Optimal System Reconfiguration and Placement of Distributed Generations Using Search Group Algorithm

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Abstract: Due to inherent resistance available in power distribution systems, the power loss in power systems cannot be denied. However, for an efficient and economical operation, minimal power loss is highly desired. For this purpose, this paper suggests a search group algorithm (SGA) to optimize both the system configuration and allocation of distributed generation (DG) in the distribution power systems. The suggested SGA method might be practiced to determine the optimal solution for system configuration, position and capacity of DGs to reduce power loss. The suggested SGA method resulted in optimal results for these 33- and 69-bus systems which have been compared with the results of available algorithms. For all case studies, power losses obtained by SGA were better than other methods available in previous studies. Hence, the effectiveness of the SGA has been proved in defining DGs allocation and reconfiguration in distribution power systems.

Keywords: Search group algorithm; distribution power system; reconfiguration; distributed generations

1. Introduction

There is substantial power loss due to deficiencies in the power distribution systems. Due to the enormous amount of power loss, the system experiences both inefficient performance and poor voltage profile. In order to improve both efficiency and voltage, system reconfiguration is highly desired. Moreover, distribution generations (DG), which are integrated locally in the form of wind turbines, solar photovoltaic (PV), diesel generators, etc., are also of assistance in reducing power loss, enhancing the voltage profile, and improving the system capacity. Nevertheless, there are certain limitations of both system reconfiguration and DGs allocation as these might lead to ineffective and undesired network performance. To avoid these limitations, for the reconfiguration option, the radial topology of the feeders in the distribution system must be maintained. While for the DG option, the position and size of DG units should be determined such that the minimum power loss satisfies operational constraints, including power balance, bus voltage, and line capacity [1].

To minimize the power losses, the option of distribution system reconfiguration has been studied by various researchers. For this purpose, many evolutionary algorithms have been applied such as particle swarm optimization (PSO) [2], improved harmony search algorithm [3], Genetic algorithm (GA) [4], biased random key GA (BRKGA) [5], harmony search algorithm (HSA) [6], plant growth simulation algorithm (PGSA) [7], fireworks algorithm (FWA) [8], GA with varying population (GAVP) [9], cuckoo search algorithm (CSA) [10], and bacterial foraging optimization (BFO) [11]. For enhancement of the distribution system, recently several

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research works have proposed to use a combination of system reconfiguration and allocation of DGs. For this purpose, an optimization method was proposed in [12]. This method is capable to search out the optimum configuration and optimal placement of DGs in the distribution system. With the engagement of this optimization tool, a reduction in power loss was observed. Loss sensitivity factor (LSF) is engaged in this method, for the optimal positions of DG units. Next, the HSA technique is employed to search for the optimal system configuration and optimal size of DG units. To validate the HSA implementation, 33 bus and 69 bus networks with several load conditions were engaged, which revealed in better efficiency of HSA than both GA and refined GA. In another study available in the literature [13], system reconfiguration together with DG placement has been studied via FWA for 33 bus and 69 bus networks. In this study, the objectives were to optimize the power loss and voltage profile. This can be understood as enhanced voltage profile and reduced power loss. Here, The DG positions were defined using voltage stability index (VSI) and LSF. An improved equilibrium optimization algorithm (IEOA) [14] was suggested to deal with optimal integration of reconfiguration with DGs allocation. For validation purposes, the performance of IEOA was validated using 33-bus and 69-bus networks for three load conditions and its superiority was confirmed. A sine–cosine algorithm (SCA) was combined with levy flights by Raut et al. [15] for reconfiguration with DGs distribution. It was a multi-objective optimization problem and here the objectives were power loss and VSI. A simultaneous and optimal reconfiguration and DGs outputs method were suggested using firefly (FF) [16]. In another available study, the engagement of a heuristic-based algorithm known as uniform voltage distribution-based constructive reconfiguration algorithm (UVDA) resulted in better network reconfiguration associated with the DGs allocation [17]. The grey wolf optimizer has been combined with PSO for handling reconfiguration problem while considering DG [18]. An improved CSA technique was applied to handle the issues of reconfiguration and DG integration for reduced power loss and voltage stability index [19]. In order to minimize the infeasible configurations of the system, the graph theory was proposed. The radial topology constraint can also be checked with the graph theory. Adaptive shuffled frogs leaping algorithm (ASFLA) was employed to deal with the integration of system reconfiguration and DGs allocation [20]. The test systems including 33 bus and 69 bus with several circumstances showed that the ASFLA improved the past results by the FWA method in the literature [2]. The gravitational search algorithm (GSA) and general algebraic modeling system (GAMS) were combined to deal with issues of optimal DGs allocation and system reconfiguration [21]. Moreover, this combination was used to study both the load and uncertainties of renewable-based DGs. To decrease power loss, a hybrid fuzzy-Bees method was applied via reconfiguration and DG allocation [22]. This method is also capable of improving voltage profile and balancing the feeder load in the distribution system. In another study, particle artificial bee colony algorithm (PABC) combined with HSA was also employed to optimize system configuration along with optimal allocation of DGs and shunt capacitors for voltage profile improvement, power loss reduction, and line loading reduction [23]. Some other recently developed evolutionary algorithms have been applied for optimal reconfiguration and DG allocation, such as neural network algorithm (NNA) [24], stochastic fractal search (SFS) [25], and wild geese algorithm (WGA) [26]. Based on the literature review, only few studies are available regarding simultaneous DG placement and optimal system reconfiguration. The simultaneous approach can lead to maximum loss reduction. However, the solution of combined optimization problem is complicated due to availability of various variables and constraints of different types and there is no best optimization algorithm to solve this problem.

Search group algorithm (SGA) was proposed by Goncalves et al. [27], which is a robust optimization method. The main idea is that in the first iterations of the optimization process the SGA tries to find promising regions on the domain (exploration), and as the iterations pass by, the SGA refines the best design in each of these promising regions (exploitation). In particular, SGA has the advantage of generating a good balance between exploration and exploitation, which offers a powerful search capability to find the optimal solution. SGA has proven its superior performance to particle swarm algorithm (PSO), genetic algorithm (GA), firefly algorithm (FA), and harmony search (HS) for topology optimization problems [27].

