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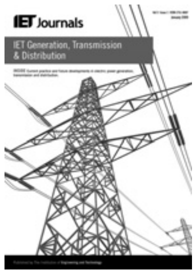

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Enhanced gravitational search algorithm for multi-objective distribution feeder reconfiguration considering reliability, loss and operational cost

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Abstract: Power loss reduction can be considered as one of the main purposes for distribution system operators. Reconfiguration is an operation process used for this optimisation by means of changing the status of switches in a distribution network. Recently, all system operators tried their best in order to obtain well-balanced distribution systems to decrease the operation cost, improve reliability and reduce power loss. This study presents an efficient method for solving the multi-objective reconfiguration of radial distribution systems with regard to distributed generators. The conventional distribution feeder reconfiguration (DFR) problem cannot meet the reliability requirements, because it only considers loss and voltage deviation as objective functions. The proposed approach considers reliability, operation cost and loss simultaneously. By adding the reliability objective to the DFR problem, this problem becomes more complicated than before and it needs to be solved with an accurate algorithm. Therefore this study utilises an Enhanced Gravitational Search Algorithm called EGSA which profits from a special mutation strategy in order to reduce the processing time and improve the quality of solutions, particularly to avoid being trapped in local optima. The proposed approach has been applied to two distribution test systems including IEEE 33 and 70-node test systems.

1 Introduction

Generally, distribution networks are structured in mesh shape but operated in radial configuration. The reconfiguration of a distribution system is a process that modifies feeder topological structure by managing the open/close status of sectionalising and tie-switches in a distribution system and its target is to find a radial operating configuration that optimises certain objectives while satisfying all the operational constraints without islanding of any node(s). Since traditional optimisation methods have some constraints including continuity and derivability of the objective function, the discrete inherence of the switch values and radial constraint prevent the use of classical optimisation techniques to solve the distribution feeder reconfiguration (DFR) problem. Therefore most of the algorithms in the literature are established upon heuristic search techniques. During the years, lots of heuristic search techniques have been applied to solve the reconfiguration problem. The research works in this area can be categorised into two major groups: (i) the papers did not consider the effect of distributed generators (DGs) on DFR problem, that is [1–30] and (ii) this paper which evaluated the presence performance of DGs on DFR problem [31–35]. It is clear that although there is a vast body of research on the DFR problem without consideration of DGs effects, little attention has been paid to the consideration of DGs influence on DFR problem.

Zhou *et al.* [1] presented the use of the power flow method based on a heuristic algorithm to determine minimum loss configuration for radial distribution networks. Niknam [2] proposed a hybrid evolutionary algorithm based on particle swarm optimisation (PSO) and honey bee mating optimisation (HBMO) algorithms for multi-objective DFR. Niknam *et al.* [3] presented a hybrid fuzzy algorithm for multi-objective DFR. Delbem *et al.* [4] proposed a tree encoding and two genetic operators to improve the evolutionary algorithms performance of network reconfiguration problems. Debaprya [5] presented a fuzzy multi-objective approach to solve the network reconfiguration problem. Jianming *et al.* [6] presented an improved genetic algorithm (GA) with infeasible solution disposing for DFR problem. Ashisa *et al.* [7] proposed an artificial immune system-ant colony optimisation (AIS–ACO) hybrid approach for multi-objective DFR problem. Savier and Das [8] proposed a loss allocation to consumers before and after reconfiguration of radial distribution networks. Bernardon *et al.* [9] presented a fuzzy multi-criteria decision making algorithm in order to reconfigure electric distribution system. Gomes *et al.* [10] presented a new distribution system reconfiguration approach using optimal power flow and sensitivity analysis in order to reduce loss. Raju and Bijwe [11] presented an approach based on sensitivity and heuristics for loss reconfiguration of distribution system. Assadian *et al.* [12] presented a guaranteed convergence PSO in cooperation with graph theory to distribution network reconfiguration in order to save energy. Chiang and Rene [13, 14] presented a solution procedure employing simulated annealing to search for the solution. Mendoza *et al.* [15] proposed a new methodology for minimal loss reconfiguration using GA with the help of fundamental loops. They have utilised loop vectors to ensure the generation of feasible individuals, but this approach fails to search the isolation of principal interior nodes of the distribution networks and therefore requires mesh checks. Abdelaziz *et al.* [16, 17] presented a modified Tabu search algorithm for distribution system reconfiguration, also they proposed a modified PSO for distribution system reconfiguration.

Swarnkar *et al.* [18] proposed a new codification for various meta-heuristic techniques to solve the reconfiguration problem of distribution networks. Their proposed codification was based upon the fundamentals of graph theory which not only restricts the search space but also avoids tedious mesh checks.

Carpaneto and Chicco [19] presented a hyper-cube ant colony optimisation for distribution system reconfiguration in order to achieve minimum loss. Falaghi *et al.* [20] utilised ant colony optimisation-based method for placement of sectionalising switches in distribution networks using a fuzzy multi-objective approach. Wang and Cheng [21] proposed a plant growth simulation algorithm for configuration of large distribution systems. Kashem *et al.* [22] proposed 'distance measurement technique algorithm' which firstly found a loop and then in order to improve load balancing a switching option was determined in that loop. Lopez and Opaso [23] presented a procedure for online reconfiguration. Niknam [24, 25] proposed two evolutionary techniques established on norm2 for multi-objective DFR. McDermott *et al.* [26] proposed a heuristic non-linear constructive method for the DFR problem. Su and Lee [27] proposed a technique to decrease power loss and enhance the voltage profile using improved mixed-integer hybrid differential evolution technique for distribution systems. Chiou *et al.* [28] proposed a technique established on variable scaling hybrid differential evolution for solving network reconfiguration in order to reduce power loss and to enhance voltage profile of distribution systems. Arun and Aravindhababu [29] proposed a new reconfiguration scheme considered for voltage stability enhancement of radial distribution systems. Morton and Mareels [30] presented brute force solution to list and appraise all feasible radial configurations for a distribution system. Since in this method number of feasible radial configurations increases exponentially with increase in the number of distribution feeders, it cannot be utilised for a real distribution network.

Recently, a great number of factors including environmental effects of electric power generation, significant advances in several generation technologies, deregulation of power systems and tight constraints over the construction of new transmission lines for long distance power transmission, encourage consumers and distribution companies to use DGs more. Khodr *et al.* [31] proposed an approach for DFR problem comprising DGs using Benders decomposition approach. Wu *et al.* [32] suggested an ACO algorithm to solve the multi-objective DFR problem with consideration of DGs in order to obtain optimal power loss and load balance of radial networks. Franco *et al.* [33] modelled the problem of DFR considering the presence of DGs as a mixed-integer linear programming (MILP) problem and solved it with MILP solvers. Olamaei *et al.* [34] proposed a new approach on the basis of PSO algorithm to solve the DFR problem considering DGs. Nasiraghdam and Jadid. [35] presented a novel multi-objective artificial bee colony algorithm to solve the DFR problem and hybrid DGs sizing. Hence, the effects of DGs on distribution systems are investigated in the proposed approach. Since there are many candidate switching combinations in distribution systems, the DFR problem is modelled as a complicated combinatorial, non-differentiable, constrained optimisation problem. Therefore finding a strong and robust algorithm which can cope with the difficulty of DFR problem is crucial. One of the most new evolutionary algorithms is gravitational search algorithm (GSA) which has been presented by Rashedi *et al.* [36] in 2009. GSA is applied in optimisation problem with different objective functions in [36] and obtained results are compared with PSO and residual gas analyser (RGA). It has been demonstrated that obtained results of GSA are better than those obtained by PSO and RGA algorithms [36]. The GSA concept is simple and known as a powerful optimisation algorithm; besides significant privileges of this algorithm it has some drawbacks too, such as it might be trapped in local optima in some cases. In this regard, a new self-adaptive learning strategy (SALS) is implemented to cope with these problems. This approach proposes two updating techniques to enhance the performance of the original GSA algorithm. One of them is designed to exchange the information between the particles whereas the other one is considered to help the algorithm to escape from being trapped in local optima. Each particle self-adaptively selects one of these two methods to obtain a better situation. The particles prefer to choose the technique with better effectiveness. The effectiveness of each strategy is evaluated by a probability model which is based on the ability of methods to provide more optimal solutions. By means of this modification, the proposed algorithm is called enhanced GSA (EGSA).

Since the presented problem is a multi-objective optimisation problem (MOP), it requires a multi-objective method for solving. This paper utilises a Pareto-based approach which can obtain a set of optimal solutions instead of one. In this regard, an external repository is defined to save all Pareto-optimal solutions computed in each iterate of the optimisation algorithm. Power system operators can select one of these solutions in accordance with their previous experience. Also, this paper takes advantage of a fuzzy decision method to find the best Pareto-optimal solution among all the Pareto solutions as the best compromise solution. To verify the suitability of the presented algorithm, it is applied to IEEE 33-bus and 70-bus test systems. Simulation results prove the ability of the proposed algorithm in finding the global optima in the optimisation problems. The main contributions of this paper are

- Proposing an EGSA.
- Considering the reliability [energy not supplied (ENS)] objective in the DFR problem.
- Considering the effects of DGs on different objective functions.

