Wild Geese Algorithm for The Combination Problem of Network Reconfiguration and Distributed Generation Placement

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Abstract: Due to operating at low voltage and high current level, the power loss caused by the distribution network (DN) is usually higher than that of other parts of the power system. Thus, power loss reduction is one of the important mission in operation the DN. This paper presents a method of simultaneous execution of network reconfiguration (REC) and distributed generation placement (DGP) based on a new swarm intelligent (SI) namely wild geese algorithm (WGA) to reduce power loss considering the improvement of voltage and current profiles as well as satisfy the constraints including radial topology, distributed generation capacity limit and power balance. The efficiency of the proposed WGA is evaluated on the 33-node and 69-node systems at two cases of REC and REC-DGP. The performance of WGA is contrasted with two SI-based methods including well-known particle swarm optimization (PSO) and recent developed pathfinder algorithm (PFA). The obtained results demonstrate that REC and REC-DGP are effective solutions to reduce power loss and improve voltage and current profiles of the DN, wherein REC-DGP achieves higher efficiency than REC. Furthermore, the statistical results show that WGA outperforms PSO and PFA for both problems in indexes of worst, average, standard deviation values of the fitness function and the computation time. The contrasted results with the previous performed methods also point that WGA can reach the better results than other ones for the REC and REC-DGP problems. Thus, WGA can be a potential method for the REC-DGP problem.

Keywords: Wild geese algorithm; reconfiguration; distributed generation; power loss; distribution network.

1. Introduction

A. Motivations

Low voltage level and high power loss in the distribution network (DN) are the factors that make to increase the operating costs of the DN and the power system [1]. Therefore, finding approaches to reduce power loss on the DN has attracted much attention of researchers. One of the effective approaches to reduce power loss is to adjust the existing DN structure by changing the state of some switches on the DN. This process is called reconfiguration (REC). Although it is inexpensive to implement the REC technique on practical DNs, it is a complex discrete problem, wherein the number of possible structures may reach to 2 exponent n for a DN with n switches. In addition to the REC technique, distributed generation placement (DGP) is also an effective solution for loss reduction on the DN. distributed generation (DG) is small power sources installed at the DN [2], [3]. In recent years, the presence of DGs on the DN has being increased due to the strong development of renewable energy sources as well as the great technical and economic benefits. However, the presence of DGs on the DN also increases the complexity of operating the DN. Their improper installation location and capacity can negatively affect to the DN's performance. Therefore, selection of the optimal parameters of DGs such as location and installation capacity is also a problem that needs attention. In addition, these parameters certainly influence the REC process. Therefore, the problem of combining REC and DGP (REC-DGP) needs to be carried out to promote the performance of the DNs. However, due to the discrete and continuous variable combination and the high search space, the REC-DGP problem becomes more complex that requires efficient solving methods.

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B. Background and related works

In recent years, many works have carried out the REC-DGP problem for technical and economic goals by different methods. In [4], thief and police algorithm (TPA) is presented for the REC-DGP problem considering to capacitor placement for power loss, operational costs and voltage stability. One of strong points of this work is that the TPA performance has been compared with the popular methods such as particle swarm optimization (PSO) and genetic algorithm (GA). However, the final results and convergence characteristics are only presented, statistical results between methods have not been analyzed to show advantages of the proposed TPA over the compared methods. In [5], moth-flame optimization (MFO) is presented for the REC-DGP problem for power loss, voltage profile and stability of the DN. However, the obtained results of MFO is only compared with the other previous methods, the statistical results of MFO has not also displayed to show the stability of the proposed method. In [6], tabu search algorithm (TSA) is successful presented to the REC-DGP problem for loss and switching cost reduction. In this work, TSA has shown the better performance over PSO in terms of convergence and optimal result. In [7], the REC-DGP problem for power loss reduction and voltage improvement is solved by salp swarm algorithm (SSA). However, the final results of SSA is only compared with the previous methods in literature, the statistical results of SSA has not discussed for demonstrating the SSA's stability. In addition to using methods based on original metaheuristic algorithms as aforementioned approaches, there are also some works using methods based on the modified or improved algorithms for the REC-DGP problems. In [8], improved equilibrium optimization (IEO) is proposed for the REC-DGP problem to decrease power loss and increase the DN's voltage. In this work, based on the statistical result comparison, IEO outperforms EO for the REC-DGP problem. In [9], enhanced sine-cosine algorithm (ESCA) is successful applied for the REC-DGP problem for the power loss reduction and other technical and economic goals. In this work, the authors have shown the higher performance of ESCA over the original SCA and other methods in literature. In [1], modified whale optimization algorithm (MWOA) is successful proposed for the REC-DGP problem for the power loss reduction and voltage stability improvement. However, the effectiveness of MWOA is only compared with some pervious methods in literature, the statistical results of MWOA has not been presented and the MWOA has not also compared with the original WOA version. In addition to the methods mentioned above, there are also some methods that have been successfully used for the REC-DGP problem such as butterfly optimizer [10], gravitational search algorithm [11], water cycle algorithm [12], three-dimensional group search algorithm (3DGSO) [13], fireworks algorithm [14], sine-cosine algorithm [15], combination of grey wolf optimizer and PSO (GWO-PSO) [16]. It can be shown that the REC-DGP problem is mainly solved by metaheuristic methods. The applied methods have also proven their effectiveness for this problem. However, the stability and reliability of many methods for the REC-DGP problem through the statistical results have not been analyzed clearly confirmed. This situation may lead to a difficult method choice for the REC-DGP problem. Moreover, the reality has shown no universal algorithm reaching the high efficiency for all problems [17]. Therefore, the applying and testing of new methods for the REC-DGP problem should continue to be implemented in order to supplement effective methods for the REC-DGP problem.