In this work, we propose a search group algorithm (SGA), a well-established optimization algorithm for the optimal reconfiguration and DGs allocations in the distribution system. Both exploration and exploitation of the design domain are balanced in SGA which makes it more distinctive from other methods. SGA has successfully been implemented for several engineering optimization problems [27]–[32]. For power systems, SGA provides the best performance in power systems research, for which reason, it is engaged in power system optimization in this study. For distribution systems, the objective is DG allocation, optimal reconfiguration, and reduced power loss. The SGA optimized the position and capacity of DGs and reconfigured the system simultaneously. IEEE 33-bus and 69-bus distribution systems were investigated.

The main contributions of this paper are given as follows:

1. A new SGA was proposed to solve the optimal reconfiguration and DGs allocations in the distribution system.
2. The proposed SGA was validated with 33-bus and 69-bus distribution systems.
3. System power loss is significantly reduced after the optimal reconfiguration and DGs allocations using SGA. In detail, SGA obtained power losses of 72.30% and 84.03% for 33-bus and 69-bus systems.
4. The optimal results were found by the proposed SGA and were compared with the literature results obtained through other methods. It was identified that the proposed SGA demonstrated the best optimization results.

The remainder of the paper is structured as follows, problem formulation regarding optimal reconfiguration and DGs allocation is discussed in section 2. The next section describes the concept of the proposed SGA. Section 4 outlines how the SGA can be applied to the considered problem. Section 5 discusses the simulation results and comparisons of results with published results. Lastly, the conclusion of the study is provided in section 6.

2. Problem formulation

The purpose of DG allocation and optimal reconfiguration is to minimize power loss (P_L). It can be done via the optimal setting of opened switches, and DG units sizes and positions. The optimization problem is solved considering the operational constraints of a radial distribution system. Therefore, the optimal reconfiguration and DGs allocations problem can be expressed as follows [33]:

$$OF = \text{Min}(P_L) = \text{Min}\left(\sum_{k=1}^{N_L} R_k I_k^2\right) \tag{1}$$

where R_k denotes the resistance of k^{th} branch, I_k signifies the current passing through that branch, whereas N_L represents the number of branches in a distribution system.

The operational constraints for the above-mentioned optimization problem lie in power balance, voltage, thermal, DG generation and penetration, and radial configuration. The details of the mathematical representation of each constraint are provided below:

(i) *Real and reactive power balance:* The power of a distribution system must be conserved both for real and reactive powers as follows:

$$P_{SS} + \sum_{i=1}^{N_{DG}} P_{DG,i} = \sum_{j=1}^{N_B} P_{D,j} + \sum_{k=1}^{N_L} P_{L,k} \tag{2}$$

$$Q_{SS} + \sum_{i=1}^{N_{DG}} Q_{DG,i} = \sum_{j=1}^{N_B} Q_{D,j} + \sum_{k=1}^{N_L} Q_{L,k} \tag{3}$$

where P_{SS} and Q_{SS} refer to active and reactive power outputs of slack bus, respectively; $P_{DG,i}$ and $Q_{DG,i}$ denote active and reactive power outputs of i^{th} DG unit, respectively; N_{DG} reflects the total number of DG units to be connected; $P_{D,j}$ and $Q_{D,j}$ signify active and reactive power demands at

j^{th} bus, respectively; N_B represents the total number of buses; while $P_{L,k}$ and $Q_{L,k}$ depict active and reactive power losses in k^{th} branch, respectively.

(ii) *Voltage constraints:* At the boundaries, the amplitude of bus voltage amplitude restricts as:

$$V_{\min,i} \le V_i \le V_{\max,i}; \quad i = 1,...,N_B \tag{4}$$

where $V_{min,i}$ and $V_{max,i}$ denote voltage limits at the i^{th} bus.

(iii) *Thermal constraints:* The flowing current follows the given condition:

$$|I_k| \le |I_{\max,k}|; \quad k = 1,...,N_L \tag{5}$$

where $I_{max,k}$ indicates the permissible maximum flow of current through k^{th} branch.

(iv) *DG generation constraints:* There are certain minimum and maximum limitations on the power, which restrict the power output of DG units and can be written as:

$$P_{DG\min,i} \le P_{DG,i} \le P_{DG\max,i}; \quad i = 1,...,N_{DG} \tag{6}$$

where $P_{DG\min,i}$ and $P_{DG\max,i}$ denote the limited sizes of i^{th} DG.

(vi) *DG penetration constraints*: The DG units level penetration restrictions can be written as follows [13]:

$$0.1 \times \sum_{j=2}^{N_B} P_{D,j} \le \sum_{i=1}^{N_{DG}} P_{DG,i} \le 0.6 \times \sum_{j=2}^{N_B} P_{D,j} \tag{7}$$

(vii) *Radial configuration constraint*: The radial topology must be ensured for the distribution network and all loads are served, which can be described as follows [2], [34]:

$$\det(A) = \begin{cases} 1 \text{ or } -1 & \text{(radial system)} \\ 0 & \text{(not radial)} \end{cases} \tag{8}$$

where A is a branch-bus incidence matrix in a distribution system. A_{ij} is set to 1 or −1 if the ith branch connected from/to the jth bus, otherwise A_{ij} is set to 0.

3. Search group algorithm

SGA is a metaheuristic optimization algorithm and its description is available in the literature [27]. In order to determine optimal solutions, the balance between design domain exploration and exploitation is maintained via the SGA. In this scheme, initially the promising regions of the domain are searched out during initial optimization iterations and this process is named exploration. In the next iterations using these promising regions, the best design is identified in this scheme, which is called exploitation. This procedure is controlled by the perturbation constant (α). Additionally, new solutions are created with the aid of a mutation operator and these solutions are entirely different from the solutions obtained from the current search group. The search group helps to create new individual solutions, and this search group contains only a few members of the population. The details of each SGA step are described below in detail.
First, from the search domain, the initial population P is randomly created:

$$P = \begin{bmatrix} x_1^1 & x_2^1 & \cdots & x_N^1 \\ x_1^2 & x_2^2 & \cdots & x_N^2 \\ \vdots & \vdots & \vdots & \vdots \\ x_1^{n_{pop}} & x_2^{n_{pop}} & \cdots & x_N^{n_{pop}} \end{bmatrix} \tag{9}$$

where n_{pop} is the population size and n is the number of decision variables.