2 Problem formulation

The objective functions and constraints of the DFR are proposed as follows:

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2.1 Objective functions

- Operation cost

$$f_1(X) = \sum_{i=1}^{N_{\rm Dg}} {\rm Price}_{{\rm Dg},i} \times P_{{\rm Dg},i} + {\rm Price}_{\rm Sub} \times P_{\rm Sub} + \sum_{j=1}^{N_{\rm Sw}} {\rm Price}_{{\rm SW},j} \times \left|S_j - S_{0,j}\right| \tag{1}$$

$$X = \Big[{\rm Tie}_1, {\rm Tie}_2, \ldots, {\rm Tie}_{N_{\rm Tie}}, Sw_1, Sw_2, \ldots, Sw_{N_{\rm Tie}}, P_{\rm Dg1}, P_{\rm Dg2}, \ldots, P_{{\rm Dg}N_{\rm Dg}}\Big] \tag{2}$$

${\rm Price}_{{\rm Dg},i}$ is the price of the ith DG, ${\rm Price}_{\rm Sub}$ is the price of substation and ${\rm Price}_{\rm SW}$ is the switching cost. $P_{{\rm Dg}i}$, $P_{\rm Sub}$ are the active power outputs of the ith DG and substation, respectively. $N_{\rm DG}$ is the number of DG. ${\rm Tie}_i$ is the state of the ith tie switch with 0 and 1 corresponding to open and close states, respectively. ${\rm Sw}_i$ is the sectionalising switch number that forms a loop with ${\rm Tie}_i$. $N_{\rm Tie}$ is the number of tie switches. S_j and $S_{0,j}$ are the new and original states of jth switch, respectively. $N_{\rm Sw}$ is the number of switches.

- Loss [28]

$$f_2(X) = \sum_{i=1}^{N_{\rm Branch}} R_i \times |I_i|^2 \tag{3}$$

where R_i and I_i are the resistance and actual current of the ith branch, respectively, and $N_{\rm Branch}$ is the number of branches.

- ENS

Since this objective function has not been considered too much in the literatures, it is scrutinised in this section. To this end consider, a distribution network with n nodes in which $n > 1$ and consider node 0 as the source of this network.

Assume that all nodes except the source have an active power P_i [kW], $i \in \{1, 2, \ldots, n-1\}$. The objective function's value at each node can be computed in terms of the reliability parameters of the distribution network [37]. In this regard, a distribution branch between nodes i and j is associated with the following parameters: a failure rate λ_{ij} [fail/km-yr], an average reconstruction time $t'_{i,j}$ [h/fail], an average reparation time $t_{i,j}$ [h/fail] and a line length $d_{i,j}$ [km]. The reparation time is the time that elapsed to reestablish the service to a faulty zone after the failure has been fixed, and the reconstruction time is the time taken to reconnect, to the network, a no fault zone that is being affected by a power outage. Assume that every distribution branch incorporates a sectionalising device on it in which, when a network reconfiguration process is triggered, such devices can be activated to change the network topology. In accordance with [37], the ENS at the node can be calculated as follows

$${\rm ENS}_i = P_i \sum_{i,j \in V, i \neq j} \left(U_{i,j} + U'_{i,j}\right) \tag{4}$$

where $V = \{0, 1, \ldots, n-1\}$ is the bunch of nodes in distribution network, $U_{j,I}$ is service unavailability related to the reparation time of all the branches connecting the node i and $U'_{j,i}$ is service unavailability associated with the reconstruction time of all the branches connecting this node. In other words, $U_{j,i}$ and $U'_{j,i}$ are related to reparation time and restoration time of all downstream branches and upstream branches of node i. It is worthwhile to note that the summation in (4) has to be understood as the sum of all the unavailability related to the ith node. The unavailabilities $U_{j,i}$ and $U'_{j,i}$ are defined as follows

$$U_{j,i} = \lambda_{j,i} \times d_{j,i} \times t_{j,i} \tag{5}$$

$$U'_{j,i} = \lambda_{j,i} \times d_{j,i} \times t'_{j,i} \tag{6}$$

Finally, the ENS of the whole distribution network is computed as the summation of all nodes except the node 0, as follows

$$f_3(X) = {\rm ENS} = \sum_{i=2}^{N_{\rm Bus}} {\rm ENS}_i \tag{7}$$

It is crucial to note that the ENS objective function is defined copiously in [38], where two reconfiguration algorithms which minimise the ENS of medium-voltage distribution network have been presented. To have a better illustration of the ENS, a simple distribution system shown in Fig. 1 is used as an example. For instance, the ENS of node 3 (${\rm ENS}_3$) can be determined as follows: if there is a failure by ${\rm branch}_{1,2}$ and ${\rm branch}_{2,3}$, the electrical power to feed ${\rm bus}_3$ is stopped since these are repaired and if there is failure by ${\rm branch}_{3,4}$, the electrical power to feed ${\rm bus}_3$ is stopped, and the sectionalise switch of the feeder will be closed again. Therefore the ${\rm ENS}_3$ can be formulated as

$${\rm ENS}_3 = P_3 \times \left(U_{1,2} + U_{2,3} + U'_{3,4}\right) \tag{8}$$

2.2 Constraints

- Distribution line absolute power limits

$$\left|P_{ij}^{\rm Line}\right| < P_{ij,{\rm Max}}^{\rm Line} \tag{9}$$

where $P_{ij}^{\rm Line}$and$P_{ij,{\rm Max}}^{\rm Line}$ are tpower flowing over the distribution branches and the maximum power transmitted between the nodes i and j, respectively.

- Distribution power flow equations

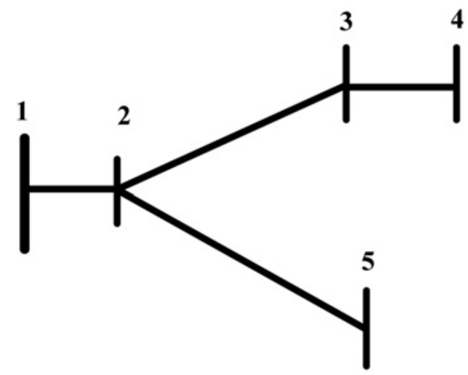

Fig. 1 *Simple single line distribution network*

$$P_i = \sum_{i=1}^{N_{\mathrm{Bus}}} V_i V_j Y_{ij} \cos\left(\theta_{ij} - \delta_i + \delta_j\right) \tag{10}$$

$$Q_i = \sum_{i=1}^{N_{\mathrm{Bus}}} V_i V_j Y_{ij} \sin\left(\theta_{ij} - \delta_i + \delta_j\right) \tag{11}$$

where P_i and Q_i are the net injected active and reactive powers at the ith bus. V_i and δ_i are the amplitude and angle of the voltage at the ith bus, respectively. Also, Y_{ij} and θ_{ij} are the amplitude and angle of the branch admittance between the ith and jth buses.

- Bus voltage limit

$$V_{\mathrm{Min}} \le V_i \le V_{\mathrm{Max}} \tag{12}$$

where V_{Min} and V_{Max} are the minimum and maximum allowable voltage value of the ith node, respectively. Also, V_i is the voltage magnitude of the ith node.

- Radial structure of the network

$$N_{\mathrm{Branch}} = N_{\mathrm{Bus}} - N_{\mathrm{Source}} \tag{13}$$

where N_{Bus} and N_{Source} are the number of buses and number of substations, respectively.

- Transformers limits

$$\left|I_{t,i}\right| \le I_{t,i}^{\mathrm{Max}} \quad i = 1, 2, \ldots, N_t \tag{14}$$

where $I_{t,\,i}$ and $I_{t,i}^{\mathrm{Max}}$ are the current amplitude and its maximum allowable value of the ith transformer, respectively. N_t is the number of transformers.

- Feeders limits

$$\left|I_{f,i}\right| \le I_{f,i}^{\mathrm{Max}} \quad i = 1, 2, \ldots, N_{\mathrm{Feeder}} \tag{15}$$

where $I_{f,i}$ and $I_{f,i}^{\mathrm{Max}}$ are the current amplitude and its maximum allowable value of the ith feeder, respectively. N_{Feeder} is the number of feeders.

- As a matter of fact, DGs in distribution systems can be modelled as PV or PQ models. Since the distribution systems are unbalanced three-phase systems, and then DG can be controlled in two follow models [39]. It is worthwhile to note that when DGs are considered as PV models, they must produce reactive power to keep magnitude voltages in their proper magnitudes. In order to model the DGs as PV buses some procedures have been proposed in the literature [39]. PQ model is utilised in this paper for modelling DGs in distribution systems.

3 Enhanced GSA

3.1 Overview of original GSA

The GSA is established on the law of gravity and the concept of mass interactions. It uses the theory of Newtonian physics and its searcher agents are the collection of masses. In physics, gravitation is a tendency in which objects with mass accelerate towards each other. In Newton gravitational law, each particle attracts the other particle with a force called the 'gravitational force' [36, 40].

