meanwhile, in [17], a method was presented to solve both DG sizing and reconfiguration problem simultaneously. The main objective was to reduce the total power losses. Sensitivity analysis was done using a harmony search algorithm to solve the simultaneous process and compare it to GA and refine the genetic algorithm (RGA). Various scenarios were applied on 33- and 69-bus systems for the reconfiguration and DG sizing. The results proved that the simultaneous process was more effective than the sequential process for minimizing power losses and improving the voltage profile. Furthermore, the performance of HSA is better than that of GA and RGA.

This paper proposes a simultaneous optimization of network reconfiguration and DG output. Different from pervious works, the main objective is to simultaneously minimize the active power losses, improve the voltage profile, and maximize the DG output. The method is tested on a 33-bus system, and the results are obtained from the EP, PSO, and GSA compared to one another. To further verify the effectiveness of the proposed method, the test results are also compared with the literature. The content of this paper is arranged as follows: Sect. 2 describes the problem formation and the optimized technique and the proposed strategy to get the optimal network configuration with optimal DG output and maximum DG output. Section 3 presents the case study of the work. Section 4 presents the results and discussion. The conclusion is presented in Sect. 5.

2 Mathematical Formation and Constraints

The optimal network reconfiguration and optimal DG output can be determined based on lower power losses to improve the overall voltage profile for the network system. The following describes the objective function and constraints of the optimization.

2.1 Objective Functions of the Problem

The objective function F can be presented in the following form:

$$F = w1 \times \left(P_{\text{loss}}^{R} + \text{IVD}\right) + w2 \times \left(\frac{1}{\text{DG}_{\text{output}}}\right) \tag{1}$$

where w_1 and w_2 are the weighting factors. Both net power loss (P_{loss}^{R}) and voltage profile index (IVD) should be minimized and distributed generation output ($\text{DG}_{\text{output}}$) should be maximized.

Since the total fitness has a different objective units, the net power loss P_{loss}^{R} is taken as the ratio between the system total active power loss after reconfiguration process $P_{\text{loss}}^{\text{rec}}$ and before reconfiguration process P_{loss}^{0}, as follows:

$$P_{\text{loss}}^{R} = \frac{P_{\text{loss}}^{\text{rec}}}{P_{\text{loss}}^{0}} \tag{2}$$

The power losses equation for a distribution system is given by:

$$P_{\text{loss}} = \sum_{N=1}^{M} \left(R_N \times |I_N|^2\right) \tag{3}$$

where P_{loss} is the total active losses power in the network distribution; M is the branch number; R_N is the resistance in the branch N; and I_N is the current in the branch N.

Voltage profile index (IVD) This index penalizes the size-location pair which gives higher voltage deviations from the nominal voltage. In this way, closer the index to zero, better is the network performance. IVD is defined as follows:

$$\text{IVD} = \max_{\text{i}=2}^{\text{n}} \left(|\overline{\text{V}}_1| - |\overline{\text{V}}_\text{i}|\right) / |\overline{\text{V}}_1| \tag{4}$$

where V_i is the voltage at bus i; $i = 2, 3, \ldots, \text{nbus}$.

Maximizing the DGs output is defined as follows:

$$\mathrm{DG_{output}} = \sum_{1}^{K} \mathrm{DG}K_{\mathrm{output}} \quad (5)$$

where K is number of DG.

The main constraints that the optimization is subjected to fulfill during network reconfiguration with DGs technique are:

(1) Distributed generator operation:

$$P_I^{\min} \le P_{\mathrm{DG},I} \le P_I^{\max} \quad (6)$$

where $P_I^{\max}$ and $P_I^{\min}$ are the upper and the lower bound of DG output. All DG units should function within the acceptable limit.

(2) Power injection:

$$\sum_{I=1}^{k} P_{\mathrm{DG},I} < (P_{\mathrm{Load}} + P_{\mathrm{loss}}) \quad (7)$$

where k = number of the DG; P_{Load} is the total load of the network; P_{loss} is the total active power losses of the network. This constraint is to ensure there is no power from DGs flow to the grid, which might create a protection issue.

(3) Power balance:

$$\sum_{I=1}^{k} P_{\mathrm{DG},I} + P_{\mathrm{Substation}} = P_{\mathrm{Load}} + P_{\mathrm{loss}} \quad (8)$$

Depending on the principle of equilibrium, where the supply of power must equal its demand. The summation of power losses and power load should be equal to the total power generated from DG units and substation.

(4) Voltage bus

$$V_{\min} \le V_{\mathrm{bus}} \le V_{\max} \quad (9)$$

Each bus should have an acceptable voltage value within the limits of 0.95 and 1.05 ($\pm 5\%$ of rated value).

(5) Radial Configuration:

The network configuration must be in radial after the reconfiguration process. For this purpose, a graph theory function in MATLAB is used to determine the radiality of the network as follows:

$$TF = graphisspa\_ntree(G) \quad (10)$$

$$TF = \left\{ \begin{matrix} 1 & radial \\ 0 & not\_radial \end{matrix} \right\} \quad (11)$$

where G is the distribution network. If the network is radial, TF is equal to 1 (true), else it is 0 (false).

(6) No load isolation:

All nodes must be energized to ensure all loads receive the power sources.

2.2 Optimization Technique for Simultaneous Network Reconfiguration and DG Output

Power flow analysis is used to determine the power losses and the voltage profile for the network. The proposed strategy aims to simultaneously determine the optimal DGs output real power and optimal network reconfiguration. In this work, the optimal network reconfiguration and the DG output problem are solved using EP, PSO, FA and GSA techniques. However, a detailed description of the implementation is provided only for FA and GSA techniques, while EP algorithm was described in detail in [9] and PSO algorithm was detailed in [18].

2.2.1 Firefly

FA is a recent nature-inspired meta-heuristic optimization method. The main feature of FA is based on the flashing characteristics of the firefly [19]. The main concept of FA is based on the following set of assumptions:

(1) All fireflies are unisex that everyone is attracted to each other.
(2) The attractiveness of the fireflies is strongly proportional to their brightness. The firefly with a higher degree of brightness is attracting the less brightness one, i.e., the less bright one moves toward the higher bright one. Both brightness and attractiveness decrease as the distance between the fireflies increases. If no firefly of higher level of brightness than the particular one is found, the fireflies move randomly.
(3) The firefly brightness intensity is determined by the landscape of fitness function to be optimized, i.e., the objective function could be maximized or minimized. According to the minimization problem, the level of the brightness is proportional to the fitness function value inversely.