Each individual cost is determined after the initialization of population P. It is estimated via the evaluation of the objective function. Next, by picking n_g individuals from population P, the search group R is formed. For this purpose, a standard tournament selection is used. The search group might be mutated for each iteration for the reason that it can enhance the global search capability of SGA. In this, n_{mut} individuals from R are replaced with new individuals which are created using the current search group statistics. Searching for individuals in expanded and new regions of the search domain is the prime purpose in the mutation stage. The advantage of this multi-region search is that the search is not limited to one position. Hence, each new individual is created as follows:

$$x_j^{mut} = E[\mathrm{R}_{:,j}] + t\varepsilon\sigma[\mathrm{R}_{:,j}]; \quad \text{for } j = 1,...,n, \tag{10}$$

where x_j^{mut} represents j^{th} variable of a mutated individual, E and σ denote mean value and standard deviation operators, ε signifies a convenient random variable, t controls the extent of new individual creation, $R_{:,j}$ indicates j^{th} column of search group matrix, and n is the size of individuals. The probability of any member replacement is a function of that member's rank in the current search group. For this replacement purpose, an inverse tournament selection is employed.

Once the search group is formed and mutated, all members of the search group using the perturbation can define the family as follows:

$$x_j^{new} = R_{ij} + \alpha; \quad \text{for } j = 1,...,n, \tag{11}$$

Here, α controls the perturbation size. In the optimization, for each iteration, a certain decrement in the perturbation characterizes the SGA. The updation of α for each iteration is carried out via:

$$\alpha^{k+1} = b\alpha^k \tag{12}$$

where k denotes the iteration and b is the SGA parameter. A minimum value for α^k is applied as follows: if $\alpha^k < \alpha_{\min}$, then $\alpha^k = \alpha_{\min}$.

The parameter α^k is the key in SGA for exploring the design domain. For initial SGA iterations, with tremendous high α^k, only a specific group member might create any individual. In the design domain, these created individuals are able to visit any point and can be considered as spread out. With more iterations in SGA, the value of α^k tends to decrease. As a result, the created individuals tend to stay close and are less spread. Another prominent feature of the SGA is that more individuals are created by the member which is better ranked in a search group. Hence, for each search group member, the enhancement in the quality of objective function leads to the creation of more individuals.

The selection of a new search group is the finishing step in the SGA scheme. In SGA, both global and local phases are covered. Exploration of the maximum design space is the prime purpose in initial SGA iterations. This stage is known as the global stage. Here, from each family, the best member is used to create a new search group. However, the selection scheme is modified for the local stage. Here, all families contribute towards the creation of a new search group via the best n_g individuals. Getting benefits from the best design region is the main goal of the local phase.

4. Implementation of SGA to the optimal reconfiguration and DG allocation problem

A. Initialization

The SGA technique is to be implemented for the optimization problem of reconfiguration and DGs allocation. In this method, the control variables are represented by the initial population individual members in vector form. In this case, the control variables are opened switches, and the position and size of DGs. Each individual of the initial population can be written as:

$$P_i = \left[SW_1,...,SW_{N_{SW}}, L_{DG,1},...,L_{DG,N_{DG}}, P_{DG,1},...,P_{DG,N_{DG}} \right] \tag{13}$$

where N_{SW} is the total number of opened switches.

In the initial population, each individual is randomly created within the bounds as follows:

$$SW_i = round\left[SW_{\min,i} + rand(0,1) \times (SW_{\max,i} - SW_{\min,i}) \right], \quad i = 1,...,N_{SW} \tag{14}$$

$$L_{DG,i} = round\left[L_{DG\min,i} + rand(0,1) \times (L_{DG\max,i} - L_{DG\min,i}) \right]; \quad i = 1,...,N_{DG} \tag{15}$$

$$P_{DG,i} = P_{DG\min,i} + rand(0,1) \times (P_{DG\max,i} - P_{DG\min,i}); \quad i = 1,..., N_{DG} \tag{16}$$

where $SW_{\min,i}$ is equal to 1 and $SW_{\max,i}$ is the length of the i^{th} fundamental loop vectors, which can be found in [35]; $L_{DG\min,j}$ is equal to 2, which shows that DGs can be placed on all buses except the slack bus, and $L_{DG\max,j}$ is equal to the total number of buses in a distribution system; $P_{DG\max,j}$ and $P_{DG\max,j}$ are selected as 0 and 3 MW, respectively.

B. Cost function value

For each individual, the cost function for the optimal reconfiguration and DGs allocation problem can be computed as follows:

$$F_T = \sum_{k=1}^{N_L} R_k I_k^2 + Constraint \tag{17}$$

In this study, the inequality constraints can be imposed to fitness function as quadratic penalty terms as below:

$$Constraint = K\sum_{i=1}^{N_B} (V_i - V_i^{\lim})^2 + K\sum_{k=1}^{N_L} (I_k - I_k^{\lim})^2 + K(PE_{DG} - PE_{DG}^{\lim})^2 \tag{18}$$

where K denotes penalty constants for inequality constraint violations. There are certain dependent variables in (18) namely bus voltages, currents, and DG penetration. In case the constraints of these dependent variables are violated, the following is used to adjust the variables towards the bound:

$$x' = \begin{cases} x_{\min} & \text{if } x < x_{\min} \\ x_{\max} & \text{if } x > x_{\max} \\ x & \text{otherwise} \end{cases} \tag{19}$$

where x is the dependent variable which could be either V_i, I_k, or PE_{DG} values; x' indicates the limitations of V_i, I_k, and PE_{DG}.

