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Research Article

Simultaneous Power Network Reconfiguration and DG Allocation Using Improved Jaya Algorithm for Maximum Loadability Improvement and Power Loss Reduction

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Keywords

Jaya algorithm,
Distributed generation,
Radial distribution system,
Load capacity,
Network configuration.

Abstract

One of the most critical issues in modern complex power systems is to reduce losses and improve system load through various methods such as compensating capacitors, electronic power equipment, installing distributed generation (DG) sources and changing the system configuration. Each of these methods has its own impact on the characteristics of the power system and should be considered simultaneously to conduct a comprehensive study close to the real situation. Installing DG units and changing the layout of the network are the most widely used methods of improving power system characteristics. Due to the importance of the problem, in this study, a new method for locating and determining the optimal capacity of DG units and optimal configuration of radial distribution systems simultaneously using the Jaya optimization algorithm is proposed to reduce losses and improve system loadability. Jaya optimization algorithm is one of the newest meta-heuristic algorithms that has a high ability to solve complex high-dimensional optimization problems. One of the advantages of this algorithm is having a simple structure with high search capability. The proposed method was tested on a 33-bus test system. Simulink and MATLAB software coding environment was used to program and implement the proposed method and the results of numerical studies showed that the proposed method is well able to find the network optimal configuration, optimal location and capacity of DG units, so that losses are minimized and system load capacity is improved.

1. Introduction

A distribution network is the last stage in delivery of electric power. It carries electricity from the transmission system to consumers. Distribution systems usually have high system losses and poor voltage regulation because of the high current and low voltage level in distribution systems [1, 2]. In addition, due to the rapid expansion of distribution networks, the voltage stability of distribution systems has become an important issue. Therefore, many efforts have been made to decrease the losses and improve the voltage stability in distribution systems. Network reconfiguration and distributed generator placement are among those efforts to mitigate this problem [3].

Distribution network reconfiguration (DNR) is the process of varying the topology of distribution network by changing the closed/open status of sectionalizing and tie switches while respecting system constraints upon satisfying the operator's objectives [4]. The first publication about the DNR problem was presented by Merlin and Back [5]. They solved DNR problem through a discrete branch-and-bound type heuristic technique. Civanlar et al. [6] proposed a switch exchange method to estimate the loss reduction based on particular switching option. Since the method is based on heuristics technique, it is difficult to take a systematic way to evaluate an optimal solution. In recent years, new metaheuristic methods have been proposed for solving optimization

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problems to obtain an optimal solution of global minimum in the literature with good results. In [7], a method based on an enhanced genetic algorithm was developed for DNR problem to minimize the power loss and maximize the system reliability. Souza et al. [8] proposed two new approaches for solving the DNR problem using the Opt-aiNet (artificial immune network for optimization) and Copt-aiNet (artificial immune network for combinatorial optimization) algorithms to minimize power loss. In [9], the network reconfiguration and capacitor placement are simultaneously employed to enhance the system efficiency in a fuzzy multi-objective optimization problem by using a binary gravitational search algorithm (BGSA).

Distributed generations (DGs), which are connected to the grid at distributed level voltages are generating plant serving a customer on-site. Because of the reasons of energy security and economical benefit, the presence of DGs into distribution networks has been increasing rapidly [10,11]. Impact of DG units on power system has attracted the interest of some recent research efforts. In [12], authors proposed comparison of novel power loss sensitivity (NPLS), power stability index (PSI), and voltage stability index (VSI) methods for optimal allocation and size of DG in radial distribution network. In [13], a method based on bacterial foraging optimization algorithm (BFOA) is proposed to find the optimal location and size of DG with an objective of power losses reduction, operational costs and improving voltage stability. In [14], authors proposed a method based on the artificial neural network to find optimal DG size and locations due to complexity of multiple DG concepts. Kayal and Chanda [15] proposed a new constrained multi-objective particle swarm optimization (PSO) based wind turbine generation unit and photovoltaic array placement approach to reduce power loss and improve voltage stability of radial distribution system. In [16], a novel application of multi-objective particle swarm optimization was developed for determining the place and size of DGs, and the contract price of their generated power.