The firefly attractiveness β can be presented as the following form:

$$\beta(r) = \beta_0 e^{-\gamma r^2} \quad (12)$$

where β_0 is the attractiveness at $r = 0$; γ is the coefficient of the light absorption; r is the distance between any two fireflies. The Cartesian distance can be expressed as follows:

$$r_{lj} = \|x_l - x_j\| = \sqrt{\sum_{k=1}^{d} (x_{l,k} - x_{j,k})^2} \tag{13}$$

where $x_{l,k}$ and $x_{j,k}$ represent a k_{th} component of the Cartesian coordinate x_l and x_j of fireflies l and j, respectively.

The movement of fireflies, where firefly l is attracted to firefly j, is determined by:

$$x_l = x_l + \beta_0 e^{-\gamma r_{lj}^2}(x_j - x_l) + \alpha(\text{rand} - 0.5) \tag{14}$$

where the second term is caused by the attraction, while the third term represents the randomized parameter and the random range should be between 0 and 1 and near 1 like 0.8 that fastens the program.

The problem of network reconfiguration and DG output is solved using FA in the following manner:

Step 1 Input data are determined, such as the bus load and voltage, DG location, and the values of the resistance and reactance of the lines.

Step 2 The basic firefly parameters are set as $\beta_0 = 1$, $\gamma = 1$ and $\alpha = 0.8$.

Step 3 Generate random initial populations of firefly (x), where in this case the switches' number and the DGs output are represented, taking into consideration all the limitations and constraints. The variable used in this work for tie switches is represented by S, and DG output is represented by P_{DG}. For the simultaneous case, both the number of switches and DG output should be determined simultaneously, as follows:

$$x = \begin{bmatrix} S_{11}, & S_{12}, & \cdots & S_{1n}, & P_{\text{DG11}}, & P_{\text{DG12}}, & \cdots & P_{\text{DG1}K} \\ S_{21}, & S_{22}, & \cdots & S_{2n}, & P_{\text{DG21}}, & P_{\text{DG22}}, & \cdots & P_{\text{DG2}K} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ S_{m1}, & S_{m2}, & \cdots & S_{mn}, & P_{\text{DG}m1}, & P_{\text{DG}m2}, & \cdots & P_{\text{DG}mK} \end{bmatrix} \tag{15}$$

where m indicates the population size; n is the number of the switches; K the number of DG

Step 4 Start the iteration by solving load flow analysis to obtain power flow through all network lines. From the results, the power losses and minimum value of the voltage for the entire system can be determined.

Step 5 Evaluate the fitness for each of the population (1 to m) using equation (1). That means evaluating the summation of the power losses and the minimum value of the stability index for each hour of one day.

Step 6 Rank the population, according to the light intensity (low to high fitness) and save the best value in the following manner:

$$\begin{aligned} &[\text{F}_{\text{Index}} = \text{sort(x)}] \\ &\text{F}_{\text{best}} = \text{F}_{(1)} \end{aligned} \tag{16}$$

Step 7 Update all fireflies on matrix x (switches number and DGs output) and rank the movement taking into consideration all the limitations and constraints using the following equations:

The firefly attractiveness β is presented as the following form:

$$\beta(r) = \beta_0 e^{-\gamma r^2} \tag{17}$$

where β_0 is the attractiveness at $r = 0$; γ is the coefficient of the light absorption; r is the distance between any two fireflies. The Cartesian distance between any two fireflies l and j (which represent by row of the x matrix) can be expressed as follows:

$$r_{lj} = \|x_l - x_j\| = \sqrt{\sum_{k=1}^{d} (x_{l,k} - x_{j,k})^2} \tag{18}$$

where $x_{l,k}$ and $x_{j,k}$ represent a k_{th} component of the Cartesian coordinate x_l and x_j of fireflies l and j, respectively; d is the number of the parameters that need to be optimized. The movement of fireflies, where firefly l is attracted to brighter firefly j, is determined by:

$$x_{l,k} = x_{l,k} + \beta_0 e^{-\gamma r_{lj}^2}(x_{j,k} - x_{l,k}) + \alpha(\text{rand} - 0.5) \tag{19}$$

where the second term is caused by the attraction (with $\gamma = 1$), while the third term represents the randomized parameter (α being a randomization parameter). The random number rand(1) is usually a uniformly distributed random number in [0, 1].

Step 8 Repeat the steps from point 4 until completing the max iteration number.

Step 9 Stop the process and print out the best solution, which represents the switch number that forms the new network configuration, the output of the DGs, the power losses in this process and the voltage at each bus, and plot the total fitness during the iterations.

2.3 Gravitational Search Algorithm

GSA is a new developed random search algorithm, intended to solve optimization problems and based on the mass interactions between agents and the law of gravity. In GSA, the agents are treated as objects and their features determined by their masses, and gravity force all objects toward the heavier masses object according to the objects' global movement [20]. In this algorithm, the population individuals are referred to as masses and their performances are measured by their position masses. Each mass will have four particulars: its position, its inertial mass, its active gravitational mass, and passive gravitational mass. The position of the mass represented a solution, while its gravitational and inertial masses are corresponding to the fitness function. According to Newtonian laws, all these objects will attract each other due to the gravity force. Due to this force, all these objects will move toward the object with heavier mass. In other words, heavy masses equaled good solutions and they move slower than the lighter masses that equaled bad solutions. In this way, the exploitation step of the algorithm is guaranteed.

The problem of network reconfiguration and DG output is solved using GSA as follows:
Step 1 The position of agent c consisting of H number of mass is:

$$X_c = \left(x_c^1, \cdots, x_c^d, \cdots x_c^h\right), \text{ for c} = 1, 2, \cdots, \text{H} \tag{20}$$

where x_c^d is the position of c_{th} agent in the d_{th} dimensions, while h is the apace dimension. In simultaneous case, the detailed position of each c_{th} agent is given as:

$$x_c^h = [S_1, S_2, \ldots, S_n, P_{\text{DG}1}, P_{\text{DG}2}, \ldots, P_{\text{DG}K}] \tag{21}$$

where S is the tie switch; P_{DG} is the DG output; n is the number of the tie switches; K is the number of DG.
Step 2 Evaluate the fitness in (1) and store the best and worst solutions. $best(t)$ and $worst(t)$ are defined as:

$$best(t) = \begin{cases} \min\limits_{p\in\{1,2,\ldots,H\}} \text{fitness}_p(t) \text{ for minimization problem} \\ \max\limits_{p\in\{1,2,\ldots,H\}} \text{fitness}_p(t) \text{ for maximization problem} \end{cases}$$
$$worst(t) = \begin{cases} \max\limits_{p\in\{1,2,\ldots,H\}} \text{fitness}_p(t) \text{ for minimization problem} \\ \min\limits_{p\in\{1,2,\ldots,H\}} \text{fitness}_p(t) \text{ for maximization problem} \end{cases} \tag{22}$$