Furthermore, the Matpower 6.0 toolbox is engaged to solve the power flow analysis [36]. It can be of assistance to calculate the cost function value of each individual.

C. Overall procedure

The implementation steps for SGA with the purpose of optimal reconfiguration and DGs allocation is summarized in the following steps as follows:

1. Define power system data;
2. SGA initial parameters are set (n_{pop}, n_g, n_{mut}, α, and $k_{\max}$);
3. Initialize the population of individuals P_{ij} as in Section 4.1. Define cost function values for individuals P_{ij} in (17);
4. Select n_g best solutions from P to form the initial search group R^k. Set $k = 0$;
5. The main loop is started, $k = k + 1$;
6. Perform mutation phase for n_{mut} individuals using (10);
7. Create families (F_i) for each search group member using (11);
8. A new search group is carried out with the following sub-steps:
9. In global: the best solution from each family is used to develop search group R^{k+1};
10. For the local case: the n_g solutions from all families are used to create R^{k+1}.
11. Update α^{k+1} using (12);
12. Check termination condition, if $k > k_{\max}$, move to the next step; else go to the fourth step;
13. Solution found: $x^* = R_{1,:}$

Finally, the flowchart of the proposed method for optimal reconfiguration and DGs allocation is presented in Figure 1.

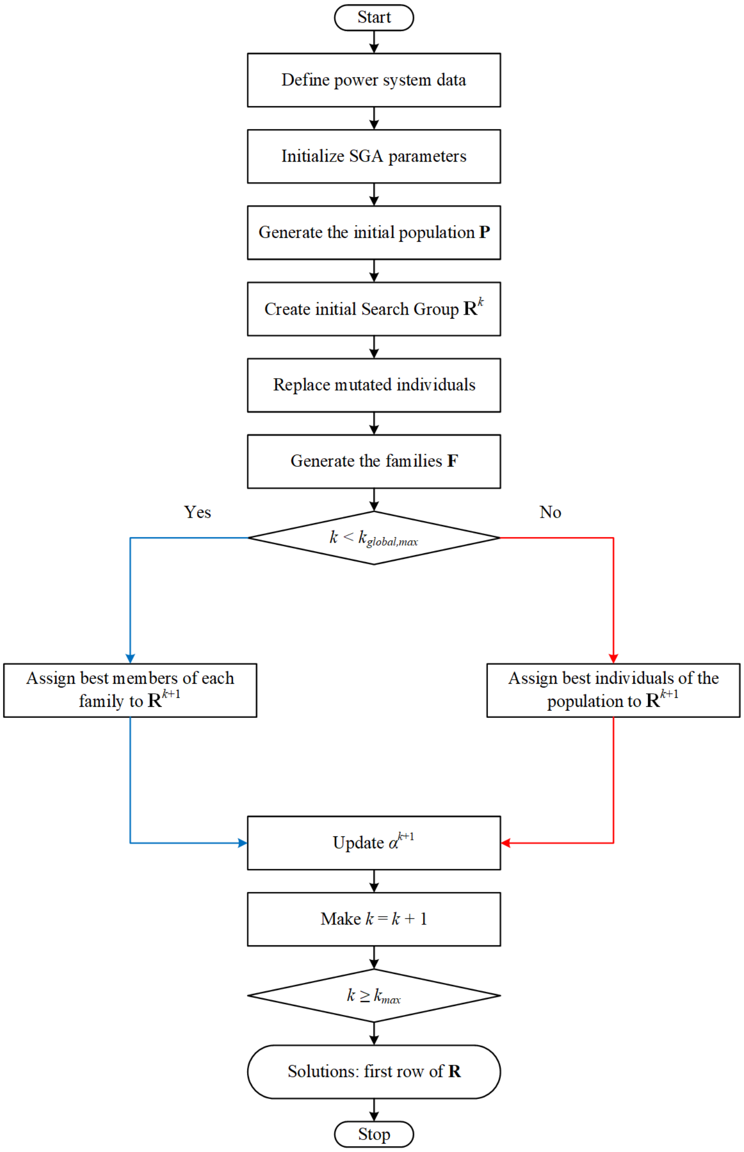

Figure 1. The flowchart for an implementation of SGA for optimal reconfiguration and DGs allocation

5. Simulation results

The SGA was implemented to solve the DG allocation and reconfiguration of 33-bus and 69-bus systems. For this study, the installation of three DGs is considered. The capacities of these DGs range from 0 to 3 MW. The proposed SGA is developed and implemented via MATLAB programming software. The values of initial parameters for SGA namely population size (n_{pop}), number of search group members (n_g), number of mutations (n_{mut}), perturbation size (α), and maximum number of iterations ($k_{\max}$) have been set to 30, 6, 2, 2, and 100 respectively. Moreover, SGA was run 30 trials independently for each test.

A. 33-bus system

There are 37 feeders, 32 sectionalize switches, and 5 initial tie switches for the considered 33-bus radial distribution system at a 12.66 kV rating. The initial tie switches for the considered system are {33-34-35-36-37}. This system exhibits 202.66 kW power loss and 0.9131 p.u the minimum bus voltage. The system data is obtained from the literature [37]. Figure 2 depicts the diagram of the 33-bus system.