To describe the presented algorithm, we assume a system with n masses in which the location of ith mass is described as follows

$$X_i = \left(x_i^1, x_i^2, \ldots, x_i^n\right) \tag{16}$$

At first, objective functions are calculated for all agents and then among all achieved results the best and worst results in each iteration are considered as $F_{\mathrm{best}}(t)$ and $F_{\mathrm{worst}}(t)$, respectively. For computing mass for each agent it is necessary to calculate the following function for each existing agent

$$Q_i(t) = \frac{f_i(t) - F_{\mathrm{worst}}(t)}{F_{\mathrm{best}}(t) - F_{\mathrm{worst}}(t)} \tag{17}$$

Mass for each agent is computed as follows

$$M_i(t) = \frac{Q_i(t)}{\sum_{i=1}^{n} Q_j(t)} \tag{18}$$

where $M_i(t)$ and $f_i(t)$ are the mass and fitness function for ith agent, respectively. After computing mass for each agent, it is possible to compute acceleration for every single one of them; to this end, total force from a set of heavier masses which is applied on each agent is computed as follows, based on Newton rules

$$F_i(t) = \sum_{j\in K\mathrm{best} \quad j\ne i} \mathrm{rand}_j()G(t)\frac{M_j(t)M_i(t)}{R_{ij}(t)+\varepsilon}\left(x_j(t) - x_i(t)\right) \tag{19}$$

where $\mathrm{rand}_j()$ is a random number between [0, 1] for the jth agent. ε is a constant small value. Based on Newton rules in classic mechanics, acceleration of each agent can be computed as follows

$$\begin{aligned} a_i(t) &= \frac{F_i(t)}{M_i(t)} \\ &= \sum_{j\in K\mathrm{best} \quad j\ne i} \mathrm{rand}_1()G(t)\frac{M_j(t)M_i(t)}{R_{ij}(t)+\varepsilon}\left(x_j(t) - x_i(t)\right) \end{aligned} \tag{20}$$

For updating position in proposed optimisation algorithm we should calculate the velocity of each agent. The velocity and the new position of each agent are computed as follows

$$v_i(t+1) = \mathrm{rand}_2() \times v_i(t) + a_i(t) \tag{21}$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{22}$$

where $\mathrm{rand}_1()$ and $\mathrm{rand}_2()$ are two random numbers between 0 and 1, $R_{ij}(t)$ is the Euclidean distance between two agents i and j, K_{best} is the squad of first K agents which have the best fitness value and the biggest mass, the value of K is decreased in each iteration in which at first iteration K is equal to number of agents and this value decreases to 1 linearly. Gravitational constant (G) has a trait like K, at first it is considered as G_0, afterwards by each iteration it decreased.

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The gravitational constant decreases during the optimisation process as follows

$$G^k = G_0 \times \exp\left(\varpi \times \frac{\text{Iter}}{\text{Iter}_{\max}}\right)$$

where G_0 and ϖ are two constants set to 100 and 20, respectively. Also, Iter and $\text{Iter}_{\max}$ are the iteration and maximum number of iteration, respectively.

The GSA algorithm has two privileges with respect to the PSO algorithm: In the PSO algorithm, direction of the movement is calculated only by usage of P_{best} and G_{best}, but in GSA movement it is calculated by means of all forces obtained by all other agents. Another difference between GSA and PSO is that in GSA existing distance between solutions is affecting the new position updating but in PSO existing distance between solutions is not affecting the new position updating.

3.2 Self-adaptive learning strategy

A new SALS technique is utilised to improve the performance of the original GSA. To this end, two strength updating approaches have been implemented probabilistically to optimise the proposed problem. Each of the suggested methods, corresponding to the optimisation problem in hand or corresponding to different iterations of one particular problem, may be more profitable than the other one. The purpose of using SALS method is to adaptively give preference to appropriate mutation strategies on the proposed problem and at different steps of the optimisation process. In this regard, a probability value is allocated to each of the updating methods. This probability value is dependent on the ability of the corresponding updating method to provide more optimal solutions. In addition, instead of using fixed probability for each strategy during the whole optimisation process, the SALS uses an appropriate adaptively updating mechanism. Each particle considering the probability of each method and using roulette wheel mechanism chooses one of the following methods to improve its solution.

Method 1: In this method, the EGSA uses an external memory to save the best so far solutions. In order to make profit of good information found by the population in the previous iterations, the EGSA saves the best solution obtained by the population up to now, named G_{best} and uses the updating approach as follows:

$$X^k_{j,\text{method1}} = X^k_j + \text{rand}\left(G^k_{\text{best}} - LF^k M^k\right) \quad j = 1, \ldots, N_1 \tag{23}$$

Where rand is the random function generator in the range of [0, 1]. M^k is the mean value of the population. N_1 is the number of particles which are selected updating Method 1. In the primary consideration, the decision of the LF can be either 1 or 2. In this study, in order to increase the exploration and exploitation capacity of the original GSA algorithm, an adaptive LF has been used. In the optimisation algorithm, the lower value of LF allows a superior search process in the first iteration of the algorithm but causes slow convergence. A larger value of LF accelerates the search procedure but it reduces the exploration capability. According to the above discussion the LF^k is defined inventively as $LF^k = \left(M^k / G^k_{\text{best}}\right)$.

Method 2: This updating method is proposed to improve the diversity of the solutions, alleviate stagnation and avoid being trapped in local optima. For each particle j, five particles are selected randomly so that $m_1 \neq m_2 \neq m_3 \neq m_4 \neq m_5 \neq j$, and a trial solution is created as

$$X^k_{j,\text{trial}} = X^k_{m_1} + \text{rand1}\left(X^k_{m_2} - X^k_{m_3}\right) + \text{rand2}\left(X^k_{m_4} - X^k_{m_5}\right), \quad j = 1, \ldots, N_2 \tag{24}$$

where, both rand1 and rand2 are the random function generator in the range of [0, 1]. N_2 is the number of particles which are selected updating Method 2. Using the following scheme, an updated solution is obtained

$$x^k_{ji,\text{method2}} = \begin{cases} x^k_{ji,\text{trial}} & \text{if}(\text{rand} \leq 0.5) \\ x^k_{ji} & \text{else} \end{cases} \tag{25}$$

where x^k_{ji} and $x^k_{ji,\text{trial}}$ are the ith member of the jth particle in iteration k for the existing and trial particle j, respectively. Finally, between $X^k_{j,\text{method2}}$ and X^k_j, one with better fitness value is selected.

In order to implement the SALS technique, firstly, the probability of both aforementioned methods are assumed to be $\text{prob}_{\text{method}} = 0.5$, (method = 1, 2), also a parameter named accumulator is defined as $a_{\text{method}} = 0$, (method = 1, 2).

In each iteration, the particles are sorted based on their fitness values while $j = 1$ represents the particle with best fitness value and $j = NPOP$ stands for the particle with the worst fitness value. Thereafter, a weight factor is allocated to each of them. The better solutions obtain larger weight factors as [41]

$$ww_j = \frac{\log(NPOP - j + 1)}{\log(1) + \cdots + \log(NPOP)}, \quad j = 1, \ldots, NPOP \tag{26}$$

The accumulator of each moving strategy is updated as [41]

$$a_{\text{method}} = a_{\text{method}} + ww_{jj}, \quad jj = 1, \ldots, N_{\text{method}} \tag{27}$$

where, N_{method} is the number of particles selecting method$^{\text{th}}$ method and ww_{jj}($jj = 1, \ldots, N_{\text{method}}$) are the weight factors corresponding to them. The probability is computed as [41]

$$\text{prob}_{\text{method}} = (1 - \theta)\text{prob}_{\text{method}} + \theta \frac{a_{\text{method}}}{K_{\max}}, \quad (\text{method} = 1, 2) \tag{28}$$

where θ is a learning rate to control the learning speed in the EGSA algorithm. It is assumed to be 0.142 in this paper. $K_{\max}$ is the maximum iteration number. Finally, the normalised probability values are calculated as follows

$$\text{prob}_{\text{method}} = \text{prob}_{\text{method}} / \left(\text{prob}_1 + \text{prob}_2\right), \quad (\text{method} = 1, 2) \tag{29}$$

In an attempt to improve the modification process more effectively, a new learning strategy is proposed such that the output solutions of the GSA would be improved. This proposed SALS uses two mutation operations in parallel to enhance the ability of the algorithm for both local and global search exploration adequately. In the EGSA solution technique, with respect to each target solution in the current population which is extracted from the GSA, one trial solution generation method is selected from the strategy pool according to its probability on the basis of (28) and (29). The selected method is subsequently applied to the corresponding target solution to generate a trial solution. Details of the method selection procedure are described as follows:

For $i = 1$ to *NPOP*
Select the method$^{\text{th}}$ mutation strategy by roulette wheel mechanism selection for the ith agent as follows:

If rand$(\cdot) < \text{Prob}_{\text{method}}$
  Select mutation Method 1 for target solution i.

Else
  Select mutation Method 2 for target solution i.