Step 3 Calculates the inertial and gravitational masses. The efficient agent is heavier and moves more slowly. By assuming the equality of the inertia and gravitational mass, the values of the masses are evaluated using the map of fitness. Furthermore, the gravitational and inertial masses could be updated by the following equations:

$$\begin{aligned} &M_{\text{Ao}} = M_{\text{Po}} = M_{oo} = M_o, \text{ o} = 1, 2, \ldots, H \\ &m_o(t) = \frac{\text{fitness}_o(t) - \text{worst}(t)}{best(t) - \text{worst}(t)} \\ &M_o(t) = \frac{m_o(t)}{\sum_{p=1}^{H} m_p(t)} \end{aligned} \tag{23}$$

where $m_o(t)$ is the value of the fitness function of agent o at iteration t, M_{Ao} is the active gravitational mass, M_{Po} is passive gravitational mass, M_{oo} is computed using fitness evaluation, and M_o is inertial mass of mass o, $\text{fitness}_o(t)$ is the agent o fitness value at time t.

Step 4 Using Newton gravitation theory to calculate the total force. The force acting on mass 'o' from mass 'p' at any time 't', could be presented in the following form:

$$\begin{aligned} &f_{op}^d(t) = G(t) \times \left(\frac{M_{\text{Ap}}(t) \times M_{\text{Po}}(t)}{R_{op}(t) + \varepsilon}\right) \times \left(x_p^d(t) - x_o^d(t)\right), \\ &G(t) = G(G_0, t) \end{aligned} \tag{24}$$

where $G(t)$ is constant of gravitational at the time t and is updated based on the initial value G_0 and time t; $M_{\text{Ap}}(t)$ and $M_{\text{Po}}(t)$ are the active and the passive gravitational masses related to the agent o, respectively; and ε is a constant term with a very small magnitude. The Euclidian distance $R_{op}(t)$ between o and p could be presented as:

$$R_{op}(t) = \|x_o(t), x_p(t)\|^2 \tag{25}$$

The total force that acts on the agent o in a dimension d is a randomly weighted d_{th} component of the forces exerted from other agents.

$$f_o^d(t) = \sum_{\substack{o=1 \\ p\neq o}}^{H} \text{rand}_p \times \quad f_{op}^d(t) \tag{26}$$

where rand_p is a random number between 0 and 1.
Step 5 Calculate the acceleration agent. Based on Newton's law of motion, the acceleration $a_o^d(t)$ of the agent o and at time t in the d_{th} direction is given as:

$$a_o^d(t) = \frac{f_o^d(t)}{M_{oo}(t)} \tag{27}$$

where M_{oo} is o_{th} agent inertial mass.
Step 6 Update the velocity and the position of an agent according to the following equations:

$$v_o^d(t+1) = \text{rand}_o \times v_o^d(t) + a_o^d(t) \tag{28}$$
$$x_o^d(t+1) = x_o^d(t) + v_o^d(t+1) \tag{29}$$

where $v_o^d(t)$ and $a_o^d(t)$ are the current velocity and the acceleration of an agent o, respectively; and rand_o is a random number between 0 and 1 that gives a randomized characteristic to the search.
Step 7 Stop the process after the maximum number of iterations finished and print the best solution.

3 Case Study

An IEEE 33-bus distribution network system was used to test the proposed method. The network consists of 37 switches, 32 sectionalizing switches, and 5 tie switches. Switch num-