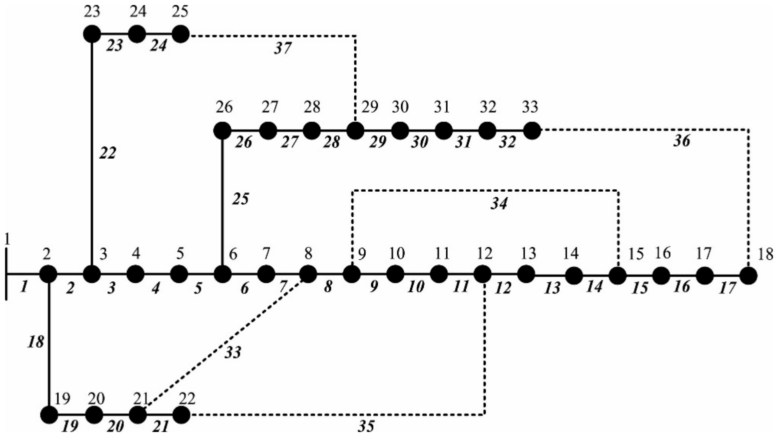

Figure 2. 33-bus system

Table 1. Comparative results of SGA and other methods for 33-bus system

Items	Opened switches	P_{DG} (MW)/(Bus)	P_L (kW)	Power loss reduction (%)	Minimum bus voltage (p.u.)
Base case	33-34-35-36-37	-	202.66	-	0.9131
SGA	7-9-14-26-31	0.4365/ (11) 1.1778/ (29) 0.6147/ (18)	56.1411	72.3002	0.9728
EOA [14]	8-27-33-34-36	0.165/ (8) 0.651/ (14) 1.413/ (29)	61.48	69.66	-
IEOA [14]	7-10-13-27-31	0.399/ (8) 0.669/ (17) 1.160/ (29)	57.40	71.67	-
HSA [12]	4-7-10-28-32	0.5258/ (32) 0.5586/ (31) 0.5840/ (33)	73.05	63.95	0.9700
GA [12]	7-10-28-32-34	-	75.13	62.92	0.9766
RGA [12]	7-9-12-27-32	-	74.32	63.33	0.9691
FWA [13]	7-11-14-28-32	0.5367/ (32) 0.6158/ (29) 0.5315/ (18)	67.11	66.89	0.9713
ISCA [15]	7-9-14-28-31	0.6484/ (30) 0.5102/ (13) 0.5324/ (16)	66.81	67.03	0.9611
FF [16]	8-9-28-32-33	0.8414/ (31) 0.3408/ (32) 0.5916/ (33)	73.95	63.51	0.9735

The SGA optimum results for the 33-bus system are tabulated in Table 1. It becomes evident from Table 1 that there is a significant reduction, i.e., 72.3002 %, in system power loss from

202.66 kW (base case) to 56.1411 kW. The convergence curves of SGA optimization for the 33-bus system are depicted in Figure 3, whereas, the bus voltages for all buses are demonstrated in Figure 4. From Figure 4, a significant improvement in the minimum bus voltage was observed, i.e., 0.9131 p.u. to 0.9728 p.u. Hence, it can be shown that optimal DG allocation simultaneously with the reconfiguration was very effective in improving the quality of the 33-bus system.

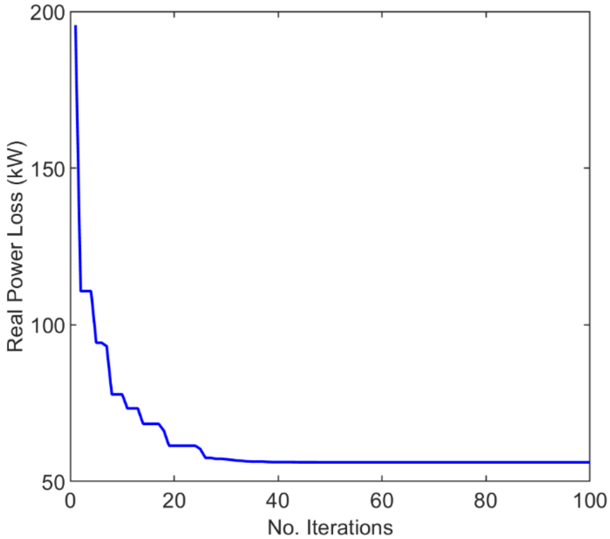

Figure 3. Convergence characteristics of SGA for 33-bus system

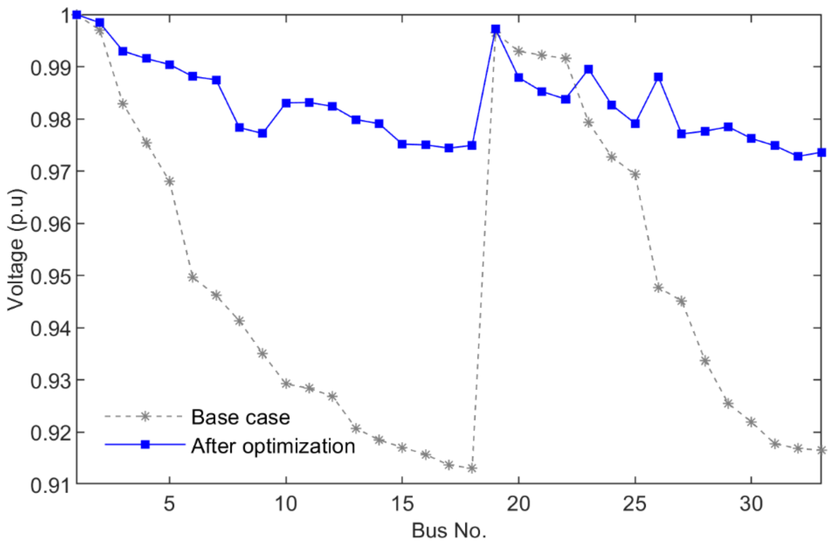

Figure 4. Voltage profiles of the 33-bus system before and after optimization using SGA

The results of previous methods are compared with our proposed SGA. These methods are available in literature and include EOA [14], IEOA [14], HSA [12], GA [12], RGA [12], FWA [13], ISCA [15], and FF [16]. The results of this comparison are outlined in Table 1. It is clear that both for power loss and voltage profile, the SGA performance was better than methods available in the literature. For instance, the power via the SGA method is 56.1411 kW, which is 2.1932% less than that by IEOA (i.e, second-best results in Table 1). Therefore, it could be inferred that the SGA method provides a better solution for the 33-bus system.

B. 69-bus system

The 69-bus radial distribution system is composed of 73 feeders, 68 sectionalize, and 5 initial tie switches at 12.66 kV. The initial tie switches for this system are {69-70-71-72-73}. The system exhibits a power loss of 225 kW and 0.9092 p.u minimum bus voltage. The system data is collected from the literature [37]. Figure 5 portrays the diagram of the 69-bus system.