C. Contributions

Wild geese algorithm (WGA) is a swarm intelligent (SI)-based metaheuristic algorithm that is inspired from the behavior of wild geese consisting of coordination in migration process, reproduction and mortality [18]. In [18], WGA has successful applied for determining the optimal value of many high-dimension test functions. However, the efficiency of WGA for the problems in engineering fields as the REC-DGP problem is still a master of concern. Thus, in this paper, WGA is proposed for the REC-DGP problem to minimize the power loss considering the improvement of voltage and current profiles and satisfy the constraints such as radial topology, DG capacity limit and power balance of the DN. The novelty of this work is that the recent developed WGA algorithm is adapted for the REC-DGP and REC problems. The performance of WGA for the REC-DGP and REC problems is compared with two other SI-based metaheuristic methods including PSO and pathfinder algorithm (PFA) in terms of final and statistical results for two test systems consisting the

33-node and 69-node systems. All of three methods consisting of WGA, PSO and PFA belong to the swarm intelligent category that is inspired from the social behavior of animal groups. While PSO is a well-known algorithm that uses the personal best position and the global best position of the whole population to generate new population [19], PFA is also a recent developed algorithm that uses the information of neighbor individual and the pathfinder of the swarm to produce new population [20]. In addition, both of the algorithms have been successful proposed for the problems in the field of power system such as DG placement [21], reconfiguration [22] and reactive power dispatch [23], [24]. Moreover, the final results of WGA are also contrasted with those of other techniques in literature such as MWOA [1], SSA [7], IEO [8] and ESCA [9].

The contributions of this work are summarized as follows:

1) Propose the REC-DGP method based on WGA for power loss reduction considering the improvement of voltage and current profiles as well as satisfy the constraints including radial topology, distributed generation capacity limit and power balance.

2) Consider the effectiveness of REC and REC-DGP solutions in reducing power loss and improving voltage and current of the DNs consisting of the 33-node and 69-node systems.

3) Evaluate the efficiency and reliability of the proposed WGA method by comparing with two other SI-based metaheuristic methods of PSO and PFA for the REC and REC-DGP problems as well as the previous methods.

D. Paper organization

The rest paper is organized as follows: Section 2 discusses the REC-DGP problem for power loss reduction. The overview of WGA and its application to the REC-DGP problem that is called the REC-DGP problem for power loss reduction is given in Section 3. Section 4 presents the calculated results and discussions of the REC and REC-DGP problems, called numerical results. The conclusion is provided in Section 5 that summaries the whole contents and main findings of this paper.