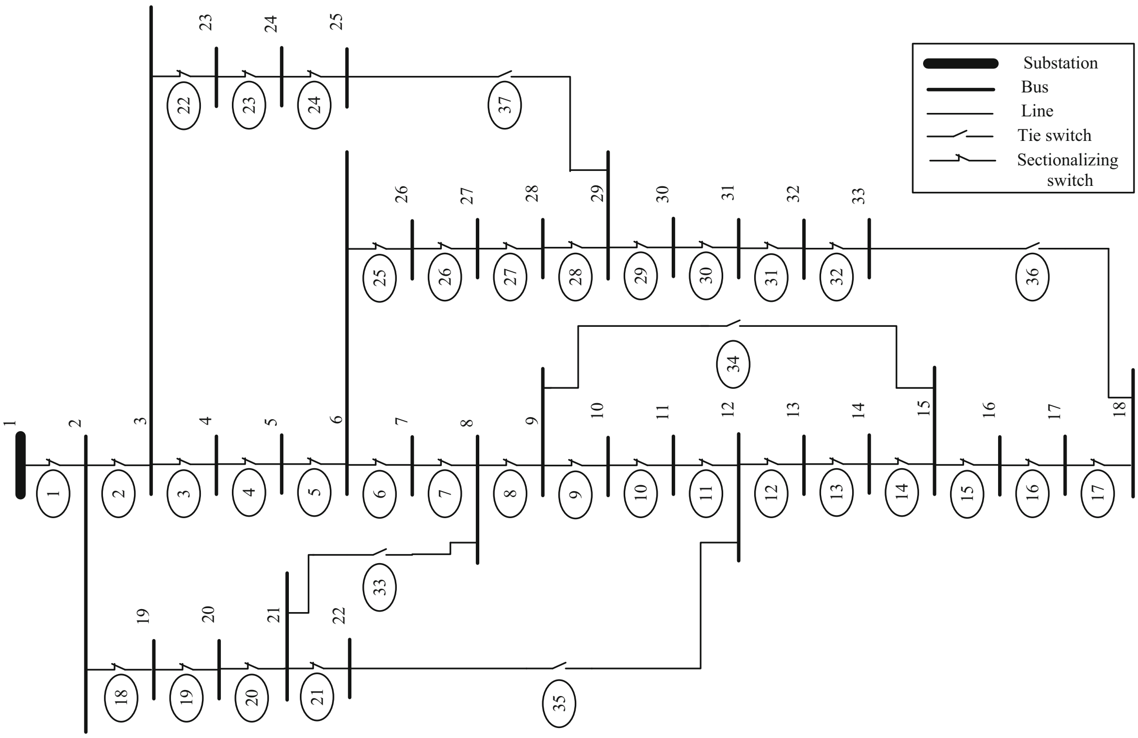

Fig. 1 IEEE 33-bus distribution network before reconfiguration process

bers 33, 34, 35, 36, and 37 are normally open for the original network, while the other switches are normally closed, as shown in Fig. 1. The total real load demand is 3715 kW, while the system voltage is 12.66 kV. The base value of the apparent power is 100 MVA. The power losses of the network at the initial configuration were 202.677 kW, with 0.913 pu. as the lowest bus voltage. The complete bus and line data are given in [21]. The DG in this test system is assumed to be a mini-hydro generation. The capacity for each DG is 2 MW. That mean and lower and upper bounds of the DG output ranged from 0 to 2 MW. In this work, the optimal location for the DGs is located at buses 31, 32, and 33. This location is based on previous work in [17]. The optimal solution is obtained for tie switch and DG output (real power). Both DG output and the tie switches were determined simultaneously.

Three cases will be analyzed to test the efficiency and robustness of the proposed strategy. Case 1 aims to minimize the power losses by simultaneous network reconfiguration with optimal DG output. Case 2 aims to minimize power losses and improve voltage profile index by simultaneous network reconfiguration with optimal DG output. Case 3 aims to minimize power losses, improve the voltage profile index, and maximize the DG output by simultaneous network reconfiguration with optimal DG output.

The algorithms were executed in MATLAB on a PC with 3.07 GHz CPU and 8-GB RAM. For the application of all of the algorithms, the population size was set to 100. The iteration size was set to 300 iterations.

4 Simulation Results and Discussion

4.1 Case 1: Aims to Minimize the Power Losses by Simultaneous Network Reconfiguration with Optimal DG Output

Table 1 summarizes the overall results for the EP, PSO, FA, and GSA related to case 1. These algorithms were applied for simultaneous network reconfiguration with optimal DG output compared to the initial case. The minimum power losses were obtained using FA, which means that FA results in better values than an EP, PSO, and GSA. As seen in Table 1, by using FA, the power losses after network reconfiguration within DG is 72.436 kW, while before reconfiguration, it is 202.6 kW. Power losses were reduced by 130.164 kWh, i.e., about 64.25% reduction compared to the initial state. The minimum voltage for all busses after reconfiguration is improved to 0.9731 pu, while before reconfiguration, it is 0.9131 pu. The normally open switches after reconfiguration are 7, 9, 28, 32, and 34, while before reconfiguration, they are 33, 34, 35, 36, and 37. DG1 output is 0.899 MW, DG2 is 0.253 MW, and DG3 is 0.601 MW. The voltage profile plots for case 1 for both initial and optimal solutions using EP, PSO, FA, and GSA are compared and shown in Fig. 2.

To prove the validity of the simultaneous network reconfiguration within the optimal DG output, the robustness test was carried out by the proposed method using the different algorithms, and the results are compared and shown in Fig. 3

Table 1 Network reconfiguration and DG output results for case 1

Case	Open switches	DG output in MW (Bus number)	Bus voltage (pu) (at bus) min max	Power losses (kW)	Losses reduction (%)
Initial	33, 34, 35, 36, 37	No DG	0.9131(18)–1(1)	202.6	–
EP	7, 10, 12, 26, 32	DG1 = 0.533, DG2 = 0.639 DG3 = 0.586	0.9692(13)–1(1)	74.528	63.32
PSO	7, 8, 28, 32, 34	DG1 = 0.513, DG2 = 0.587 DG3 = 0.576	0.9706(14)–1(1)	73.141	63.90
GSA	7, 9, 13, 28, 32	DG1 = 0.585, DG2 = 0.574 DG3 = 0.549	0.9728(14)–1(1)	72.625	64.15
FA	7, 9, 28, 32, 34	DG1 = 0.899, DG2 = 0.253 DG3 = 0.601	0.9731(14)–1(1)	72.436	64.25

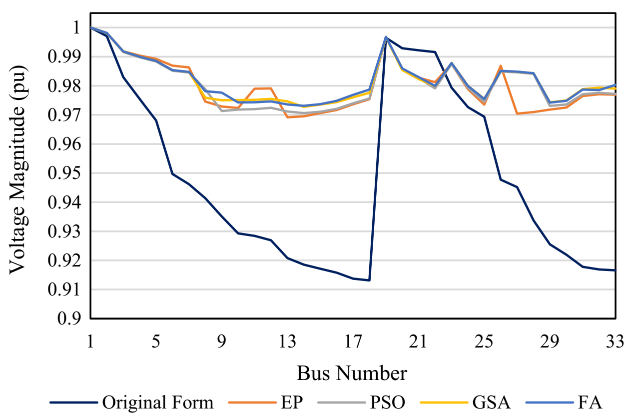

Fig. 2 Voltage profile of IEEE 33-bus network using different algorithms for case 1

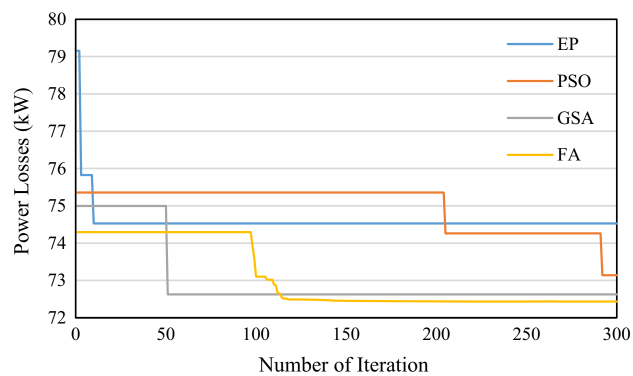

Fig. 4 Comparison of convergence performance of the simultaneous reconfiguration and optimal DG output algorithms for case 1