Recently, some researches have integrated both the DNR and DG placement problems to improve the effectively of distribution network [17–19]. In [18], the DNR problem in the presence of DG with an objective of minimizing real power loss and enhancing voltage profile in distribution network is solved based on the harmony search algorithm (HSA). In [19], a method based on fireworks optimization algorithm (FWA) is proposed for solving DNR together with DG placement to minimize power loss and improve voltage stability. Both researches [18, 19] had used the different techniques to pre-identify the candidate bus locations for DG installation such as loss sensitivity factor (LSF) [18], and voltage stability index (VSI) [19].

Due to pre-identifying of location of DGs based on LSF or VSI in initial network configuration, the above methods focused only on sizing of DG units. However, these parameters may change during network reconfiguration process and DGs installation. In addition, in distribution systems with multi-DG units, these parameters may change more noticeable because of the interaction between DGs. In this paper, a method based on cuckoo search algorithm (CSA) [20] which is a recent meta-heuristic is proposed for solving the DNR problem in the presence of distributed generation. Compared to other algorithms, CSA has fewer control parameters and is more effective [4]. Recently, CSA has been applied to solve many power system problems and other fields such as optimal power flow (OPF) [21], power system stabilizers (PSSs) [22], load frequency control (LFC) [23], and automatic generation control (AGC) [24]. The results obtained from the above problems have proven the effectiveness of CSA compared to other optimization algorithms.

In this study, the proposed method based on improved version of Jaya optimization algorithm uses power loss and loadability index as objective functions to find the optimum configuration of distribution network, and the optimum bus location and size of DGs. The algorithm is tested on 33-bus systems and results obtained are compared with other techniques available in the literature.

2. Improved Jaya Optimization Algorithm

Let $f(x)$ is the objective function to be minimized (or maximized). At any iteration i, assume that there are 'm' number of design variables (i.e. $j = 1, 2, \dots, m$), 'n' number of candidate solutions (i.e. population size, $k = 1, 2, \dots, n$). Let the best candidate best obtains the best value of $f(x)$ (i.e. $f(x)_{best}$) in the entire candidate solutions and the worst candidate worst obtains the worst value of $f(x)$ (i.e. $f(x)_{worst}$) in the entire candidate solutions. If $X_{j,k,i}$ the value of the j^{th} variable for the k^{th}candidate during the i^{th} iteration, then this value is modified as per the following Eq. (1) [25]

$$X'_{j,k,i} = X_{j,k,i} + r_{1,j,i}\left(X_{j,best,i} - |X_{j,k,i}|\right) - r_{2,j,i}\left(X_{j,worst,i} - |X_{j,k,i}|\right) \quad (1)$$

where, $X_{j,best,i}$ is the value of the variable j for the best candidate and $X_{j,worst,i}$ is the value of the variable j for the worst candidate. $X'_{j,k,i}$ is the updated value of $X_{j,k,i}$ and $r_{1,j,i}$ and $r_{2,j,i}$ are the two random numbers for the j^{th} variable during the i^{th} iteration in the range [0, 1]. The term "$r_{1,j,i}(X_{j,best,i} - |X_{j,k,i}|)$" indicates the tendency of the solution to move closer to the best solution and the term "$-r_{2,j,i}(X_{j,worst,i} - |X_{j,k,i}|)$" indicates the tendency of the solution to avoid the worst solution. $X'_{j,k,i}$ is accepted if it gives better function value. All the accepted function values at the end of iteration are maintained and these values become the input to the next iteration. The algorithm always tries to get closer to success (i.e. reaching the best solution) and tries to avoid failure (i.e. moving away from the worst solution).

Following this strategy, the local search is initially defined over a large neighborhood, and has a largely explorative character. As the algorithm progresses, a more detailed search is needed to refine the current local optimum. Hence, the search is made increasingly exploitative, and the area around the optimum is searched more thoroughly.

Since the search process of Jaya is nonlinear and highly complicated, linearly and nonlinearly decreasing movement value with no feedback taken from the best candidate fitnesses cannot truly reflect the actual search process. In the beginning of the search process, the particles are far away from the optimum point and hence a movement value is needed to globally search the solution space. Conversely, when the best solution found by the population improves greatly after some iteration, i.e., the particles find a near optimum solution, only small movements are needed and movement value must be set to small values. Based on this, in this study, we proposed improved Jaya algorithm (IJOA) in which the movement value is set as a function of each particles fitness during search process as follows:

$$R_1 = \frac{1}{t} \times \frac{r_{1,j,i}}{1 + exp\ (-f(X_{j,k,i}))} \quad (2)$$

$$R_2 = \frac{1}{t} \times \frac{r_{2,j,i}}{1 + exp\ (-f(X_{j,k,i}))} \quad (3)$$

$$X'_{j,k,i} = X_{j,k,i} + R_1(X_{j,best,i} - |X_{j,k,i}|) - R_2(X_{j,worst,i} - |X_{j,k,i}|) \quad (4)$$