2. The REC-DGP problem for power loss reduction

Due to operating at the low voltage level, power loss of DN often takes a high part in total power loss of the power system. Thus, power loss reduction is an important mission in operation of the DN. The objective function of the REC-DGP is defined as follows:

$$\sum \Delta \mathrm{P}\,(\mathrm{X}) = \sum_{i=1}^{n_{br}} \Delta \mathrm{P}_i \tag{1}$$

Where, $\sum \Delta \mathrm{P}\,(\mathrm{X})$ is power loss of the DN that is caused by the solution X of the REC-DGP problem. $\Delta \mathrm{P}_i$ is the ith branch's power loss. n_{br} is the number of branches of the DN.

The solution of the REC-DGP problem has to satisfy the following constraints:

The power limit of DGs: The DG capacity has to is in the permitted limits as follows:

$$P_{DG,k} \le P_{DGmax,k}\,;\, k = 1,2,\ldots,n_{dg} \tag{2}$$

Where, $P_{DG,k}$ and $P_{DGmax,k}$ are power and rated power of the DG k.

The radial topology: each node has to be served from only it upfront node. This constraint is ensured by the following equation [25], [26]:

$$|det(Y)| = 1 \tag{3}$$

Where, $det(Y)$ is determination of matrix Y. Y is a $(n_{br} \times n_{bu})$ matrix that presents the connection configuration of the DN for the solution X. $Y(i,j)$ is set to 0 if there is not any connection between branch i and node j. $Y(i,j)$ is set to -1 or 1 if branch i is linked to or from node j.

Power balance:

$$\begin{cases} P_s + \sum_{k=1}^{n_{dg}} P_{DG,k} = P_L + \sum \Delta \mathrm{P} \\ Q_s + \sum_{k=1}^{n_{dg}} Q_{DG,k} = Q_L + \sum \Delta \mathrm{Q} \end{cases} \tag{4}$$

Where, $P_s + \mathrm{j}Q_s$ is power of supplied by the slack bus. $P_{DG,k} + jQ_{DG,k}$ is power of the DG k. $P_L + jQ_L$ is load demand. $\sum \Delta \mathrm{P} + \mathrm{j} \sum \Delta \mathrm{Q}$ is the power loss of the DN.

Voltage and current limits: The voltage and current should be in the permitted ranges.

$$V_{Lo} \le V_j \le V_{Hi}\,;\, j = 1,2,\ldots,n_{bu} \tag{5}$$

$$KI_i \leq KI_{Hi,i}\,; i = 1,2,\ldots,n_{br} \quad (6)$$

Where, $[V_{Lo}, V_{Hi}]$ are the permitted voltage ranges that is often selected to [0.95, 1.0]. KI_i and $KI_{Hi,i}$ are respectively the current carrying factor and its rated value of the branch i. $KI_{Hi,i}$ is often selected to 1, meanwhile KI_i is found by quotient of current in branch i and its rated current.

3. Wild geese algorithm for the REC-DGP problem

The WGA is inspired on the behavior of wild geese's lives consisting of migration, food searching, reproduction and death in the wild goose population. Wherein, the position of each wild goose is considered as a candidate solution of the optimization problem. The WGA is adapted for the REC-DGP problem are follows:

A. Generate the current wild goose population

The solution vector of the REC-DGP problem consists of open switches, location and capacity of DGs. For encoding of open switches, the binary variables can be used to represent the status of switches, wherein the zero and one states represent respectively for opened and closed switches [27]–[30]. However, by using this encoding technique, the number of variables in each solution will be very high for the large-scale DNs because the number of variables must be set equal to the number of branches of the DN. Therefore, in this study, in order to reduce the number of variables of the solution vector, the open switches are represented by integer variables that indicate the open switch position in the closed loops of the DN. For location and capacity of DGs, integer variables are used to indicate the installation node and real variables are chosen to indicate the capacity of the DGs. In order to solve the REC-DGP problem, the wild goose population is first generated as follows:

$$X_i = R_1(X_H - X_L) + X_L; i = 1,2,\ldots,N_{ini} \quad (7)$$

Where, $X_i = [x_1, x_2, \ldots, x_D]$ is the position of the wild goose i. R_1 is a $(1 \times D)$ vector of random numbers in the interval (0,1). D is number of variables of the problem. N_{ini} is the initial number of geese in the population. $[X_L, X_H]$ is the boundary vectors that contains allowed limit about open switches, location and capacity of DGs. For open switch variables, X_L is selected to 1, wherein X_H represents the size of the mesh loops containing the possible open switches. For DG location variables, X_L is selected to 2 and X_H is the number of nodes of the DN. For DG capacity variables, X_L is selected to 0 and X_H is the limit of DGs as shown in (2).