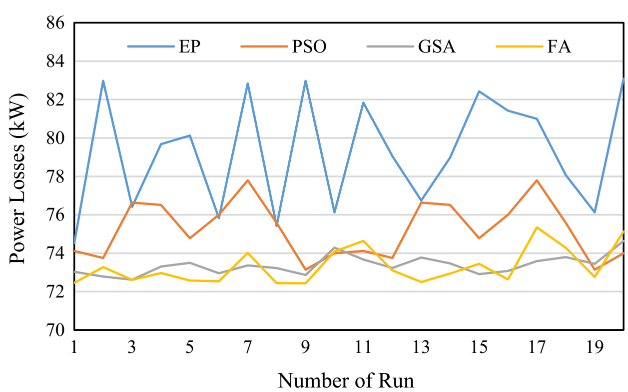

Fig. 3 Comparison of robustness test of the simultaneous reconfiguration and optimal DG output algorithms for case 1

for case 1. The robustness test can be defined as the test used to check the quality of the algorithms to give answers closed to gather for all runs. That means an algorithm which gives the same answer at each run or gives answers closed to gather for all runs is better than the algorithm which gives different answers at each run. It is clearly seen that by using GSA or FA, the results values are consistent with EP or PSO for case 1. Thus, it can be said that GSA and FA are highly robust compared to the EP and PSO. In our work, we take 100 initial populations (fixed initial populations) for all algorithms used. In this case, the results of FA and GSA are better than those of EP and PSO. When the initial populations change, the result for each algorithm will change (the optimal solution), but if we compare between the algorithms at the same size of initial populations, FA and GSA will be better than EP and PSO. For each algorithm, there is a sub-optimal solution, which represents the minimum value during the 20 times simulation run of the program. According to case 1, the values are 74.528, 73.141, 72.625, and 72.436 kW of EP, PSO, FA, and GSA, respectively.

Moreover, based on the global solutions for each algorithm, the convergence performance for these global values are also compared and shown in Fig. 4 for case 1. It is clearly observed that FA resulted in the minimum value of power losses compared to the other algorithms in case 1, as shown in Fig. 4.

4.2 Case 2: Aims to Minimize Power Losses and Improve Voltage Profile Index by Simultaneous Network Reconfiguration with Optimal DG Output

Figure 5 shows the flow chart for simultaneous network reconfiguration with optimal DG output. Table 2 summarizes the overall results for the EP, PSO, FA, and GSA related to case 2. The optimal main fitness F according to Eq. (1) without DG maximization is 0.4105, obtained using FA, which is better than the EP, PSO, and GSA. As seen from Table 2, by using FA, the power losses after network reconfiguration within DG are 72.361 kW, while before reconfiguration, it is 202.6 kW. Power losses were reduced by 130.239 kWh, i.e., about 64.28% reduction compared to the initial state. It was observed that the power reduction in case 2 is better than in case 1. The minimum voltage for all busses after reconfiguration is improved to 0.9750 pu, while before reconfiguration, it is 0.9131 pu. The normally open switches after reconfiguration are 7, 10, 13, 28, and 32, while before reconfiguration, they are 33, 34, 35, 36, and 37. DG1 output is 0.6756 MW, DG2 is 0.516 MW, and DG3 is 0.6334 MW.

The voltage profile plots for case 2 for both initial and optimal solutions using EP, PSO, FA, and GSA are compared and shown in Fig. 6.

It can be observed from Figs. 2 and 6 that all buses voltage magnitudes for all algorithms are improved to a value larger than their respective initial states. FA obtained the best voltage profile for cases 1 and 2. The minimum values for the voltage profile plots in case 2 is better than in case 1.

Figure 7 shows the robustness test for case 2. It is clearly seen that by using GSA or FA, the results values are consistent with EP or PSO for case 2. Thus, it can be said that GSA and FA are highly robust compared to the EP and PSO. For each algorithm, there is a sub-optimal solution, which represents the minimum value during the 20 times simulation run of the program. According to case 2, the values are 0.4223, 0.4116, 0.4117, and 0.4105 for EP, PSO, GSA, and FA, respectively.

The convergence performance for these global values are also compared and shown in Fig. 8 for case 2. It is clearly observed that, FA resulted in the minimum value of the fitness F compared to other algorithms in case 2, as shown in Fig. 8.

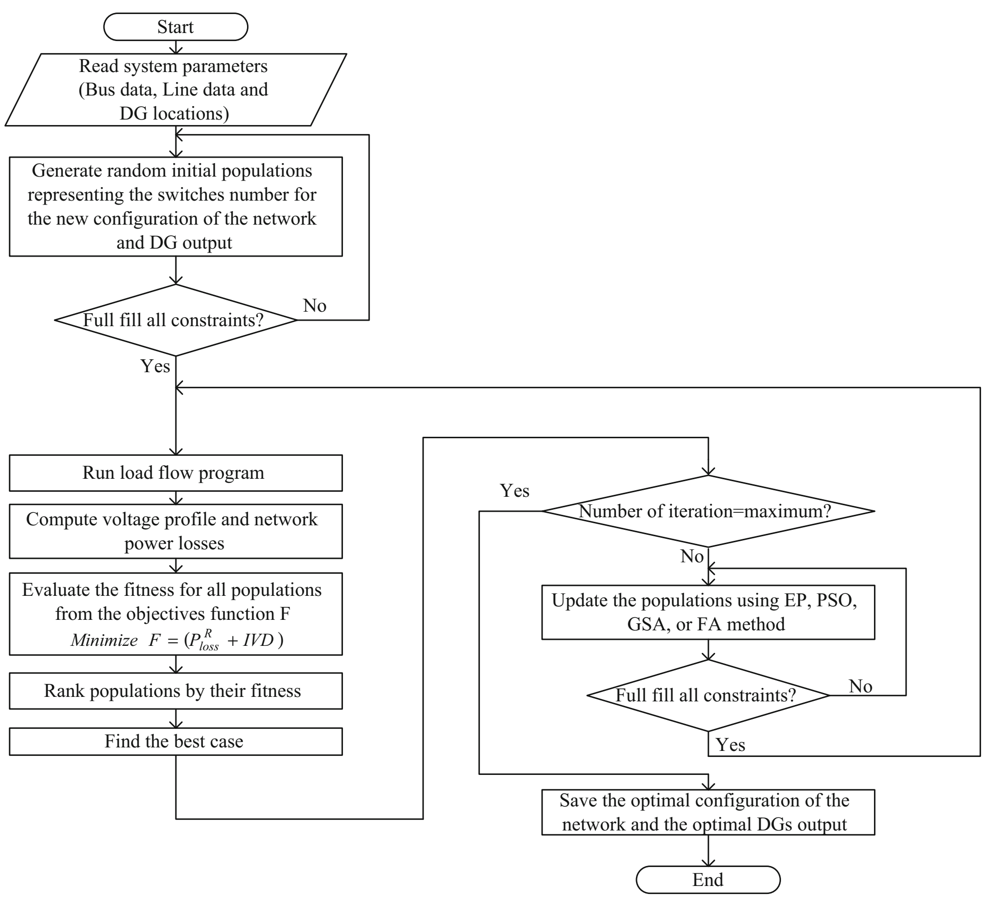

Fig. 5 Flowchart for simultaneous network reconfiguration with optimal DG output for case 2