Endif

Endfor (refers to index i)

4 Multi-objective solution methodology

4.1 Normalised objective functions using the fuzzy method

Since the objective functions are imprecise and are not in the same range, therefore fuzzy sets are implemented to substitute each objective function as a value between 0 and 1. A fuzzy set is generally shown by a membership function (μ_i). The ith objective function of F_i is depicted by a membership function μ_i and defined as (39) [42]

$$\mu_i(X) = \begin{cases} 1 & \text{if} \quad F_i(X) \le F_i^{\min} \\ \dfrac{F_i^{\max} - F_i(X)}{F_i^{\max} - F_i^{\min}} & \text{if} \quad F_i^{\min} < F_i(X) < F_i^{\max} \\ 0 & \text{if} \quad F_i(X) \ge F_i^{\max} \end{cases} \tag{30}$$

4.2 Pareto-optimal solution

The Pareto-optimal method is a suitable approach for the MOP which can obtain a set of solutions instead of one. This method works based on the dominance concept, the vector $\boldsymbol{X}_1$ dominates $\boldsymbol{X}_2$, when the following conditions are satisfied [43]

$$\begin{aligned} &\forall \quad i = \{1,\ 2,\ \ldots,\ N_{\text{obj}}\}, \quad F_i(\boldsymbol{X}_1) \le F_i(\boldsymbol{X}_2) \\ &\exists \quad j \in \{1,\ 2,\ \ldots,\ N_{\text{obj}}\}, \quad F_j(\boldsymbol{X}_1) < F_j(\boldsymbol{X}_2) \end{aligned} \tag{31}$$

where N_{obj} is the number of objective functions.

4.3 Fuzzy decisionmaker

In the proposed approach, a repository is implemented to save all non-dominated solutions in each iterate. The solutions that are saved in this repository in all iterations are sorted by a type of decision making function. Therefore it is possible to select the best solution by selecting the top solutions in this collection [43] as follows

$$N_{\mu j} = \frac{\sum_{k=1}^{N_{\text{obj}}} \beta_k \times \mu_{jk}}{\sum_{j=1}^{m} \sum_{k=1}^{n} \beta_k \times \mu_{jk}} \tag{32}$$

where β_k is the weight factor for the kth objective functions and m is the number of non-dominated solutions. The weight values β_k can be selected by the operator based on the importance of the objective function. The solution with the maximum membership function N_μ is the most preferred compromise solution based on the adopted weight factors.

5 Application of proposed algorithm to multi-objective distribution feeder reconfiguration

To implement the EGSA on the proposed MOP, it is necessary to execute the following steps:
Step 1: Define the input data.
Step 2: Convert the constraint MOP to an unconstrained one by the following equation (see (33))
$f_1(X), f_2(X)$ and $f_3(X)$ are the objective functions described in (1), (3) and (4), respectively. N_{eq} and N_{ueq} are the number of equality and inequality constraints, respectively, $h_j(X)$ and $g_j(X)$ are the equality and inequality constraints, respectively, and L_1 and L_2 are the penalty factors. Since the constraints should be met, the values of the parameters should be high; in this paper, the values have been considered to be 10 000.

To this end, at first, the distribution load flow is run based on the control variables. According to the obtained results of distribution load flow, the objective function value $f(X)$ is calculated and the constraints are checked. Then, the augmented objective function is calculated by using the values of function and constraints. In other words, the penalty factor method is utilised to handle the inequalities constraints. In this regard, each control vector which violates constraints will be fined by these penalty factors.

$$J(\overline{X}) = \begin{bmatrix} J_1(\overline{X}) \\ J_2(\overline{X}) \\ J_3(\overline{X}) \end{bmatrix}_{3\times 1} = \begin{bmatrix} f_1(\overline{X}) + L_1\left(\sum_{j=1}^{N_{\text{eq}}} \left(h_j(\overline{X})\right)^2\right) + L_2\left(\sum_{j=1}^{N_{\text{ueq}}} \left(\text{Max}\left[0,\ -g_j(\overline{X})\right]\right)^2\right) \\ f_2(\overline{X}) + L_1\left(\sum_{j=1}^{N_{\text{eq}}} \left(h_j(\overline{X})\right)^2\right) + L_2\left(\sum_{j=1}^{N_{\text{ueq}}} \left(\text{Max}\left[0,\ -g_j(\overline{X})\right]\right)^2\right) \\ f_3(\overline{X}) + L_1\left(\sum_{j=1}^{N_{\text{eq}}} \left(h_j(\overline{X})\right)^2\right) + L_2\left(\sum_{j=1}^{N_{\text{ueq}}} \left(\text{Max}\left[0,\ -g_j(\overline{X})\right]\right)^2\right) \end{bmatrix} \tag{33}$$

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Therefore this control vector will be deleted automatically in the next step.
Step 3: An initial population X_i which must meet constraints, is generated randomly.
Step 4: Calculate the objective functions values and normalise them by fuzzy decisionmaker in accordance with (30). The augmented objective function (33) is evaluated by using the load flow result. Also, for each individual (X_i) the membership values of all different objectives are computed.
Step 5: Apply the Pareto method in order to obtain normalised objective function of previous step and save non-dominate solutions in the repository. Compute the weight factor for all non-dominate solutions.
Step 6: Sort all agents according to their weight factors and select the best agent (X_{best}) and worst agent (X_{worst}) among them.
Step 7: Calculate mass for all agents according to (17) and (18).
Step 8: Compute the force which is applied to each agent and its acceleration according to (19) and (20), respectively. The velocity of each agent is computable having its acceleration according to (21).
Step 9: Update the position of each agent according to (22).
Step 10: If any element of each agent breaks its inequality constraints then the position of the individual is fixed at its maximum/minimum operating point. Therefore this can be formulated as

$$X_{i,j}^{k+1} = \begin{cases} x_{i,j}^{k+1} & \text{if} \quad x_{j,\min} \langle x_{i,j}^{k} \langle x_{j,\max} \\ x_{j,\min} & \text{if} \quad x_{i,j}^{k} \langle x_{j,\min} \\ x_{j,\max} & \text{if} \quad x_{i,j}^{k} \rangle x_{j,\max} \end{cases} \tag{34}$$

Step 11: Objective functions are calculated for new agents also $X_{P_{\text{best}}}$ and $X_{G_{\text{best}}}$ are selected again, if the new X_{best} dominates the EX-X_{best} solution then the EX-X_{best} replaces with new one.
Step 12: If the current iteration number (iteration$_{\max}$) reaches the predetermined maximum iteration number, the search procedure stops, otherwise, it goes to Step 6.
Step 13: The last achieved X_{best} is the solution of the problem.

6 Simulation results

MATLAB programming codes for the EGSA, distribution load flow algorithm and proposed objectives functions are developed and incorporated for the simulation purposes in this paper. The performance and advantages of the proposed reconfiguration algorithm are demonstrated on two widely referred systems including 33-node and 70-node systems. Also, for validating the obtained results they are compared with those in the literatures and in cases where there is no literature for comparison the obtained results are compared with two common evolutionary algorithms including PSO and GA. It is worthwhile to note that the comparison is based on reduction in power loss, operation cost and ENS values. In this regard, the rest of this approach is divided into two sections involving two case systems in which each section includes three subsections related to each objective function. Also, in each subsection, the effect of distributed generation on considered objective function is demonstrated.

In order to clarify mechanism and ability of the proposed algorithms in solving optimisation problems, the value of parameters related to these algorithms are depicted in Table 1.

Table 1 Parameters of proposed algorithm

Algorithm parameters	Population size	Maximum iteration	K	G_0	ϖ
proposed algorithm	100	200	100	100	20
PSO	100	200	—	—	—
GA	100	300	—	—	—

6.1 Case 1: 33-node test system

The one line diagram of this test system is depicted in Fig. 2. This test system consists of four DGs at buses #6, #12, #16 and #31. It should be noted that all DGs have a 500 MW capacity. Substation cost is 0.04$/kWh and DGs costs are 0.043, 0.042, 0.042 and 0.043$/kWh for DG6, DG12, DG16 and DG31, respectively. Also, switching cost is 0.041$ for each switching. Tables 2 and 3 show the essential data for 33-bus test system. Also, it is noteworthy that power nodes are presented in [44].

6.1.1 Minimisation of power loss: For the sake of comparison and to validate the performance of the proposed algorithm, the obtained results are compared with those in the literatures. It can be seen that the proposed approach can obtain the same or better values with respect to other algorithms; this statement demonstrates the potential and effectiveness of the proposed approach in solving the optimisation problem. It is worthwhile to note that because of the small search space of this case study, the proposed algorithm can manage to obtain the optimum value which other algorithms could; therefore the superiority of the proposed algorithm with respect to others is not clear here. It is necessary to note that all control variables are remained within their permissible limits. Furthermore, the best result, worst result, average and standard deviation for GA, PSO and EGSA in 50 runs are depicted in Table 4. It is clear that the EGSA obtained a lower value and has a better standard deviation and worst result with respect to other algorithms. The CPU times of the proposed algorithm and other algorithms are shown in the last column in Table 4. It is clear that the convergence of the proposed algorithm is not a time consuming process which is considered as an important characteristic in power system operation studies.