In the IJOA, the amount of movement changes according to the rate of fitness improvement. According to Eq. (4), during the search of IJOA, while the fitness of a particle is far away from the real global optimal, the value of movement will be large resulting in strong global search abilities and locating the promising search areas. Meanwhile, when the fitness of a particle is achieved near the real global optimal, the value of movement will be set small, depending on the nearness of its fitness to the optimal value, to facilitate a finer local explorations and hence accelerate convergence. Therefore, the main difference between Jaya and IJOA is in the movement definition. First in IJOA, the movement is associated with fitness value (Eq. (4)). Second movement value is same for all particles in in Jaya; meanwhile every particles has its own movement value in IJOA.

For the purpose of evaluating the performance of proposed optimization algorithm, two widely used benchmark functions including generalized Schaffer (f_1), and Griewank (f_2), are utilized. Their mathematical expressions are stated by Eq. (5) and (6). In the simulation, the search space is defined between $[-600, 600]^D$, and D=10 is the dimension of problem or number of unknown variables.

$$f_1(\vec{x}) = \frac{sin^2(\sum_{i=1}^{D} x_i^2) - 0.5}{\left(1 + 0.001(\sum_{i=1}^{D} x_i^2)\right)^2} + 0.50 \quad (5)$$

$$f_2(\vec{x}) = \frac{1}{4000}\left(\sum_{i=1}^{D}(x_i - 100)^2\right) - \left(\prod_{i=1}^{D} COS\left(\frac{x_i - 100}{\sqrt{i}}\right)\right) + 1.0 \quad (6)$$

The obtained results using proposed method (i.e. IJOA) and other similar optimization algorithms such as GA, ICA, PSO algorithm, HHO algorithm, and Jaya are listed in Tables 1 and 2. In the experiments, the number of initial population for all algorithms are set to 30 and the algorithm is continued for convergence point with 20 iterations without any change. All the listed values in tables are the average of 20 unrelated and separate implementation of different optimization algorithms on benchmark functions. The best performance is obtained by IJOA.

Table 1. Performance of different algorithms on generalized Schaffer function ($\boldsymbol{f_1(\vec{x})}$)

algorithms	Performance		
	Mean	SD	Iterations
GA	$9.21\,E-6$	$2.85\,E-5$	179
PSO	$7.45\,E-11$	$3.91\,E-8$	171
HHO	$8.52\,E-14$	$5.21E-12$	82
ICA	$4.76\,E-11$	$8.21\,E-9$	102
Jaya	$7.54\,E-11$	$7.22\,E-5$	128
IJOA	0	0	68

Table 2. Performance of different algorithms on Griewank function ($\boldsymbol{f_2(\vec{x})}$)

algorithms	Performance		
	Mean	SD	Iterations
GA	$3.93\,E-9$	$6.42\,E-8$	205
PSO	$6.53\,E-12$	$3.81\,E-12$	172
HHO	$7.55\,E-15$	$5.13\,E-17$	85
ICA	$3.96\,E-13$	$4.81\,E-12$	115
Jaya	$7.29\,E-12$	$2.67\,E-13$	144
IJOA	$7.19\,E-19$	$1.56\,E-22$	81

3. Proposed Method

This paper proposes an intelligent method based on IJOA for power network reconfiguration and DG allocation simultaneously. In recent years, evolutionary optimization have been applied successfully for engineering problems [26- 42].Both methods of using DG units and network reconfiguration separately can improve the characteristics of the system, and if these two methods are used simultaneously in the power network, much better results will be obtained. In this study, the distribution network reconfiguration and DG installation method have been used simultaneously to improve the system characteristics. In solving problems related to determining the optimal configuration of distribution systems and location of DG resources, the proper definition of the objective function is of great importance. Usually in defining the objective function of the optimization algorithm, various indicators such as the amount of active power losses, system reliability, voltage profile and system loadability are considered. In these studies, the optimal state of the switches, the location of the DG sources, the active power capacity of the DG sources and the reactive power capacity of the DG sources must be determined so that the objective function moves towards the desired value. One of the most widely used indicators in the design of compensation systems in power networks is the actual power loss of the system. Based in Figure. 1, the value of Net Active Power Loss (NAPL) can be calculated using following equations:

$$I_{i+1} = \frac{V_i\angle\delta_i - V_{i+1}\angle\delta_{i+1}}{R_{i+1} + jX_{i+1}} \quad (7)$$

$$P_{i+1} - jQ_{i+1} = V_{i+1} \times I_{i+1} \quad (8)$$

$$P_{loss,i} = \frac{R_i(P_i^2 + Q_i^2)}{V_i^2} \quad (9)$$

$$Q_{loss,i} = \frac{X_i(P_i^2 + Q_i^2)}{V_i^2} \quad (10)$$

$$NAPL = \sum_{i=1}^{N_l} P_{loss,i} \tag{11}$$

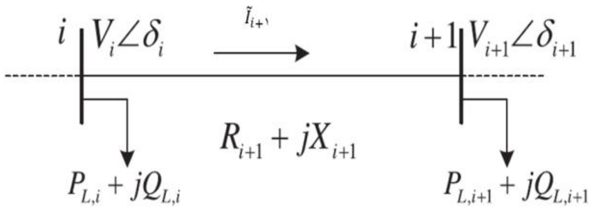

Figure 1. Single diagram of power network line for NAPL calculation

Another indicator used in the design of compensators is the voltage profile. In order to calculate the voltage profile, the Eq. (12) is used. The lower the value of this indicator is desired in an ideal network,

$$V_{profile} = \sum_{i=1}^{NB} |1 - V_i| \tag{12}$$

Another important indicator is related to the maximum load of the system. The maximum load of the system is the amount of load that can be pulled from the network, without the voltage profile at any of the system backs below the desired value. In order to find the maximum loadability of the system, the amount of active and reactive power of all buses should be increased with incremental steps such as $\lambda = 0.01$, so that the voltage profile reaches below the desired value (instability limit).

$$P = \lambda P_n \left(\frac{V}{V_n}\right) \tag{13}$$

$$Q = \lambda Q_n \left(\frac{V}{V_n}\right) \tag{14}$$

In this paper, the objective function is formulated considering net active power loss and maximum loadability simultaneously as defined in (15). Moreover, Eq. (16) illustrates a simple particle in the IJOA.

$$Fitness\ \ function = min\left(\frac{NAPL}{\lambda_{max}}\right) \tag{15}$$

$$Answer_i = \begin{bmatrix} Tie_1^i, \dots, Tie_L^i, Lo.DG_1^i, \dots, Lo.DG_m^i, Size.DG_1^i, \\ \dots, Size.DG_m^i \end{bmatrix} \tag{16}$$

In Eq. (15), the minimization of the objective function leads to net active power loss reduction and loadability enhancement without need of any weight factor as secondary problem.

3.1. Test System

The 33-bus distribution system, which is a small-scale distribution networks, includes 37 branches, 32 sectionalizing switches and 5 tie switches. The line and load data of this system are taken from [43]. The total real and reactive power loads of the system are 3.72MW and 2.3 MVAr, respectively. Figure 2 shows the single line diagram of this network.

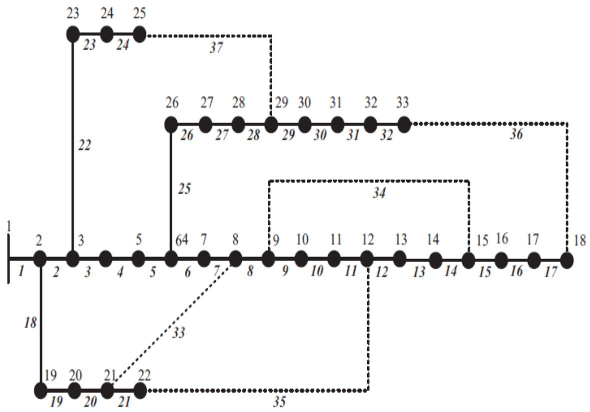

Figure 2. Single line diagram of test network [43]

In the simulation of network, six scenarios are considered to analyze the superiority of the proposed method.

- Scenario 1: Base case (without reconfiguration and distributed generators).
- Scenario 2: The system is only reconfigured.
- Scenario 3: Allocation and size of DGs are optimized on base case.
- Scenario 4: Allocation and size of DGs are optimized after reconfiguration of the network.
- Scenario 5: The system is reconfigured after DGs installed based on scenario 3.
- Scenario 6: The System is simultaneous reconfigured and optimized allocation and size of DGs.