Table 2 Network reconfiguration and DG output results for case 2

Case	Open switch	DG output in MW (Bus NO)	Bus voltage (pu) (at bus) min max	$F_R = P_{\text{loss}}^R + \text{IVD}$	Power losses (kW)	Losses reduction (%)
Initial	33, 34, 35, 36, 37	No DG	0.9131(18)–1(1)	1.1135	202.6	–
EP	7, 8, 9, 28, 32	DG1 = 0.7024	0.9710(9)–1(1)	0.4223	73.971	63.49
		DG2 = 0.6390				
		DG3 = 0.6224				
PSO	7, 10, 13, 28, 32	DG1 = 0.6120	0.9738(29)–1(1)	0.41199	72.421	64.30
		DG2 = 0.5200				
		DG3 = 0.6340				
GSA	7, 9, 13, 28, 32	DG1 = 0.6450	0.9742(14)–1(1)	0.4117	72.425	64.25
		DG2 = 0.5200				
		DG3 = 0.5800				
FA	7, 10, 13, 28, 32	DG1 = 0.6756	0.9750(29)–1(1)	0.4105	72.361	64.28
		DG2 = 0.5160				
		DG3 = 0.6334				

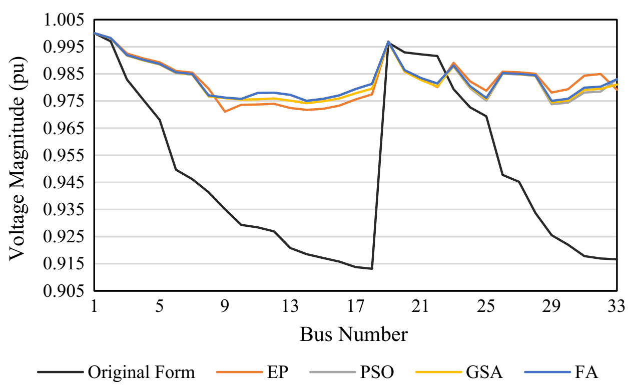

Fig. 6 Voltage profile of IEEE 33-bus network using different algorithms for case 2

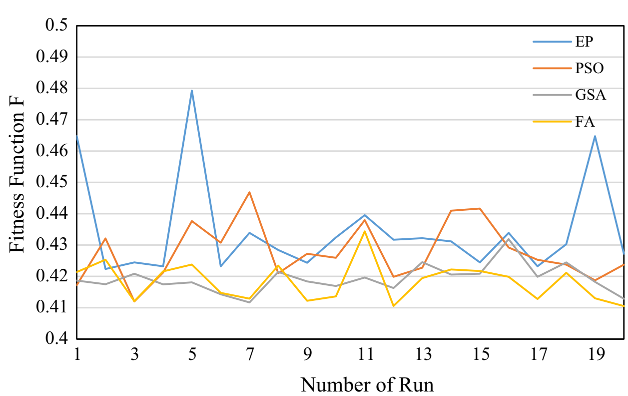

Fig. 7 Comparison of robustness test of the simultaneous reconfiguration and optimal DG output algorithms for case 2

The results proved that case 2 resulted in better solution than case 1, which means that minimizing power losses and simultaneously improving voltage profile index resulted in

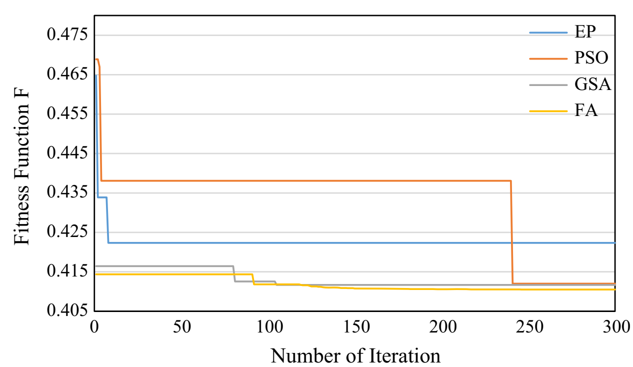

Fig. 8 Comparison of convergence performance of the simultaneous reconfiguration and optimal DG output algorithms for case 2

optimal solution that is better than minimizing power losses alone. To validate the proposed method, the performance of case 2 is compared with published results in [17] as shown in Table 3. It is clear that the proposed method, which is based on PSO, GSA, or FA, is producing better results than published work, while EP obtained value of power losses larger than HSA.

In order to show the advantage of simultaneously optimizing the network reconfiguration and DG output, a comparison between sequential and simultaneous optimization is done using FA. In sequential case, network reconfiguration was done first and then DG sizing was optimized, while in simultaneous case both reconfiguration and DG sizing were done at the same time. For sequential case, power losses after network reconfiguration is 86.43 kW. The minimum voltage for all busses after reconfiguration is improved to 0.96413 pu. The normally open switches after reconfiguration are 7, 14, 9, 32, and 37. DG1 output is 0.6005 MW, DG2 is 0.1522

Table 3 Comparison of simulation result of 33-bus system

Method	Open switches	DG output (MW) (at bus)	Power losses (kW)	Losses reduction (%)
HSA [17]	7, 10, 14, 28, 32	0.5586 (31), 0.5258 (32), 0.5840 (33)	73.050	63.95
EP	7, 8, 9, 28, 32	0.7024 (31), 0.6390 (32), 0.6224 (33)	73.971	63.49
PSO	7, 10, 13, 28, 32	0.6120 (31), 0.5200 (32), 0.6340 (33)	72.421	64.30
GSA	7, 9, 13, 28, 32	0.6450 (31), 0.5200 (32), 0.5800 (33)	72.425	64.25
FA	7, 10, 13, 28, 32	0.6756 (31), 0.5160 (32), 0.6334 (33)	72.361	64.28

Table 4 Network reconfiguration and DG output results for case 3 for different weights