In order to depict the effect of DGs in power loss objective function, Table 5 shows the obtained values of power loss for PSO, GA and proposed algorithm at presence of DGs in

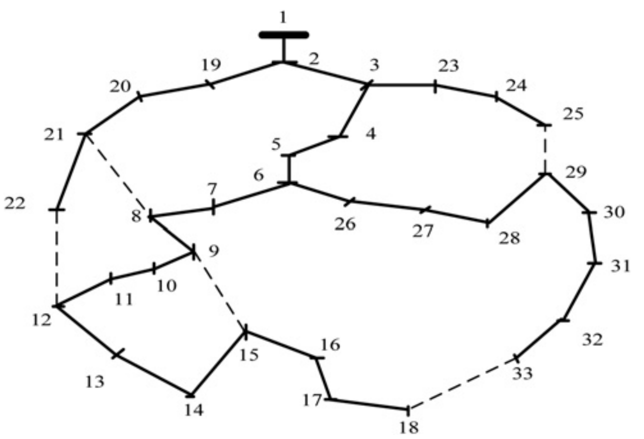

Fig. 2 *One line diagram of 33-node test system*

Table 2 Branch data for the 33-bus test system

Branch number	From bus	To bus	*R*	*X*	*U*	*U*′
1	1	2	0.0922	0.0470	0.8000	0.1000
2	2	3	0.4930	0.2512	0.4000	0.0100
3	3	4	0.3661	0.1864	0.1000	0.0600
4	4	5	0.3811	0.1941	0.5000	0.0600
5	5	6	0.8190	0.7070	0.2000	0.0200
6	6	7	0.1872	0.6188	1.0000	0.0300
7	7	8	0.7115	0.2351	1.0000	0.0100
8	8	9	1.0299	0.7400	0.8000	0.0200
9	9	10	1.0440	0.7400	0.7000	0.0200
10	10	11	0.1967	0.0651	0.4000	0.0200
11	11	12	0.3744	0.1298	0.1000	0.0300
12	12	13	1.4680	1.1549	0.3000	0.0400
13	13	14	0.5416	0.7129	0.5000	0.0100
14	14	15	0.5909	0.5260	0.2000	0.0500
15	15	16	0.7462	0.5449	0.6000	0.0900
16	16	17	1.2889	1.7210	0.2000	0.0900
17	17	18	0.7320	0.5739	0.6000	0.1000
18	2	19	0.1640	0.1565	0.7000	0.1000
19	19	20	1.5042	1.3555	0.9000	0.0200
20	20	21	0.4095	0.4784	0.5000	0.0800
21	21	22	0.7089	0.9373	0.1000	0.0700
22	3	23	0.4512	0.3084	0.5000	0.0400
23	23	24	0.8980	0.7091	0.4000	0.0200
24	24	25	0.8959	0.7071	0.3000	0.0700
25	6	26	0.2031	0.1034	0.8000	0.0900
26	26	27	0.2842	0.1447	0.2000	0.0600
27	27	28	1.0589	0.9338	0.8000	0.0500
28	28	29	0.8043	0.7006	0.8000	0.0200
29	29	30	0.5074	0.2585	0.7000	0.0200
30	30	31	0.9745	0.9629	0.5000	0.0400
31	31	32	0.3105	0.3619	0.1000	0.0600
32	32	33	0.3411	0.5302	0.4000	0.0200

distribution system. From this table it is clear that the power loss value is decreased drastically with respect to Table 4. It means that DGs can play a powerful role in power loss decreasing in distribution systems. Also, the proposed algorithm could obtain better results with respect to PSO and GA algorithms which prove the ability of the proposed algorithm in finding the global optima once again.

6.1.2 Minimisation of operation cost: This subsection considers the operation cost of DGs in 33-node distribution system. The obtained result of the proposed algorithm is compared with those obtained by GA and PSO algorithms in Table 6. From this table, it is clear that the proposed algorithm converges to 159.6885$/kW which is the lowest operation cost in Table 6. From this table, it is clear that all DGs operate at their minimum values as the cost of generation of electricity by DGs is more expensive than the electricity cost of substation.

6.1.3 Optimisation of ENS: The reliability metrics such as ENS, which are important characteristics in power system operation, usually are ignored in DFR problem. Therefore the most important contribution of this paper is considering ENS objective besides other objectives including power operation cost of distributed generation and power loss. Tables 7 and 8 show the optimum values and related control variables for ENS objective for 33-node distribution system with and without considering distributed generation, respectively.

From these tables, it can be inferred that the proposed algorithm can converge to a better solution with respect to other algorithms, which proves the ability of the proposed algorithm for solving the complex DFR optimisation problem.

Table 3 Tie switch data related to the 33-bus test system

Tie switch number	From bus	To bus	*R*	*X*	*U*	*U*′
33.0000	8.0000	21.0000	2.0000	2.0000	0.4000	0.0400
34.0000	9.0000	15.0000	2.0000	2.0000	0.6000	0.0500
35.0000	12.0000	22.0000	2.0000	2.0000	0.8000	0.0100
36.0000	18.0000	33.0000	0.5000	0.5000	0.3000	0.0200
37.0000	25.0000	29.0000	0.5000	0.5000	1.0000	0.0600

Table 4 Loss without DG

Algorithms	Control vector of the best solution					Power loss, kW				CPU time, s
	Sw1	Sw2	Sw3	Sw4	Sw5	Best solution	mean	worst solution	Standard deviation	
Multi-objective HBMO [45]	37	32	14	9	7	139.53	—	—	—	~8
Optimum [46]	37	32	14	9	7	139.53	—	—	—	647.03
Goswami and Basu [47]	37	32	14	9	7	139.53	—	—	—	0.87
McDermott *et al.* [26]	37	32	14	9	7	139.53	—	—	—	1.99
Shirmohammadi and Hong [48]	37	32	14	10	7	140.26	—	—	—	0.14
Vanderson Gomes *et al.* [46]	37	32	14	9	7	139.53	—	—	—	1.66
DPSO–HBMO (Niknam [25])	37	32	14	9	7	139.53	—	—	—	~8
DPSO (Niknam [25])	37	32	14	9	7	139.53	—	—	—	~8
PSO–ACO (Niknam [24])	37	32	14	9	7	139.53	—	—	—	~8
DPSO–ACO (Niknam [49])	37	32	14	9	7	139.53	—	—	—	~8
HBMO (Niknam *et al.* [3])	37	32	14	9	7	139.53	—	—	—	~8
GA	37	34	30	9	7	140.282	141.693	143.94	1.431	27.43
PSO	37	30	14	19	7	139.982	140.236	141.921	0.605	18.32
EGSA	**37**	**32**	**14**	**9**	**7**	**139.53**	**139.53**	**139.53**	**0**	**6.73**

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Table 5 Loss with DG

Algorithms	Control vector of the best solution									Power loss, kW			
	Sw1	Sw2	Sw3	Sw4	Sw5	Bus#6	Bus#12	Bus#16	Bus#31	Best solution	Mean	Worst solution	Standard deviation
GA	37	34	30	9	7	500	300	300	500	70.948	73.410	79.033	2.540
PSO	37	30	14	19	7	500	300	300	500	68.421	69.811	70.948	1.290
EGSA	37	30	14	9	7	500	300	300	500	68.421	68.548	70.948	0.565

Table 6 Operation cost with DG

Algorithm	Control vector of the best solution									Operation cost, $/kW			
	Sw1	Sw2	Sw3	Sw4	Sw5	Bus#6	Bus#12	Bus#16	Bus#31	Best solution	Mean	Worst solution	Standard deviation
GA	37	7	35	14	31	500	500	500	500	159.8205	159.9062	160.0363	0.0744
PSO	7	9	32	14	37	500	499.4951	500	499.8460	159.7550	159.7913	159.8205	0.0222
EGSA	31	9	28	14	7	500	500	500	500	159.6885	159.7164	159.7285	0.0193

Table 7 ENS without DG

Algorithm	Control vector of the best solution					ENS, kWh/yr			
	Sw1	Sw2	Sw3	Sw4	Sw5	Best solution	Mean	Worst solution	Standard deviation
GA	37.000	34.000	30.000	9.000	7.000	53 798.200	54 248.000	54 773.802	409.173
PSO	37.000	30.000	14.000	19.000	7.000	53 299.338	53 399.000	53 798.200	210.308
EGSA	19.000	34.000	35.000	17.000	37.000	53 299.338	53 299.338	53 299.338	0.000

Table 8 ENS with DG

Algorithm	Control vector of the best solution									ENS, kWh/yr			
	Sw1	Sw2	Sw3	Sw4	Sw5	Bus#6	Bus#12	Bus#16	Bus#31	Best solution	Mean	Worst solution	Standard deviation
GA	37	35	34	19	9	500	300	300	500	29 844.18	30 174.92	30 806.83	307.36
PSO	37	35	19	15	9	500	300	300	500	29 724.28	29 807.65	29 844.18	44.41
EGSA	37	35	19	9	8	500	300	300	500	29 657.70	29 661.03	29 760.05	14.89

6.1.4 Optimisation of different objective functions simultaneously: Since the main purpose of this paper is to solve the MOP, this goal is scrutinised by explaining the tables which show the multi-objective control variables and their related objective function values. Also, the Pareto fronts for different objective functions are depicted in this section in order to prove the ability of the proposed algorithm in solving complex MOPs. In this regard, Table 9 shows the best compromise solution accompanied with the related control variables for different objective functions which are optimised simultaneously. It is worthwhile to note that the best compromise solutions are obtained by applying (32). Also, the system operator can change the importance factor of different objective functions according to his/her decision. In this regard, if one objective is more important than others, the system operator can cope with this by increasing the related importance factor of the considered objective function. Therefore this process helps the system operator have extensive choices.