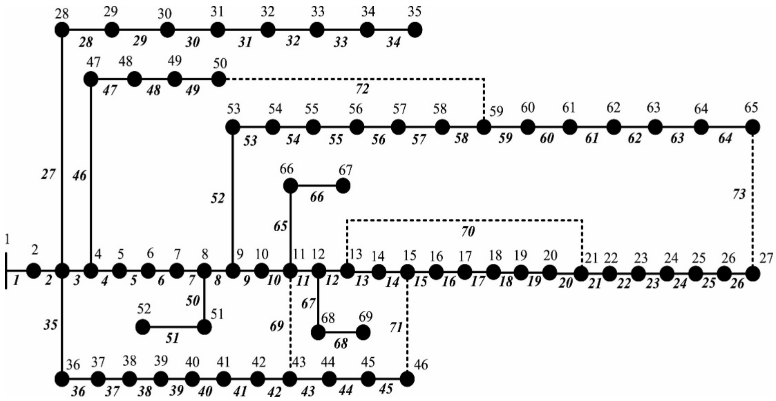

Figure 5. 69-bus system

Table 2. Comparative results of SGA and other methods for 69-bus system

Items	Opened switches	P_{DG} (MW)/(Bus)	P_L (kW)	Power loss reduction (%)	Minimum bus voltage (p.u.)
Base case	69-70-71-72-73	-	225	-	0.9092
SGA	14-56-63-69-70	0.3698/ (12) 1.4136/ (61) 0.4977/ (27)	35.9289	84.0316	0.9798
EOA [14]	12-18-56-63-69	0.522/ (27) 1.463/ (61) 0.278/ (66)	37.55	83.31	-
IEOA [14]	12-57-63-69-70	0.362/ (12) 0.518/ (26) 1.400/ (61)	36.3986	83.82	-
HSA [12]	13-17-58-61-69	1.0666/ (61) 0.3525/ (60) 0.4527/ (62)	40.3	82.08	0.9736
GA [12]	10-15-45-55-62	-	46.5	73.38	0.9727
RGA [12]	10-14-16-55-62	-	44.23	80.32	0.9742
FWA [13]	13-55-63-69-70	1.1272/ (61) 0.2750/ (62) 0.4159/ (65)	39.25	82.55	0.9796
ISCA [15]	12-19-57-63-69	0.1001/ (61) 0.4106/ (62) 0.4616/ (65)	39.73	82.34	0.9798
FF [16]	12-19-57-61-69	0.2517/ (60) 1.2328/ (61) 0.4525/ (62)	40.30	82.08	0.9816

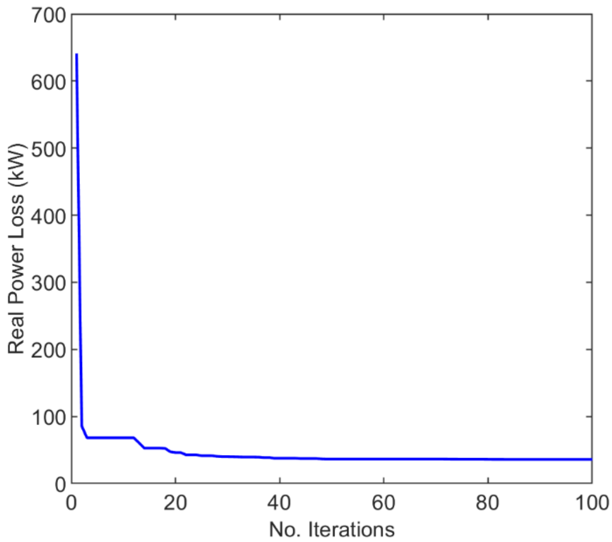

Figure 6. Convergence characteristics of SGA for 69-bus system

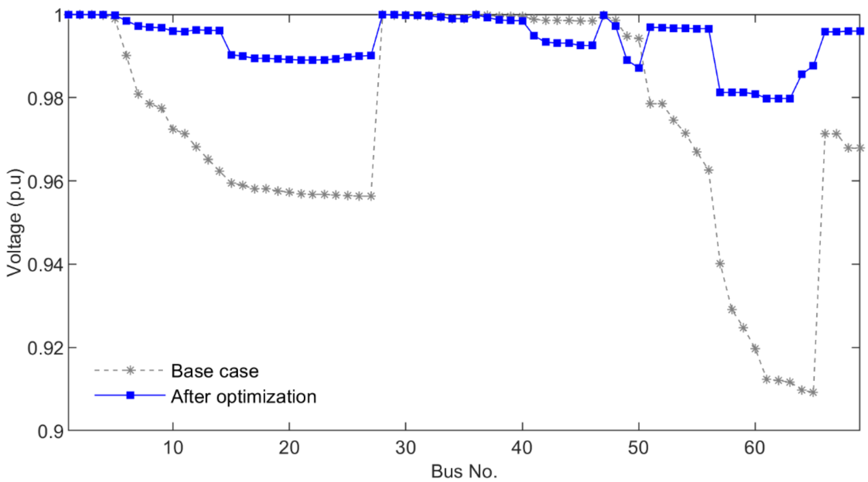

Figure 7. Voltage profiles of the 69-bus system before and after optimization using SGA

The optimization results obtained from the SGA method for the 69-bus system are tabulated in Table 2. It is demonstrated from Table 2 that the SGA method leads to a reduction in the power loss of the system i.e., 225 kW to 35.9289 kW, i.e., 84.0316 %, through optimal DG allocation and reconfiguration simultaneously. The convergence curve of SGA optimization and voltage profile of the 69-bus system are depicted in Figures 6-7 respectively. A significant improvement in the bus voltages was observed. A considerable improvement in minimum bus voltage is noted which from 0.9092 p.u. to 0.9798 p.u. From obtained results, we can see that the SGA method has significantly improved the system performance both for voltage profile and power loss. This illustrates that the reconfiguration needs to consider the optimal position and size of DG units simultaneously.