The solution to the REC-DGP problem includes open switches on branches and DG installation locations at nodes as well as DG capacity. So, after being randomly initialized, the geese population should be modified as follows:

$$x_{i,d} = \begin{cases} round(x_{i,d}); if\ d \in [1,2,\ldots,n_{os}] \\ round(x_{i,d}); if\ d \in [n_{os+1}, n_{os+2}, \ldots, n_{os} + n_{dg}] \\ x_{i,d} \qquad ; otherwise \end{cases} \quad (8)$$

From each generated REC-DGP solution, the node and branch parameters of the DN are updated. Based on the variables indicating the position and power of the DGs, the DN's node parameter is updated. For the open switch variables, they are mapped into closed loop vectors of the DN to determine the open switches. For example, the radial DN in Figure 1 has 6 nodes, 7 branches and 2 open switches. In which, the search space of the first open switch is the closed loop vector of {s1, s2, s4, s5} that is defined by closing s5. Similarly, the search space of the second open switch is the vector of {s1, s2, s3, s4, s6, s7} which is determined by closing s7. Then, the value of the open switch variables is considered as the order index of the switches in the closed loops.

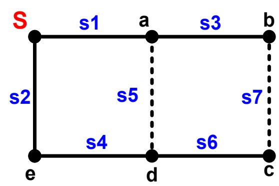


Figure 1. The DN with 2 open switches

In order to evaluate the quality of each solution, the DN configuration X_i is checked the radial topology constraint by using (3). If this condition is satisfied, the power flow is executed using the Newton method [31]. Then, if the power balance constraint in (4) is maintained, the fitness value of each solution (F_i) which includes objective function in (1) and the voltage and current constraints in (5) and (6) is calculated as follows:

$$F_i = \sum \Delta P\ (X_i) + \rho.[max(V_{Lo} - V_{min}(X_i),0) + max(V_{max}(X_i) - V_{Hi}, 0) + max(KI_{max}(X_i) - KI_{Hi}, 0)] \quad (9)$$

Where, ρ is the penalty factor. $V_{min}(X_i)$, $V_{max}(X_i)$ and $KI_{max}(X_i)$ are the minimum, maximum voltage amplitudes and the maximum current carrying factor of the solution X_i, respectively.

In case of the radial topology and power balance constraints in (3) and (4) do not satisfy, a very high value will be assigned to the fitness value of the configuration X_i. Based on the fitness value of the goose population, the best wild goose (G_{best}) of the population is also determined.

B. Generate new solutions by the mechanisms of coordinated group migration and walking for searching food mechanisms

In order to generate new geese, the population is arranged in ascending order of the fitness value. Then, the new solutions are generated by two techniques including the coordinated group migration and food searching mechanisms. Details of each are follows:

During migration process, the wild geese often fly in a certain order. The position of each goose depends on the position of adjacent geese. Based on this idea, velocity of the goose i at the next iteration (V_i^{t+1}) is depended on the velocity of upfront and rear geese as well as position of adjacent geese that is defined as follows:

$$V_i^{t+1} = R_2V_i^t + R_3(V_{i+1}^t - V_{i-1}^t) + R_4(P_i^t - X_{i-1}^t) + R_5(P_{i+1}^t - X_i^t) + R_6(P_{i+2}^t - X_{i+1}^t) - R_7(P_{i-1}^t - X_{i+2}^t) \quad (10)$$

Where, V_i^t, X_i^t and P_i^t are the current velocity, position and the best position of the goose i. R_2 to R_7 are random number vectors in [0, 1].

Moreover, the best goose of the population guides for flying of the whole population. Thus, the position of each goose is updated by the coordinated group migration mechanism as follows:

$$X_i^m = P_i^t + R_8R_9\left((G_{best} + P_{i+1}^t - 2P_i^t) + V_i^{t+1}\right) \quad (11)$$

Where, X_i^m is the new position of the goose i generated by the coordinated group migration mechanism. R_8 and R_9 are random number vectors in [0, 1].