Case	Weight	Open switch	DG output in MW (Bus NO)	Bus voltage (pu) (at bus) min max	$F = w1 \times (P^R_{\text{loss}} + \text{IVD}) + w2 \times (\frac{1}{DG_{\text{output}}})$	Power losses (kW)	Losses reduction (%)
Initial	–	33, 34, 35, 36, 37	No DG	0.9131(18)–1(1)	1.1135	202.6	–
EP	w1 = 0.5	5, 10, 12, 26, 32	DG1 = 0.344	0.9779(26)-1.009(32)	0.8914	131.4	35.1
	w2 = 0.5		DG2 = 1.8				
			DG3 = 1.283				
	w1 = 0.6	11, 26, 12, 31, 33	DG1 = 1.961	0.9885(7)–1.0138(32)	0.8334	127.4	37.1
	w2 = 0.4		DG2 = .918				
			DG3 = 0.561				
	w1 = 0.7	5, 26, 10, 12, 32	DG1 = 0.517	0.9742(26)–1(1)	0.7794	104.1	48.6
	w2 = 0.3		DG2 = 1.269				
			DG3 = 1.134				
	w1 = 0.8	31, 10, 35, 27, 33	DG1 = 1.241	0.9792(11)–1(1)	0.6972	94.1	53.6
	w2 = 0.2		DG2 = 0.987				
			DG3 = 0.37				
	w1 = 0.9	33, 27, 35, 10, 31	DG1 = 1.055	0.9726(11)–1(1)	0.5941	85.2	57.9
	w2 = 0.1		DG2 = 0.809				
			DG3 = 0.382				
PSO	w1 = 0.5	7, 26, 35, 9, 32	DG1 = 1.269	0.9830(10)–1.0110(32)	0.87	125.5	38.1
	w2 = 0.5		DG2 = 1.042				
			DG3 = 1.145				
	w1 = 0.6	32, 12, 10, 26, 5	DG1 = 0.482	0.9744(26)–1.005(32)	0.8446	115.0	43.2
	w2 = 0.4		DG2 = 1.533				
			DG3 = 1.136				
	w1 = 0.7	10, 25, 8, 31, 33	DG1 = 2	0.9840(10)–1.0071(31)	0.7597	109.9	45.8
	w2 = 0.3		DG2 = 0.148				
			DG3 = 1.047				
	w1 = 0.8	9, 32, 7, 27, 13	DG1 = 0.776	0.9773(13)–1(1)	0.6766	86.1	57.5
	w2 = 0.2		DG2 = 1.019				
			DG3 = 0.717				

Table 4 continued

Case	Weight	Open switch	DG output in MW (Bus NO)	Bus voltage (pu) (at bus) min max	$F = w1 \times (P_{loss}^{R} + \text{IVD}) + w2 \times (\frac{1}{DG_{output}})$	Power losses (kW)	Losses reduction (%)
	w1 = 0.9	9, 27, 34, 32, 7	DG1 = 0.655	0.9701(14)–1(1)	0.5824	74.3	63.3
	w2 = 0.1		DG2 = 0.677				
			DG3 = 0.527				
GSA	w1 = 0.5	25, 10, 32, 20, 12	DG1 = 0.875	0.9671(11)–1(1)	0.9708	101.0	50.1
			DG2 = 0.975				
			DG3 = 0.838				
	w2 = 0.5						
	w1 = 0.6	10, 12, 20, 28, 31	DG1 = 1.017	0.9669(11)–1(1)	0.9517	98.2	51.5
	w2 = 0.4		DG2 = 0.545				
			DG3 = 0.819				
	w1 = 0.7	10, 25, 8, 33, 32	DG1 = 1.213	0.9838(26)–1(1)	0.7535	97.1	52.1
	w2 = 0.3		DG2 = 0.772				
			DG3 = 0.899				
	w1 = 0.8	12, 9, 27, 7, 32	DG1 = 1.032	0.9813(10)–1(1)	0.6629	84	58.5
	w2 = 0.2		DG2 = 0.630				
			DG3 = 0.868				
	w1 = 0.9	32, 27, 34, 10, 7	DG1 = 0.829	0.9776(10)–1(1)	0.5581	77.2	61.9
	w2 = 0.1		DG2 = 0.631				
			DG3 = 0.734				
FA	w1 = 0.5	26, 11, 15, 34, 33	DG1 = 0.58	0.9741(15)–1(1)	1.1502	98.2	51.5
	w2 = 0.5		DG2 = 0.696				
			DG3 = 0.833				
	w1 = 0.6	6, 13, 32, 8, 27	DG1 = 0.595	0.9738(7)–1(1)	0.9644	81.5	59.8
	w2 = 0.4		DG2 = 0.689				
			DG3 = 0.869				
	w1 = 0.7	12, 32, 11, 26, 7	DG1 = 0.670	0.9713(27)–1(1)	0.8460	77.6	61.7
	w2 = 0.3		DG2 = 0.536				
			DG3 = 0.865				
	w1 = 0.8	7, 32, 8, 10, 26	DG1 = 0.735	0.9710(10)–1(1)	0.7153	74.6	63.2
	w2 = 0.2		DG2 = 0.563				
			DG3 = 0.683				
	w1 = 0.9	34, 28, 32, 7, 10	DG1 = 0.556	0.9753(14)–1(1)	0.5741	73.4	63.8
	w2 = 0.1		DG2 = 0.680				
			DG3 = 0.618				

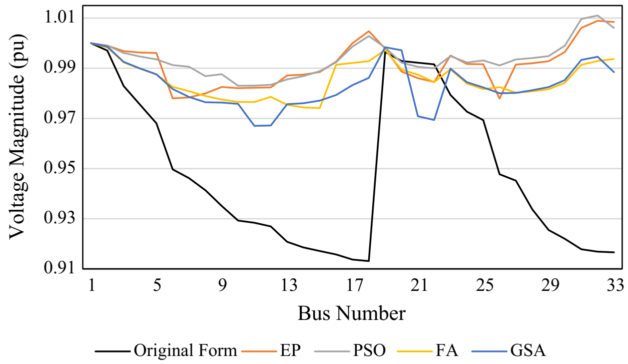

Fig. 9 Voltage profile of IEEE 33-bus network using different algorithms for case 3 at $w1 = w2$

MW, and DG3 is 0.2598 MW. While for simultaneous case, the power losses after network reconfiguration within DG are 72.361 kW. The minimum voltage for all busses after reconfiguration is improved to 0.9750 pu. The normally open switches after reconfiguration are 7, 10, 13, 28, and 32. DG1 output is 0.6756 MW, DG2 is 0.516 MW, and DG3 is 0.6334 MW. It is observed that simultaneous case gives better results than sequential case.