The results of SGA for the 69-bus system were also compared with results of other published optimization methods such as EOA [14], IEOA [14], HSA [12], GA [12], RGA [12], FWA [13], ISCA [15], and FF [16]. The comparative analysis is given in Table 2. SGA obtained an optimized power loss of 35.9289 kW and a minimum voltage bus of 0.9798 p.u. It becomes evident from Table 2, that the SGA method is far better than previously proposed methods for the above-mentioned purposes. Therefore, SGA proves to be the best optimal method for the 69-bus system.

6. Conclusion

In this study, the implementation of the SGA optimization method in power distribution systems is demonstrated. This optimization method is applied successfully both for power distribution systems' optimal reconfiguration and DG allocation. The main objective of the optimization problem is to minimize real power loss. The proposed SGA was tested on 33 bus and 69 bus systems. From the results, it is concluded that optimal DG allocation and reconfiguration were completed in an effective way for reducing power loss and improving the voltage profile of the system. For 33 bus and 69 bus systems, the SGA method leads to a power loss of 72.3002 % and 84.0316 %, respectively. Additionally, to see the improvement in performance, the SGA results have been compared with results published in the literature for other optimization methods. For both of the mentioned systems, the SGA proves to be the best optimization method in terms of distribution power systems performance. For future research studies, the SGA optimization method can be implemented for other power system optimization problems.

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8. References

[1]. P. P. Biswas, R. Mallipeddi, P. N. Suganthan, and G. A. J. Amaratunga, "Optimal reconfiguration and distributed generator allocation in distribution network using an advanced adaptive differential evolution," in *2017 IEEE Symposium Series on Computational Intelligence (SSCI)*, Nov. 2017, pp. 1–7.

[2]. A. Y. Abdelaziz, F. M. Mohammed, S. F. Mekhamer, and M. A. L. Badr, "Distribution Systems Reconfiguration using a modified particle swarm optimization algorithm," *Electric Power Systems Research*, vol. 79, no. 11, pp. 1521–1530, Nov. 2009.

[3]. Pavan Khetrapal, "Distribution Network Reconfiguration of Radial Distribution Systems for Power Loss Minimization Using Improved Harmony Search Algorithm", International Journal on Electrical Engineering and Informatics - Volume 12, Number 2, June 2020

[4]. J. Z. Zhu, "Optimal reconfiguration of electrical distribution network using the refined genetic algorithm," *Electric Power Systems Research*, vol. 62, no. 1, pp. 37–42, May 2002.

[5]. [5] H. de Faria, M. G. C. Resende, and D. Ernst, "A biased random key genetic algorithm applied to the electric distribution network reconfiguration problem," *J Heuristics*, vol. 23, no. 6, pp. 533–550, Dec. 2017.

[6]. R. Srinivasa Rao, S. V. L. Narasimham, M. Ramalinga Raju, and A. Srinivasa Rao, "Optimal Network Reconfiguration of Large-Scale Distribution System Using Harmony Search Algorithm," *IEEE Transactions on Power Systems*, vol. 26, no. 3, pp. 1080–1088, Aug. 2011.

[7]. P. V. V. Rama Rao and S. Sivanagaraju, "Radial Distribution Network Reconfiguration for Loss Reduction and Load Balancing using Plant Growth Simulation Algorithm", International Journal on Electrical Engineering and Informatics - Volume 2, Number 4, 2010

[8]. A. Mohamed Imran and M. Kowsalya, "A new power system reconfiguration scheme for power loss minimization and voltage profile enhancement using Fireworks Algorithm," *International Journal of Electrical Power & Energy Systems*, vol. 62, pp. 312–322, Nov. 2014.

[9]. M. Abdelaziz, "Distribution network reconfiguration using a genetic algorithm with varying population size," *Electric Power Systems Research*, vol. 142, pp. 9–11, Jan. 2017.