3.2. Performance of the Proposed Method

The obtained results using the proposed method are listed in Table 3. In the implementation of IJOA, the number of candidates in the initial population is considered equal to 40 and the criterion of maximum number of repetitions is used as a stop condition. The IJOA then starts searching and stops after 100 iterations. The results showed that the IJOA converges to the global optimal point before 100 iterations, and this number of iterations (100 iterations) is a good value to stop the algorithm. In the studies, the load of each bus is fixed and in accordance with the values mentioned in [34]. In the normal state of the system, in which the condition of the disconnectors has not changed and the sources of distributed generation have not been installed, the amount of actual power loss has been equal to 202.68 kW.

The system's voltage profile before reconfiguration and installing the DG sources is shown in Figure 3. According to this figure, it can be seen that the lowest voltage is related to bus number 18 and is equal to 0.9108 prionite. Also, the maximum load of the system was 2.48. This value of voltage (0.9108 prionite) and load capacity is not suitable for a power distribution system and should be corrected. For this purpose, in this dissertation, two methods of system reconfiguration and optimal installation of distributed generation resources have been used. It can be seemn that using proposed method, the value of minimum voltage (V_{min}), system maximum loadability ($\boldsymbol{\lambda_{max}}$) are improved significantly. Moreover, the power loss is cedcreas dramatically. The best results are obtained in scenario 6 that network reconfiguration and DG allocation are performed concurrerntly.

Table 3. Performance of the proposed method

Scenario	NAPL	NAPL reduction (%)	V_{min}	λ_{max}
1	202.68	-	0.9108	2.48
2	138.65	31.26	0.9477	3.22
3	72.65	64.86	0.9793	3.37
4	56.77	71.65	0.9821	4.25
5	60.17	69.54	0.9876	4.26
6	54.26	75.12	0.9811	4.76

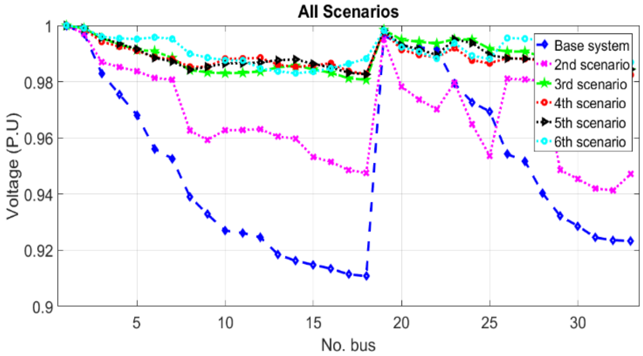

Figure 3. Voltage profile using IJOA and different cases

The value changes of the competency function during the optimization process are shown in Figure 4 for three different implementations. In this figure, the horizontal axis represents the number of iterations of the algorithm and the vertical axis represents the value of the competency function. It can be seen that the Jaya optimization algorithm was able to find the optimal state and converge after 62 iterations.

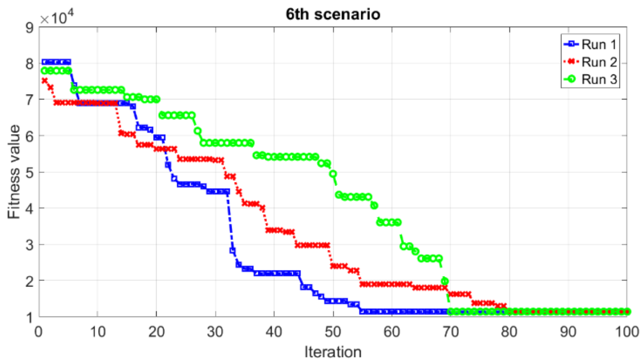

Figure 4. Convergence of IJOA

3.3. Comparison

In the following, the performance of the proposed method is compared with other similar methods. The Jaya optimization algorithm, the firework algorithm (FWA), and the harmonic search algorithm (HSA) were used for this purpose. In addition, for a more accurate comparison with the proposed method, the number of candidates in these algorithms is considered equal. The results obtained by these optimization algorithm are listed in Table 2, 3 and 4. Based on the configuration determined by the Jaya algorithm in the sixth scenario, the keys 11, 28, 31, 33 and 34 should be opened and three DGs should be installed on the buses seven, 18 and 25. In this case, the amount of losses was 59.21 kW and the minimum voltage was 0.9806 P.U. By comparing the results obtained by the Jaya algorithm and the IJOA, it can be seen that the IJOA has a better performance than the Jaya algorithm. The same results are obtained for FWA and HAS. Figure 5 shows the value of fitness function for different methods. It can be seen that proposed method, IJOA, has much better performance than other methods.