Unlike the migratory mechanism, in the process of walking for searching food, each goose tends to follow the its upfront individual. This idea is mathematically described as follows:

$$X_i^w = P_i^t + R_{10}R_{11}(P_{i+1}^t - P_i^t) \quad (12)$$

Where, X_i^w is the new position of the goose i generated by the mechanism of walking for searching food. R_{10} and R_{11} are random number vectors in [0, 1].

The reproduction of GWA is performed by the combination of the coordinated group migration mechanism and the walking for searching food mechanism as shown (13). In which, the probability that each mechanism is selected is the same.

$$X_i^{t+1} = \begin{cases} X_i^m;\ if\ R_{12} \le 0.5 \\ X_i^w;\ otherwise \end{cases} \quad (13)$$

The new geese are checked and adjusted to their boundaries $[X_L, X_H]$ to ensure each solution in its permitted ranges as follows:

$$X_{i,d}^{t+1} = \begin{cases} X_{i,d}^{t+1};\ if\ X_{L,d} \le X_{i,d}^{t+1} \le X_{H,d} \\ X_{L,d};\ if\ X_{i,d}^{t+1} \le X_{L,d} \\ X_{H,d};\ if\ X_{i,d}^{t+1} \ge X_{H,d} \end{cases} \quad (14)$$

Then, the new geese are modified to map with the REC-DGP by using (8) and evaluated the quality by calculating the fitness value using (9). From the fitness value of each new goose, the best position of each goose is updated as follows:

$$P_i^{t+1} = \begin{cases} X_i^{t+1}\ ; & if\ F_i^{t+1} < F_{p,i}^t \\ P_i^t & ; otherwise \end{cases} \quad (15)$$

$$F_{p,i}^{t+1} = \begin{cases} F_i^{t+1}\ ; & if\ F_i^{t+1} < F_{p,i}^t \\ F_{p,i}^t & ; otherwise \end{cases} \quad (16)$$

In addition, the best goose of the current population (G_{best}) is also updated by the comparison between the its current fitness value and the best one of each new goose.

C. Reduce the population size

The weaker goose will be died and the number of geese in the population will reduce to the final population size (N_{final}) as follows:

$$N = round\left(N_{ini} - \left(N_{ini} - N_{final}\right)\frac{NFE_t}{NFE_{max}}\right) \quad (17)$$

Based on the new population size, the process of generating new position and updating the best position of each goose continues to performance until the current number of fitness evaluation (NFE_t) reaches to the maximum value NFE_{max}. The flowchart of GWA for the REC-DGP problem is shown in Figure 2.

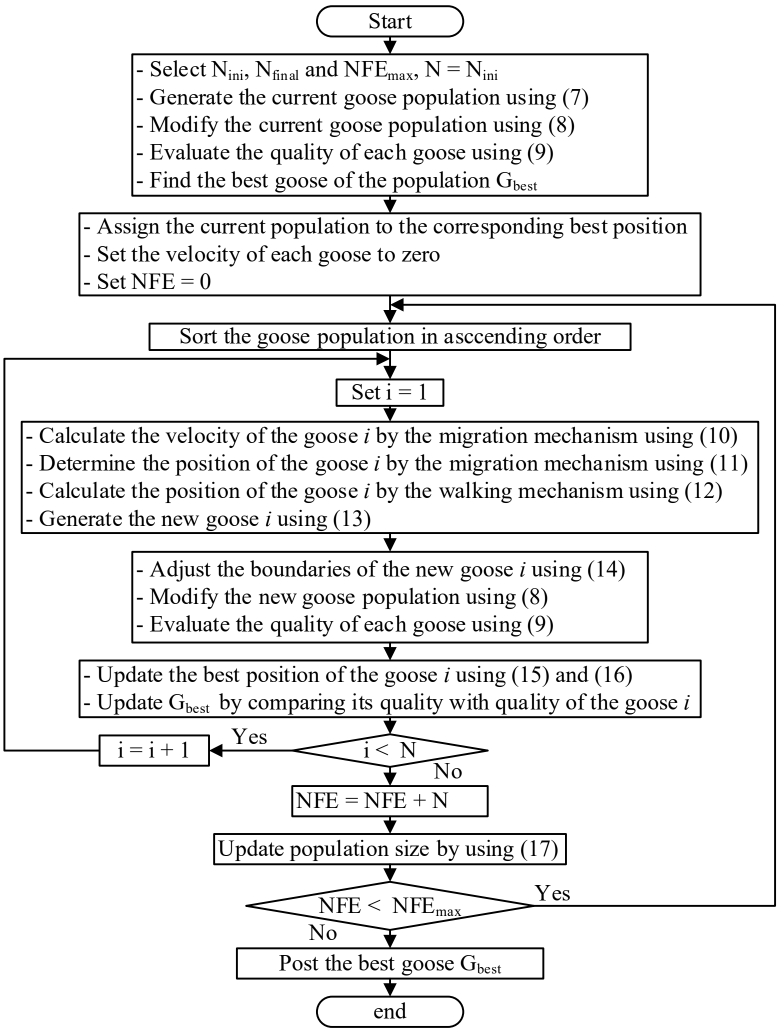
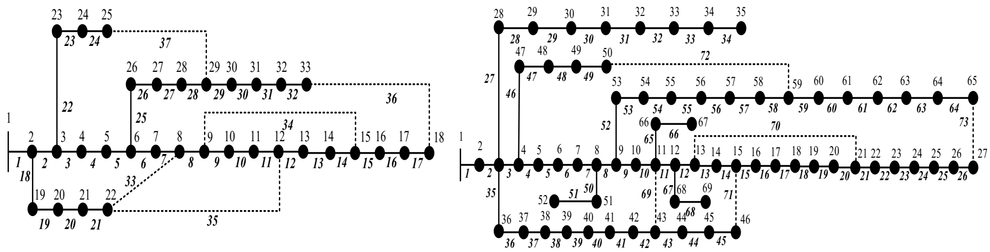