Table 9 Best compromise solution accompanies the related control variables for multi-objective optimisation problem

Algorithm	Open switch					DG output				Objective functions		
	Sw1	Sw2	Sw3	Sw4	Sw5	Bus#6	Bus#12	Bus#16	Bus#31	Cost, $	ENS, kWh/yr	Loss, kW
GA	33	34	35	32	28	493.8545	499.9354	499.9144	499.98	157.7501	26859.74	102.1719
PSO	33	34	8	32	37	496.3639	451.9589	427.2528	419.6242	157.1756	28815.42	99.67945
EGSA	7	34	8	32	37	500	400.6408	500	476.7485	157.1104	26851.91	91.39688

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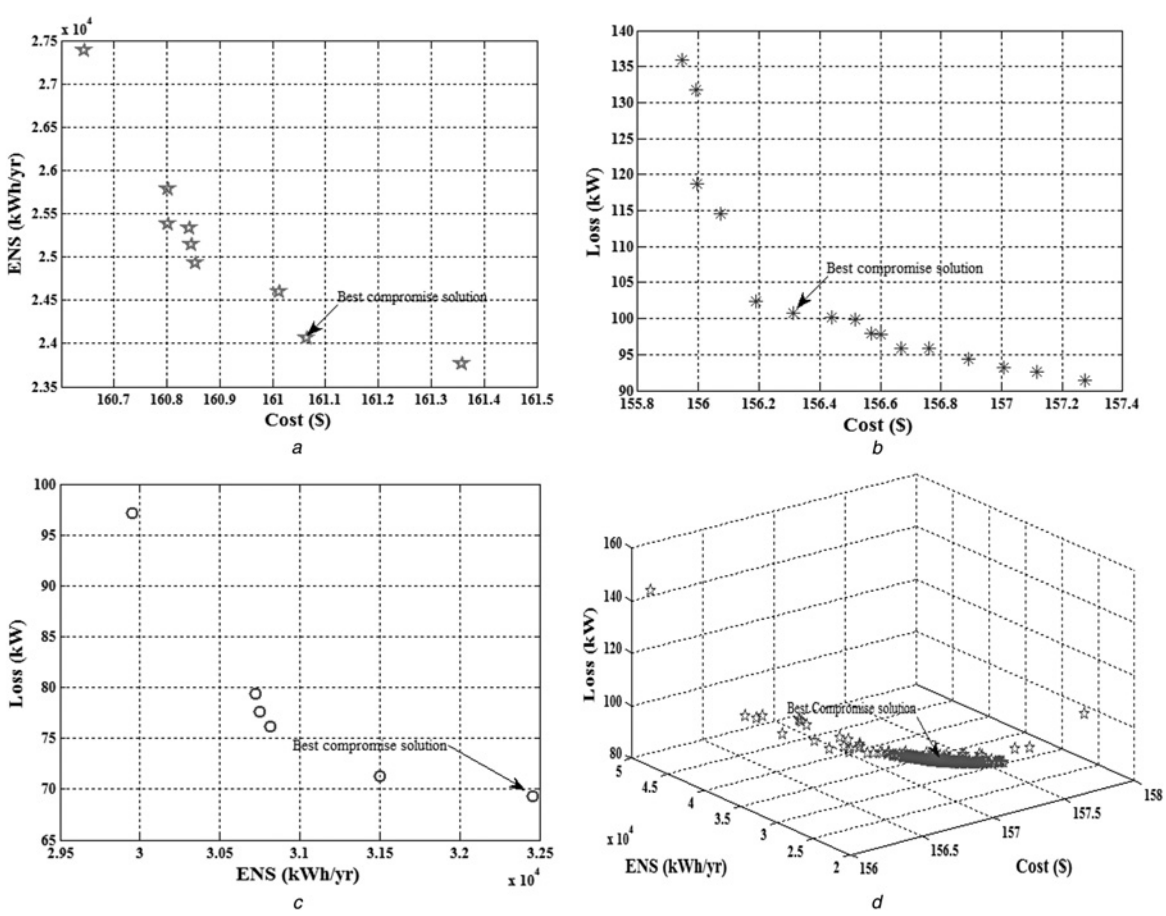

Fig. 3 *Pareto front for different objective functions related to 33-node test system*

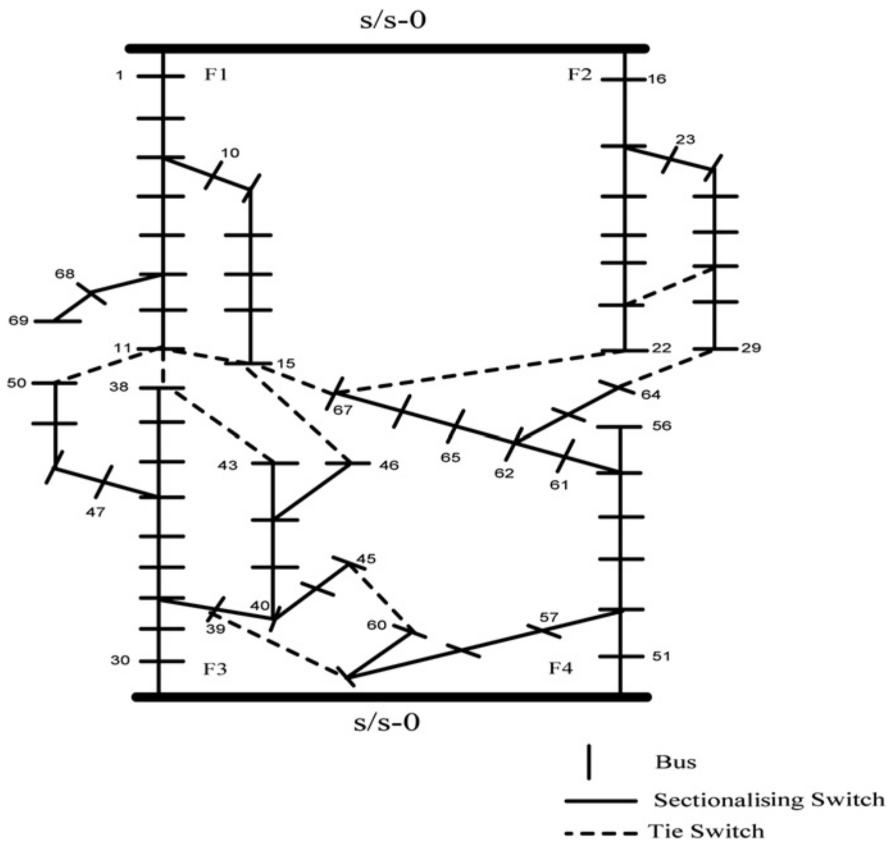

Fig. 4 *One line diagram of 70-node test system*

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Table 10 Branch data for the 70-bus test system

Branch number	From bus	To bus	*R*	*X*	*U*	*U'*
1	1	2	1.00E-06	1.00E-06	0.8	0.1
2	2	3	1.097	1.074	0.4	0.1
3	3	4	1.463	1.432	0.1	0.06
4	4	5	0.731	0.716	0.5	0.06
5	5	6	0.366	0.358	0.2	0.02
6	6	7	1.828	1.79	1	0.03
7	7	8	1.097	1.074	1	0.1
8	8	9	0.731	0.716	0.80	0.02
9	9	10	0.731	0.716	0.70	0.02
10	5	11	1.08	0.734	0.4	0.02
11	11	12	1.62	1.101	0.1	0.03
12	12	13	1.08	0.734	0.3	0.04
13	13	14	1.35	0.917	0.5	0.01
14	14	15	0.81	0.55	0.2	0.05
15	15	16	0.681	0. 544	0.6	0.09
16	8	69	1.08	0.734	0.2	0.09
17	69	70	1.62	1.101	0.6	0.1
18	2	17	1.097	1.074	0.7	0.1
19	17	18	0.366	0.358	0.9	0.02
20	18	19	1.463	1.432	0.5	0.08
21	19	20	0.914	0.895	0.1	0.07
22	20	21	0.804	0.787	0.5	0.04
23	21	22	1.133	1.11	0.4	0.02
24	22	23	0.475	0.465	0.3	0.07
25	18	24	2.214	1.505	0.8	0.09
26	24	25	1.62	1.101	0.2	0.06
27	25	26	1.08	0.734	0.8	0.05
28	26	27	0.54	0.367	0.8	0.02
29	27	28	0.54	0.367	0.7	0.02
30	28	29	1.08	0.734	0.5	0.04
31	29	30	1.08	0.734	0.1	0.06
32	2	31	0.366	0.358	0.5	0.04
33	31	32	0.731	0.716	0.4	0.02
34	32	33	0.731	0.716	0.3	0.07
35	33	34	0.804	0.787	0.8	0.09
36	34	35	1.17	1.145	0.2	0.06
37	35	36	0.768	0.752	0.8	0.05
38	36	37	0.731	0.716	0.4	0.02
39	37	38	1.097	1.074	0.4	0.04
40	38	39	1.463	1.432	0.6	0.05
41	33	40	1.08	0.734	0.8	0.01
42	40	41	0.54	0.367	0.3	0.02
43	41	42	1.08	0.734	1	0.06
44	42	43	1.836	1.248	0.8	0. 1
45	43	44	1.296	0.881	0.4	0.01
46	41	45	1.188	0.807	0.1	0.06
47	45	46	0.54	0.367	0.5	0.06
48	43	47	1.08	0.734	0.2	0.02
49	36	48	0.54	0.367	1	0.03
50	48	49	1.08	0.734	1	0.01
51	49	50	1.08	0.734	0.8	0.02
52	50	51	1.08	0.734	0.7	0.02
53	2	52	0.366	0.358	0.4	0.02
54	52	53	1.463	1.432	0.1	0.03
55	53	54	1.463	1.432	0.3	0.04
56	54	55	0.914	0.895	0.5	0.01
57	55	56	1.097	1.074	0.2	0.05
58	56	57	1.097	1.074	0.6	0.09
59	53	58	0.27	0.183	0.2	0.09
60	58	59	0.27	0.183	0.6	0.1
61	59	60	0.81	0.55	0.7	0.1
62	60	61	1.296	0.881	0.9	0.02
63	56	62	1.188	0.807	0.5	0.08
64	62	63	1.188	0.807	0.1	0.07
65	63	64	0.81	0.55	0.5	0.04
66	64	65	1.62	1.101	0.4	0.02
67	63	66	1.08	0.734	0.3	0.07
68	66	67	0.54	0.367	0.8	0.09
69	67	68	1.08	0.734	0.2	0.06