Table 4. Performance of the Jaya

Scenario	NAPL	NAPL reduction (%)	V_{min}	λ_{max}
2	139.98	30.93	0.9413	2.41
3	74.26	63.26	0.9778	3.15
4	58.79	71.00	0.9802	3.23
5	62.98	68.93	0.9826	3.86
6	59.21	71.23	0.9806	4.02

Table 5. Performance of the FWA

Scenario	NAPL	NAPL reduction (%)	V_{min}	λ_{max}
2	139.98	30.93	0.9413	2.31
3	88.68	56.24	0.9680	3.13
4	83.91	58.59	0.9612	3.14
5	68.28	66.31	0.9712	4.09
6	67.11	66.89	0.9713	4.18

Table 6. Performance of the HSA

Scenario	NAPL	NAPL reduction (%)	V_{min}	λ_{max}
2	138.06	31.88	0.9342	2.14
3	96.97	52.26	0.9670	2.89
4	97.13	52.07	0.9479	3.12
5	-	-	-	3.67
6	73/05	63/95	0.9700	3.93

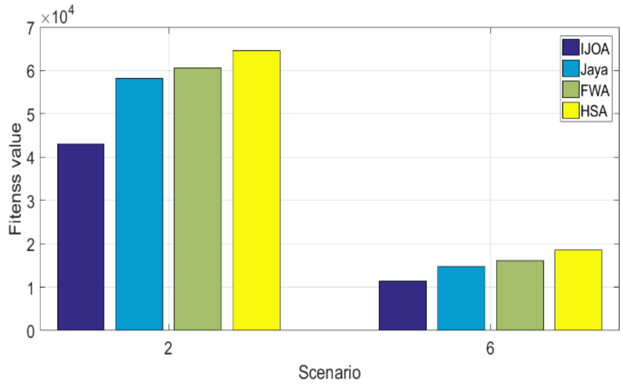

Figure 5. Performance of different methods

4. Conclusion

In this study, a new method based on simultaneous reconfiguration of the distribution system and placement of DG resources to reduce losses and improve system load capacity was presented. In this method, IJOA was used to determine the status of switches, the capacity of DG resources and their location. In order to investigate the effect of each of the compensatory measures, reconfiguration and installation of DG sources, six different scenarios were investigated. In these six cases, each of these cases was examined separately, one after the other, simultaneously. An IEEE standard 33-bus system was also used to evaluate the proposed method. Prior to the reconfiguration and installation of distributed generation sources, the amount of losses was very high and the maximum load was not adequate.

The results showed that reconfiguration the system could significantly reduce the amount of losses. For example, under normal load conditions with initial configuration and without the use of DG sources, the amount of losses was 202.68 kW and the minimum voltage in this system was 0.91 P.U. By changing the system configuration, the amount of losses decreased from 202.68 kW to 138.65 kW, which showed the effect of changing the system configuration. In addition, in this case, the minimum voltage reached 0.94 P.U, which was much better than the previous case (0.91 prionite). Improvements in the voltage profile and the amount of losses showed that changing the system arrangement has a high impact on the performance and security of the distribution system. Another important point was that the simulation results showed that the effect of installing DG resources in reducing losses is much greater than reconfiguration the system. For example, in the 33-bus system, after reconfiguration of the system, the amount of losses reached 138.65 kW, while the amount of losses for the network with DG sources is 72.65 kW. In the first case, the NAPL decreased by 31.26% and in the second case, by 64.86%. Therefore, it is observed that the impact of DG sources is greater in reducing losses. Overall, the simulation results showed that the simultaneous installation of DG sources and the change of system layout lead to the best results. In the next step, the performance of the proposed method was tested and evaluated in different performances. To do this, the proposed method was performed 3 times independently and the results showed that the proposed method has a very good performance in different performances. Having the same performance in different performances is an important feature that a good optimization algorithm should have. If the optimizer algorithm converges to different points in different performances, this algorithm is not reliable and we can not be sure that the answer it provides is the best possible answer.

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