Figure 2. The WGA for the REC and REC-DGP problem

4. Numerical results

The REC-DGP method based on WGA is coded in Matlab 2016a. Its performance is compared with PSO and PFA. Both of PSO an PFA are also the SI-based metaheuristic algorithms and their metaphor looks like to that of WGA. While PSO uses the personal best position and the global best position of the whole population to generate new population [19], PFA uses the information of neighbor individual and the pathfinder of the swarm for creating new population [20]. The performance of WGA, PSO and PFA are evaluated on two DNs consisting of the 33-node and 69-node systems as shown in Figure 3 [32], [33]. In addition, in order to evaluate the efficiency of the REC-DGP for reducing power loss of the DNs, the REC-DGP solution is also compared with the REC only in term of power loss reduction. The steps of WGA for the REC problem is similar to those of the REC-DGP problem except that variables related to DGs are excluded from the candidate solutions.



a) The 33-node system b) The 69-node system

Figure 3. The 33-node and 69-node systems

A. The 33-node system

The 12.66 kV 33-node system in Figure 3.a has 33 nodes, 37 branches with their rated current of 255A [34] and the total load 3.72 + j2.3 MVA. At the initial configuration, there is five open switches of 33-34-35-36-37. The power loss, minimum voltage amplitude and maximum current carrying factor of the initial configuration are respectively 202.6863 kW, 0.9131 pu and 0.8250 pu. The number of DGs installed in the DN is selected to three DGs with 2 MW for each. The penalty factor ρ for vilolating the voltage and current constraints is chosen to 1000. To compare the efficiency of the above algorithms, based on the initial and final population size of WGA as well as the maximum number of fitness evaluations, the population size of PSO and PFA is chosen so that all three algorithms will stop searching with the same number of iterations. By selection of N_{ini} of 60, N_{final} of 30 and NFE_{max} of 3000, WGA will stop searching after about 68 iterations, the average number of individuals of WGA is about 3000/68 = 44.1176. Thus, the population size of PSO and PFA is selected to 44.

The optimal REC and REC-DGP results of WGA, PSO and PFA for the 33-node system are presented in Table 1. After performing REC and REC-DGP, the loss power is reduced to 139.9823 and 50.7189 kW respectively corresponding to the reduction of 30.94% and 74.98% compared to the original configuration. The smallest voltage amplitude in the system obtained by implementing using REC and REC-DGP has also increased from 0.9131 to 0.9412 and 0.9734 pu respectively corresponding to the increase of 3.08% and 6.60% compared to the original structure. In addition, the maximum load carrying factor of the system has also been respectively reduced from 0.8250 to 0.8126 and 0.4407 p.u. It shows that the optimal DGs installation combined with REC has significantly reduced the current on the branches carrying heavy loads. In comparison between REC and REC-DGP, the power loss reduction and minimum voltage improvement achieved by the latter is 44.04% and 3.52% respectively higher than those of the former and the maximum load carrying factor of the REC-DGP is also 0.3843 p.u lower than that of the REC solution. The voltage and current profiles after performing REC and REC-DGP in Figure 4 show a significant improvement, wherein REC-DGP has a much better improvement than REC.