Table 11 Tie switch data related to the 70-bus test system

Tie number	From bus	To bus	*R*	*X*	*U*	*U'*
70	10	51	0.908	0.726	0.8	0.05
71	10	39	0.381	0.244	0.8	0.02
72	16	47	0.681	0.544	0.7	0.02
73	23	68	0.254	0.203	0.5	0.04
74	30	65	0.254	0.203	0.1	0.06
75	46	61	0.254	0.203	0.4	0.02
76	44	39	0.454	0.363	0.4	0.04
77	40	60	0.454	0.363	0.6	0.05
78	22	28	0.454	0.363	0.8	0.01
79	16	10	0.681	0.544	0.3	0.02
80	68	16	0.454	0.363	1	0.06

All two-dimensional Pareto fronts for different objective functions are shown in Figs. 3*a* up to 2*d*. Fig. 3*a* shows the Pareto-optimal front for operation cost and ENS objective functions. The best operation cost and ENS values in obtained Pareto-optimal solutions are very close to their optimised values, although these objectives are optimised individually, yet the truth of the above mentioned statement is clear in all Pareto fronts. All the above features are provided by applying the SALS, because this method increases the search ability of the original GSA.

6.2 Case 2: 70-node test system

The 70-node test system which is an 11 kV radial distribution system has two substations, four feeders, 70 nodes and 78 branches (including tie branches). This test system consists of seven DGs at buses #9, #15, #22, #28, #39, #43 and #63. It should be noted that all DGs have a 500 MW capacity. Substation cost is 0.043$/kWh and DGs costs are 0.043, 0.04, 0.04, 0.043, 0.043, 0.04 and 0.043$/kWh for DG6, DG12, DG16 and DG31, respectively. Also, switching cost is 0.041$ for each switching.

The one line diagram of this test system is depicted in Fig. 4 and the system data including node powers can be found in [24]. Tables 10 and 11 show the essential data for 70-bus test system.

6.2.1 Minimisation of power loss: Table 12 illustrates a comparison of the proposed algorithm and other methods in terms of computational efficiency and performance. Before reconfiguration, the initial loss is 227.53 kW and after reconfiguration this value has decreased and reaches to 202.149 kW which is the lowest value in Table 12. It is observed that the obtained result by the proposed method is better than other methods.

In order to depict the effect of DG on power loss value, the objective function values considering the effect of DGs are extracted from 50 trial runs. Through the evolutionary process of the proposed methods, their best solution, mean, worst solution and standard deviation are (87.87599165, 85.0427088 and 82.49632211), (90.4201, 86.625 and 83.7866), (98.75196748, 87.79260179 and 84.99004509) and (2.5896, 0.9267 and 0.8168) kW. It is obvious that the proposed algorithm can reach a better solution with respect to other algorithms and it proves the supremacy of the proposed algorithm over other algorithms.

One important point is obtaining the better result with respect to other algorithms which shows that this algorithm can search in the complex optimisation problems' search space very well. Another important point is that the power

Table 12 Loss without DG

Algorithm	Control vector of the best solution	Loss, kW				
	Open switches	Best solution	Mean	Worst solution	Standard deviation	Saving in power, %
Initial network [43]	S22–67, S15–67, S21–27, S9–50, S29–64, S9–38, S45–60, S38–43, S9–15, S39–59, S15–46	227.53	—	—	—	—
Das [5]	S65–66, S15–67, S26–27, S49–50, S29–64, S9–38, S44–45, S37–38, S14–15, S39–59, S15–46	205.32	—	—	—	9.76
Niknam [49]	S65–66, S15–67, S26–27, S49–50, S29–64, S9–38, S44–45, S37–38, S14–15, S39–59, S15–46	205.32	—	—	—	9.76
Niknam [2]	S65–66, S15–67, S26–27, S49–50, S29–64, S9–38, S44–45, S37–38, S14–15, S39–59, S15–46	205.32	—	—	—	9.76
SAPSO–MSFLA [43]	S62–65, S15–67, S21–27, S49–50, S28–29, S9–38, S44–45, S38–43, S9–15, S39–59, S15–46	202.18	—	—	—	11.14
GA	S49–50, S9–38, S15–46, S65–66, S29–64, S44–45, S37–38, S39–59, S26–27, S9–15, S15–67	204.591	204.744	205.101	0.247	—
PSO	S49–50, S9–38, S15–46, S62–65, S28–29, S40–44, S38–43, S39–59, S21–27, S9–15, S15–67	202.219	203.033	204.591	1.031	—
EGSA	**S49–50, S9–38, S15–46, S62–65, S28–29, S40–44, S37–38, S39–59, S21–27, S9–15, S15–67**	**202.149**	**202.149**	**202.149**	**0**	—

loss value has decreased by about 59% according to Table 12 which shows the effect of DGs clearly.

6.2.2 Minimisation of operation cost: The operation cost of DGs is minimised in this subsection, the best, mean and worst solutions for corresponding GA, PSO and the proposed EGSA are (\$191.8618, \$191.9479 and \$192.1707), (\$191.7374, \$191.793 and \$191.8366) and (\$191.4934, \$191.6276 and \$191.7349). It is clear that the proposed algorithm can achieve better result with respect to GA and PSO algorithms which are tangible to the superiority of the proposed algorithm.

6.2.3 Optimisation of ENS: Table 13 shows the control variable and objective function value for 70-node distribution system without DGs. Meanwhile, the best, mean, worst and standard deviation of the ENS value in the case of considering DGs (for GA, PSO and EGSA) are (32933.60997, 31933.93297 and 30128.23197), (33625, 32439 and 30825), (34788.79797, 32972.47497 and 31329.48697) and (561.9779, 374.9366 and 333.2094) kWh/yr, respectively. From Table 13 and these results, it is clear that the proposed algorithm can obtain better result with respect to other algorithms. Also, from comparing these results, it is comprehensible that the ENS value has decreased by about 80% by considering DGs. The important point is that considering DGs in distribution system will improve system reliability, in other words, the probability of not supplying some loads will be decreased. According to the standard deviation values in Table 13, it is obvious that the proposed algorithm can obtain the best solution in each run, since the standard deviation of results for 50 runs is zero.

6.2.4 Optimisation of different objective functions simultaneously: This subsection solves the proposed problem as MOP. The best compromise solution between all Pareto-optimal solutions for different objective functions are tabulated in Tables 14 and 15.

Owning some choices that satisfied our purpose could help to select one economical and practical choice among all solutions. In this regard, Pareto-optimal solution which can obtain a squad of results is a very significant and acceptable method for solving the MOP. That is why the Pareto-optimal solution method is applied to solve the proposed MOP. Furthermore, all Pareto-optimal fronts for different objective functions are shown in Fig. 5. From this figure, it is clear that the best obtained value for each objective function in all Pareto fronts is very close to its optimised value, although this objective is optimised individually. Such important optimal solutions could not have been discovered without the proposed multi-objective optimisation method.

The SALS method in the EGSA approach appears to work well for solving the MOPs. The results confirm that the multi-objective EGSA method is an impressive tool for solving the single-objective and MOPs.

The convergence plots of GA, PSO and EGSA are shown in Fig. 6 for the power loss objective function. This figure demonstrates that the proposed algorithm converges to the

Table 13 ENS without DG

Algorithm	Control vector of the best solution											ENS, kWh/yr			
	Sw1	Sw2	Sw3	Sw4	Sw5	Sw6	Sw7	Sw8	Sw9	Sw10	Sw11	Best solution	Mean	Worst solution	Standard deviation
GA	49	8	72	68	65	62	40	41	78	10	80	151 220	151 640	152 532.2	445.6796
PSO	49	8	72	68	65	62	40	41	78	15	80	150 905.9	151 000	151 220	151.7189
EGSA	49	8	72	68	65	62	40	41	78	15	80	150 905.9	150 905.9	150 905.9	0

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Table 14 Control variables related to optimisation of operation cost, ENS and loss simultaneously

Algorithm	Open switch											DG output						
	Sw1	Sw2	Sw3	Sw4	Sw5	Sw6	Sw7	Sw8	Sw9	Sw10	Sw11	Bus#9	Bus#15	Bus#22	Bus#28	Bus#39	Bus#43	Bus#63
GA	52	71	48	67	74	62	76	77	78	15	80	500	500	500	500	500	500	500
PSO	52	71	72	68	66	62	76	77	78	79	80	500	500	486.3486	500	500	500	500
EGSA	52	71	72	67	74	62	76	77	78	79	80	500	500	500	500	481.16	500	495.2803

Table 15 Objective function values related to optimisation of operation cost, ENS and loss simultaneously

Algorithm	Cost, \$	ENS, kWh/yr	Loss, kW
GA	191.5643	31 996.27	88.77354
PSO	191.7395	31 370.67	90.94191
EGSA	191.6511	31 048.1	88.88613

global optimal solution after 7 and 9 iterations for 33 and 70 nodes test systems while other algorithms converge to global solutions after more iterations. In other words, the presented method can obtain better results in less time with respect to other algorithms. This is a remarkable result, because the computation time is a vital issue in power system operation sector.