4.3 Case 3: Aims to Minimize Power Losses, Improve Voltage Profile Index, and Maximize the DG Output by Simultaneous Network Reconfiguration with Optimal DG Output

Table 4 summarizes the overall results for the EP, PSO, FA, and GSA related to case 3. Different weights are used for each algorithm in order to analyze the effect of maximization the DG output. It can be conducted that the power losses obtained using FA are better than the EP, PSO, and GSA at each weight. Additional, the power losses obtained in case 3 are larger than in case 2. That means case 2 is better than case 3 in minimizing power losses. In other words, obtaining the optimal output of the DG leads to power losses more than maximizing the DG output.

The voltage profile plots for case 3 for both initial and optimal solutions using EP, PSO, FA, and GSA are compared and shown in Fig. 9 at $w1 = w2$. It can be observed from Fig. 8 that all buses voltage magnitudes for all algorithms are improved to a value larger than their respective initial states.

5 Conclusion

This paper has proposed a new strategy to determine the optimal distribution network reconfiguration and DG output for the network simultaneously. Different objectives are discussed in this paper: (1) to minimize power losses, (2) to improve voltage profile index, (3) to maximize DG output. The presented method achieved the minimum power losses and the best voltage profile. The EP, PSO, FA, and GSA are the meta-heuristic methods that have been used to realize the distribution minimum main fitness. The effectiveness of the presented method has been verified on a 33-bus distribution system. The presented approach is of high quality and robustness in realizing an optimal network configuration and DG output. The results proved that the optimal reconfiguration within the optimal DG output minimized the power losses and improved the overall system voltage profile. Furthermore, the results show that the minimizing power losses with improving voltage profile index is better than other cases which are (1) minimizing power losses only, (2) minimizing power losses, improving the voltage profile, and maximizing DG output. The computational results showed that the performance of FA in minimizing power losses was better than that of HAS, EP, PSO, and GSA. The results indicate the possibility of the method to be adapted on practical real systems for planning purposes.

References

1. Taleski, K.; Rajičić, D.: Distribution network reconfiguration for energy loss reduction. IEEE Trans. Power Syst. **12**(1), 398–406 (1997)
2. Gupta, N.; Swarnkar, A.; Niazi, K.; Bansal, R.: Multi-objective reconfiguration of distribution systems using adaptive genetic algorithm in fuzzy framework. IET Gener. Transm. Distrib. **4**(12), 1288–1298 (2010)
3. Civanlar, S.; Grainger, J.; Yin, H.; Lee, S.: Distribution feeder reconfiguration for loss reduction. IEEE Trans. Power Deliv. **3**(3), 1217–1223 (1988)
4. Merlin, A.; Back, H.: Search for a minimal-loss operating spanning tree configuration in an urban power distribution system. In: In: Proceedings of the 5th Power System Computation Conf., Cambridge, UK, pp. 1–18 (1975)
5. Fan, J.-Y.; Zhang, L.; McDonald, J.D.: Distribution network reconfiguration: single loop optimization. IEEE Trans. Power Syst. **11**(3), 1643–1647 (1996)
6. Shirmohammadi, D.; Hong, H.W.: Reconfiguration of electric distribution networks for resistive line losses reduction. IEEE Trans. Power Deliv. **4**(2), 1492–1498 (1989)
7. Chang, H.-C.; Kuo, C.-C.: Network reconfiguration in distribution systems using simulated annealing. Electr. Power Syst. Res. **29**(3), 227–238 (1994)
8. Carreno, E.M.; Romero, R.; Padilha-Feltrin, A.: An efficient codification to solve distribution network reconfiguration for loss reduction problem. IEEE Trans. Power Syst. **23**(4), 1542–1551 (2008)
9. Dahalan, W.M.; Mokhlis, H.; Ahmad, R.; Bakar, A.A.; Musirin, I.: Simultaneous network reconfiguration and DG sizing using evolutionary programming and genetic algorithm to minimize power losses. Arab. J Sci. Eng. **39**(8), 6327–6338 (2014)
10. Su, C.-T.; Chang, C.-F.; Chiou, J.-P.: Distribution network reconfiguration for loss reduction by ant colony search algorithm. Electr. Power Syst. Res. **75**(2), 190–199 (2005)
11. Rao, R.S.; Narasimham, S.V.L.; Raju, M.R.; Rao, A.S.: Optimal network reconfiguration of large-scale distribution system using

harmony search algorithm. IEEE Trans. Power Syst. **26**(3), 1080–1088 (2011)
12. Rau, N.S.; Wan, Y-h: Optimum location of resources in distributed planning. IEEE Trans. Power Syst. **9**(4), 2014–2020 (1994)
13. Jabr, R.A.; Pal, B.: Ordinal optimisation approach for locating and sizing of distributed generation. IET Gener. Transm. Distrib. **3**(8), 713–723 (2009)
14. Wang, H.; Huang, J.: Joint investment and operation of microgrid. IEEE Trans. Smart Grid **8**, 833–845 (2015)
15. Wang, H.; Huang, J.: Cooperative planning of renewable generations for interconnected microgrids. IEEE Trans. Smart Grid **7**(5), 2486–2496 (2016)
16. Wu, Y.-K.; Lee, C.-Y.; Liu, L.-C.; Tsai, S.-H.: Study of reconfiguration for the distribution system with distributed generators. IEEE Trans. Power Deliv. **25**(3), 1678–1685 (2010)
17. Rao, R.S.; Ravindra, K.; Satish, K.; Narasimham, S.: Power loss minimization in distribution system using network reconfiguration in the presence of distributed generation. IEEE Trans. Power Syst. **28**(1), 317–325 (2013)
18. Dahalan, W.; Mokhlis, H.; Bakar, A.; Jamian, J.: The simultaneous application of optimum network reconfiguration and distributed generation sizing using PSO for power loss reduction. Prz Elektrotech. **89**, 137–141 (2013)
19. Gandomi, A.H.; Yang, X.-S.; Alavi, A.H.: Mixed variable structural optimization using firefly algorithm. Comput. Struct. **89**(23), 2325–2336 (2011)
20. Rashedi, E.; Nezamabadi-Pour, H.; Saryazdi, S.: GSA: a gravitational search algorithm. Inf. Sci. **179**(13), 2232–2248 (2009)
21. Baran, M.E.; Wu, F.F.: Network reconfiguration in distribution systems for loss reduction and load balancing. IEEE Trans. Power Deliv. **4**(2), 1401–1407 (1989)