Table 1. The REC and REC-DGP optimal results for the 33-node system of WGA over PSO, PFA and other methods

Case	Method	Optimal OS	DG's location and size in MW	Power loss (kW)	Loss reduction (%)	V_{min} (p.u)	Voltage enhancing (%)	V_{max} (p.u)	KI_{max} (p.u)
Initial	-	33-34-35-36-37	-	202.6863	-	0.9131	-	1.0000	0.8250
REC	WGA	7-14-9-32-28	-	139.9823	30.94%	0.9412	3.08%	1.0000	0.8126
	PSO	7-14-9-32-28	-	139.9823	30.94%	0.9412	3.08%	1.0000	0.8126
	PFA	7-14-9-32-28	-	139.9823	30.94%	0.9412	3.08%	1.0000	0.8126
	SSA [7]	7-14-9-32-37	-	139.5500	31.15%	0.9378	2.71%	-	-
	ESCA [9]	7-9-14-32-37	-	139.5500	31.15%	0.9378	2.71%	-	-
	MWOA [1]	7-14-9-32-28	-	139.9823	30.94%	0.9412	3.08%	-	-
REC-DGP	WGA	33-34-11-31-28	7 (0.956947); 25 (1.27956); 17 (0.75296)	50.7189	74.98%	0.9734	6.60%	1.0000	0.4407
	PSO	33-34-11-31-28	26 (0.922483); 25 (1.28689); 17 (0.753231)	51.6587	74.51%	0.9734	6.60%	1.0000	0.4425
	PFA	33-34-11-31-28	17 (0.752953); 7 (0.956943); 25 (1.27965)	50.7189	74.98%	0.9734	6.60%	1.0000	0.4407
	SSA [7]	6-14-11-17-28	8 (1.027); 24 (1.180) ; 31 (0.837)	56.42	72.16%	0.9762	6.91%	-	-
	ESCA [9]	7-14-9-27-30	12 (0.5672); 18 (0.7125); 25 (1.190)	53.53	73.59%	0.9651	5.69%	-	-
	IEO [8]	7-10-13-27-31	8 (0.39900); 17 (0.66900), 29 (1.1600)	57.4000	71.68%	-	-	-	-
	MWOA [1]	11-28-31-33- 34	8 (0.8299); 17 (1.3412); 31 (0.7109)	50.61	75.03%	-	-	-	-

The comparison results in Table 1 also show the high performance of WGA for the REC and REC-DGP problems. For the REC case, the results obtained by GWA are similar to those of PSO, PFA and MWOA [1] in both terms of power loss and lowest voltage amplitude. The loss reduction obtained by WGA is 0.21% lower than that of SSA [7] and ESCA [9] but the lowest voltage in the network obtained by GWA is 0.36% higher than that of SSA [7] and ESCA [9]. For the REC-DGP case, the results obtained by GWA are similar to those of PFA in both power loss and lowest voltage amplitude while the power loss reduction obtained by PSO is 0.46% lower than WGA. In comparisons with the implemented methods, the power loss reduction of WGA is only 0.05% lower than that of MWOA [1] but it is 2.81%, 1.39% and 3.30% higher than SSA [7], ESCA [9] and IEO [8], respectively. These results show that WGA is an effective method for both of the REC and REC-DGP problems.