[10]. T. T. Nguyen and A. V. Truong, “Distribution network reconfiguration for power loss minimization and voltage profile improvement using cuckoo search algorithm,” *International Journal of Electrical Power & Energy Systems*, vol. 68, pp. 233–242, Jun. 2015.
[11]. S. Naveen, K. Sathish Kumar, and K. Rajalakshmi, “Distribution system reconfiguration for loss minimization using modified bacterial foraging optimization algorithm,” *International Journal of Electrical Power & Energy Systems*, vol. 69, pp. 90–97, Jul. 2015.
[12]. R. S. Rao, K. Ravindra, K. Satish, and S. V. L. Narasimham, “Power Loss Minimization in Distribution System Using Network Reconfiguration in the Presence of Distributed Generation,” *IEEE Transactions on Power Systems*, vol. 28, no. 1, pp. 317–325, Feb. 2013.
[13]. A. Mohamed Imran, M. Kowsalya, and D. P. Kothari, “A novel integration technique for optimal network reconfiguration and distributed generation placement in power distribution networks,” *International Journal of Electrical Power & Energy Systems*, vol. 63, pp. 461–472, Dec. 2014.
[14]. A. M. Shaheen, A. M. Elsayed, R. A. El-Sehiemy, and A. Y. Abdelaziz, “Equilibrium optimization algorithm for network reconfiguration and distributed generation allocation in power systems,” *Applied Soft Computing*, vol. 98, p. 106867, Jan. 2021.
[15]. U. Raut and S. Mishra, “An improved sine–cosine algorithm for simultaneous network reconfiguration and DG allocation in power distribution systems,” *Applied Soft Computing*, vol. 92, p. 106293, Jul. 2020.
[16]. O. Badran, H. Mokhlis, S. Mekhilef, W. Dahalan, and J. Jallad, “Minimum switching losses for solving distribution NR problem with distributed generation,” *IET Generation, Transmission & Distribution*, vol. 12, no. 8, pp. 1790–1801, 2018.
[17]. A. Bayat, A. Bagheri, and R. Noroozian, “Optimal siting and sizing of distributed generation accompanied by reconfiguration of distribution networks for maximum loss reduction by using a new UVDA-based heuristic method,” *International Journal of Electrical Power & Energy Systems*, vol. 77, pp. 360–371, May 2016.
[18]. M. F. Abd El-salam, E. Beshr, and M. B. Eteiba, “A New Hybrid Technique for Minimizing Power Losses in a Distribution System by Optimal Sizing and Siting of Distributed Generators with Network Reconfiguration,” *Energies*, vol. 11, no. 12, Art. no. 12, Dec. 2018.
[19]. T. T. Nguyen, A. V. Truong, and T. A. Phung, “A novel method based on adaptive cuckoo search for optimal network reconfiguration and distributed generation allocation in distribution network,” *International Journal of Electrical Power & Energy Systems*, vol. 78, pp. 801–815, Jun. 2016.
[20]. A. Onlam, D. Yodphet, R. Chatthaworn, C. Surawanitkun, A. Siritaratiwat, and P. Khunkitti, “Power Loss Minimization and Voltage Stability Improvement in Electrical Distribution System via Network Reconfiguration and Distributed Generation Placement Using Novel Adaptive Shuffled Frogs Leaping Algorithm,” *Energies*, vol. 12, no. 3, Art. no. 3, Jan. 2019.
[21]. V. V. V. S. N. Murty and A. Kumar, “Optimal DG integration and network reconfiguration in microgrid system with realistic time varying load model using hybrid optimisation,” *IET Smart Grid*, vol. 2, no. 2, pp. 192–202, 2019.
[22]. H. B. Tolabi, M. H. Ali, Shahrin Bin Md Ayob, and M. Rizwan, “Novel hybrid fuzzy-Bees algorithm for optimal feeder multi-objective reconfiguration by considering multiple-distributed generation,” *Energy*, vol. 71, pp. 507–515, Jul. 2014.
[23]. M. K. and J. S., “Integrated approach of network reconfiguration with distributed generation and shunt capacitors placement for power loss minimization in radial distribution networks,” *Applied Soft Computing*, vol. 52, pp. 1262–1284, Mar. 2017.
[24]. T. V. Tran, B.-H. Truong, T. P. Nguyen, T. A. Nguyen, T. L. Duong, and D. N. Vo, “Reconfiguration of Distribution Networks With Distributed Generations Using an Improved Neural Network Algorithm,” *IEEE Access*, vol. 9, pp. 165618–165647, 2021.

[25]. T. Tran The, B.-H. Truong, K. Dang Tuan, and D. Vo Ngoc, “A Nondominated Sorting Stochastic Fractal Search Algorithm for Multiobjective Distribution Network Reconfiguration with Distributed Generations,” *Mathematical Problems in Engineering*, vol. 2021, p. e6638559, Feb. 2021.

[26]. Thuan Thanh Nguyen, Thanh Long Duong, Thanh Quyen Ngo, “Wild Geese Algorithm for The Combination Problem of Network Reconfiguration and Distributed Generation Placement”, International Journal on Electrical Engineering and Informatics - Volume 14, Number 1, March 2022

[27]. M. S. Gonçalves, R. H. Lopez, and L. F. F. Miguel, “Search group algorithm: A new metaheuristic method for the optimization of truss structures,” *Computers & Structures*, vol. 153, pp. 165–184, Jun. 2015.

[28]. R. L. Pedro, J. Demarche, L. F. F. Miguel, and R. H. Lopez, “An efficient approach for the optimization of simply supported steel-concrete composite I-girder bridges,” *Advances in Engineering Software*, vol. 112, pp. 31–45, Oct. 2017.

[29]. F. Carraro, R. H. Lopez, and L. F. F. Miguel, “Optimum design of planar steel frames using the Search Group Algorithm,” *J Braz. Soc. Mech. Sci. Eng.*, vol. 39, no. 4, pp. 1405–1418, Apr. 2017.

[30]. S. F. H. Noorbin and A. Alfi, “Adaptive parameter control of search group algorithm using fuzzy logic applied to networked control systems,” *Soft Comput*, vol. 22, no. 23, pp. 7939–7960, Dec. 2018.

[31]. T. H. B. Huy, P. Nallagownden, R. Kannan, and V. N. Dieu, “Energetic optimization of solar water heating system with flat plate collector using search group algorithm,” *Journal of Advanced Research in Fluid Mechanics and Thermal Sciences*, vol. 61, no. 2, pp. 306–322, 2019.

[32]. B.-H. Truong, P. Nallagownden, K. H. Truong, R. Kannan, D. N. Vo, and N. Ho, “Multi-objective search group algorithm for thermo-economic optimization of flat-plate solar collector,” *Neural Comput & Applic*, Apr. 2021.

[33]. T. H. B. Huy, T. V. Tran, D. Ngoc Vo, and H. T. T. Nguyen, “An improved metaheuristic method for simultaneous network reconfiguration and distributed generation allocation,” *Alexandria Engineering Journal*, vol. 61, no. 10, pp. 8069–8088, Oct. 202.

[34]. A. Y. Abdelaziz, F. M. Mohamed, S. F. Mekhamer, and M. A. L. Badr, “Distribution system reconfiguration using a modified Tabu Search algorithm,” *Electric Power Systems Research*, vol. 80, no. 8, pp. 943–953, Aug. 2010.

[35]. M. Sedighizadeh, M. Esmaili, and M. Esmaeili, “Application of the hybrid Big Bang-Big Crunch algorithm to optimal reconfiguration and distributed generation power allocation in distribution systems,” *Energy*, vol. 76, pp. 920–930, Nov. 2014.

[36]. R. D. Zimmerman and C. E. Murillo-Sanchez, *Matpower 6.0b1 User’s Manual*. Cornell University, Ithaca, NY: Power Systems Engineering Research Center, 2019. [Online]. Available: https://matpower.org/docs/MATPOWER-manual-6.0b1.pdf

[37]. M. E. Baran and F. F. Wu, “Network reconfiguration in distribution systems for loss reduction and load balancing,” *IEEE Transactions on Power Delivery*, vol. 4, no. 2, pp. 1401–1407, Apr. 1989.

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