From the obtained results it is clearly perceivable that the proposed algorithm can solve complex optimisation problem with large search space without any restriction irrespective of their complexities. It can be perceived from the obtained results that the optimum active powers of all DGs are all in their own limits. Also, the practical constraints like being radial are satisfied. From Fig. 6, it is clear that the proposed algorithm could obtain better results with respect to the PSO and GA algorithms. In other words, the proposed algorithm could converge to the global optima, whereas other algorithms could obtain local optima near the global one.

6.3 Further researches

The authors believe that the proposed approach, as a DFR algorithm, is comprehensive and also generic enough to be applied in real and practical applications as well as in cases where there are different types of DG technologies. The reason lies in the fact that by considering the effective objectives, the optimisation basis has been found as practical as possible. Moreover, the suggested EGSA optimisation technique has been proved to be capable of handling large-scale optimisation. As a result, any concern on the scalability of the proposed approach would be obviated.

The proposed method in this paper is general enough to be applied for various technologies of DGs (renewable or the other ones) with a little modification. For example, a wind turbine and photovoltaic unit can be accepted as the DG technologies. Hence, the only part that should be modified in the paper is modelling its output and considering its little operation cost in comparison with the microturbines and fuel cells. Hence, it is worthwhile to note that research work is underway in order to incorporate load uncertainty considering inter-temporal dependencies of load forecast errors (e.g. by time series techniques), separately model load forecast error of each bus in the stochastic multi-objective framework, and to integrate wind-based and photovoltaic-based DGs and their intermittency. The future work would make it possible to run the proposed method with these modifications and obtain the Pareto results of the DFR problem again. The proposed method can also open a window for comparing various DG technologies in the characteristics of final optimal results and can give the decisionmaker a more practical viewpoint to understand the differences between these technologies and their effects on the technical and financial concerns.

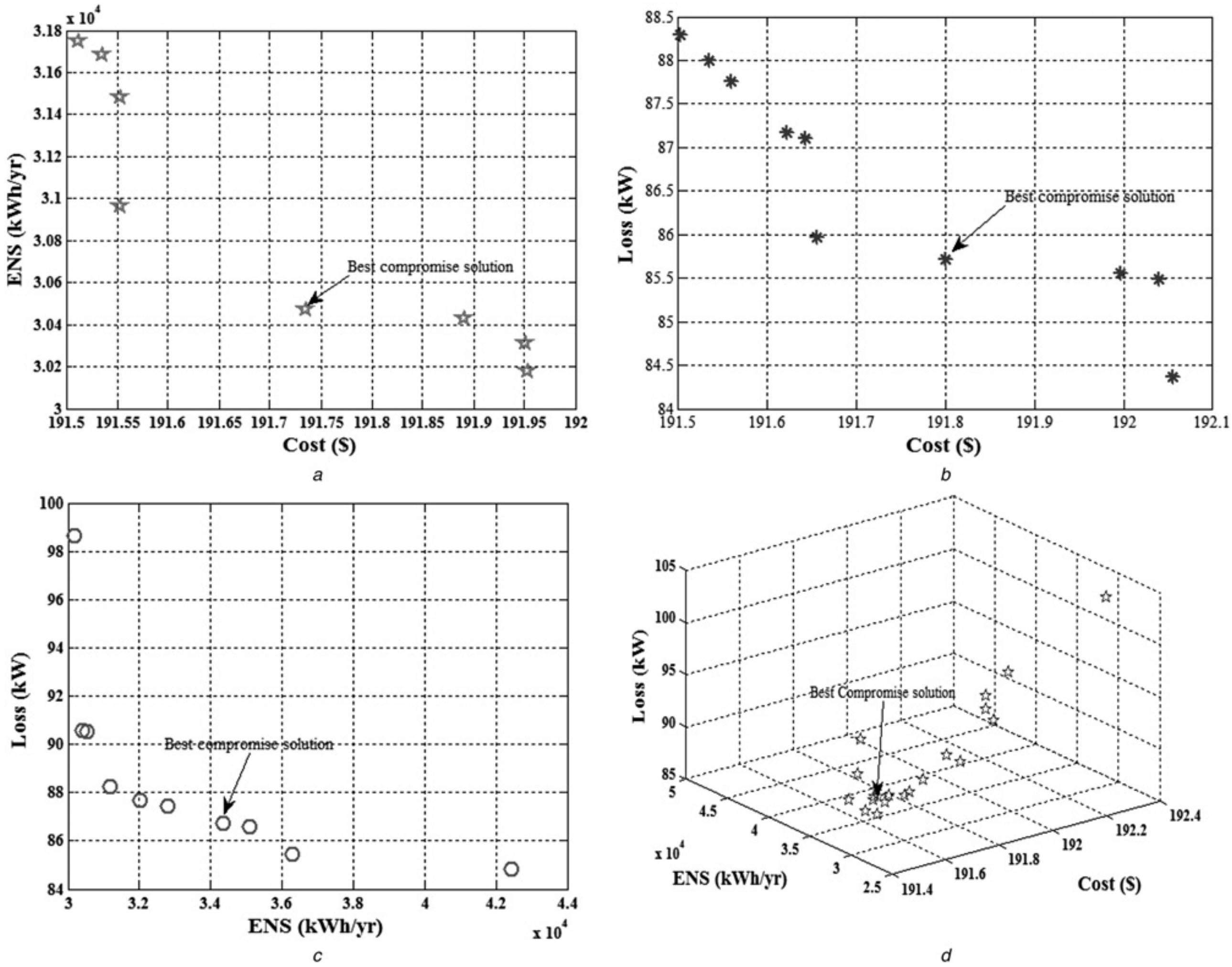

Fig. 5 *Pareto front for different objective functions related to 70-node test system*

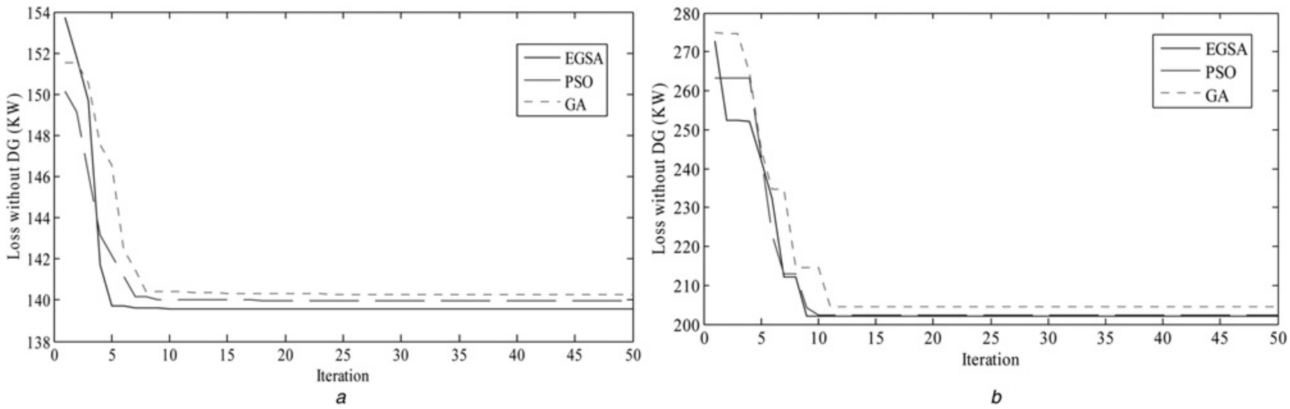

Fig. 6 *Convergence plot for loss objective function related to 33- and 70-node test systems*

7 Conclusions

A new powerful evolutionary algorithm has been presented in this paper for the DFR. The proposed DFR problem consists of minimising the power loss, operation cost of distributed generation and ENS. The considered constraints including the radial structure of the network, line thermal limits, transformer capacities and bus voltages are within their admissible ranges in this approach. The algorithm has been successfully tested in two distribution networks including 33 and 70 nodes test systems. According to the obtained results, the presented algorithm achieves a much better optimal solution in comparison with other algorithms in the literatures, in a word, the obtained results have proved the superiority of the proposed method with respect to other algorithms.

These points also can be highlighted:

- The presented optimisation algorithm has low computational time, allowing its application in the context of large scale distribution systems.
- The considered ENS objective function accompanied by other objectives paves the way to have a reliable and economic condition in distributed systems.

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