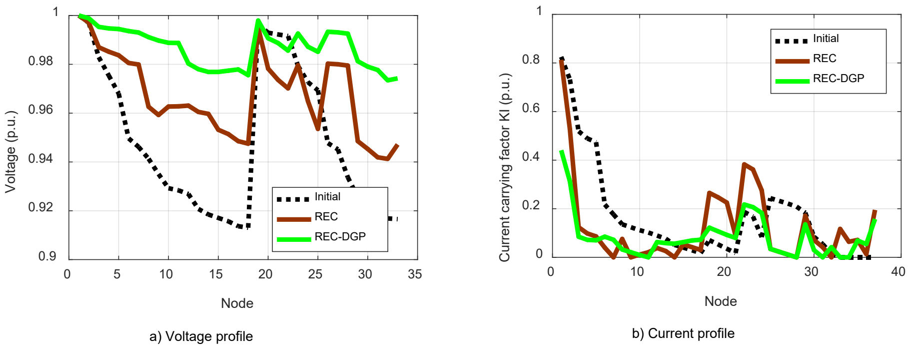
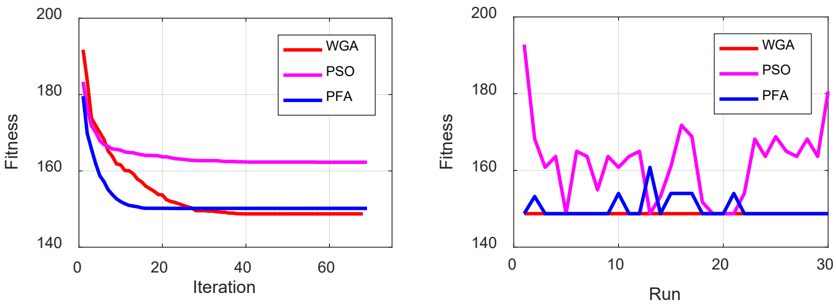


Figure 4. Voltage amplitude profile for the 33-node system by REC and REC-DGP

The results of the efficiency comparison between WGA with PSO and PFA via statistical results are presented in Table 2. For the REC problem, although all three methods have obtained the optimal results in 30 runs, the ratio of founding out the optimal structure of WGA is 83.33% and 23.33% higher than that of PSO and PFA, respectively. In addition, the statistical values such as worst (F_{worst}), average (F_{ave}), standard deviation (std) values of fitness function and the run time of WGA are also lower than those of PSO and PFA. Similarly, for the REC-DGP problem, the F_{worst}, F_{ave} and std values and the computation time of WGA are also lower than those of PSO and PFA. The lower F_{ave} and std values of WGA indicate the higher reliability and stability of GWA for the REC and REC-DGP problems over PSO and PFA. The average convergence characteristics over 30 runs and the minimum fitness value in each run for the REC problem shown in Figure 5 and the REC-DGP problem shown in Figure 6 demonstrate that WGA often converges to a better value than PSO and PFA in each run. This shows the superiority of WGA over the two SI-based PSO and PFA methods.

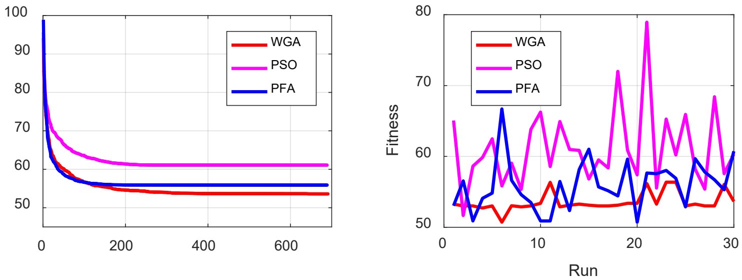
Table 2. The performance of WGA, PSO and PFA for the REC and REC-DGP problems on the 33-node system

Case	Method	Successful rate (%)	F_{worst}	F_{best}	F_{ave}	std	CPU time (s)
REC	WGA	100	148.7392	148.7392	148.7392	0	7.9641
	PSO	16.6667	192.7752	148.7392	162.2682	9.8575	8.4906
	PFA	76.6667	160.8025	148.7392	150.1684	2.8948	9.9698
REC-DGP	WGA	3.3333	56.3640	50.7189	53.6289	1.2122	82.7172
	PSO	3.3333	78.9408	51.6587	61.134	5.5520	92.4901
	PFA	3.3333	66.7015	50.7189	55.9814	3.5387	102.5661



a) Mean convergence curve b) Optimal fitness value in each run

Figure 5. The convergence curve and value over 30 runs of REC only for the 33-node system



a) Mean convergence curve b) Optimal fitness value in each run

Figure 6. The convergence curve and value over 30 runs of REC-DGP for the 33-node system

B. The 69-node system

The 12.66 kV 69-node system in Figure 3.b has 69 nodes, 73 branches [33]. The initial configuration with open switches of 69-70-71-72-73 has power loss of 224.8871 kW and minimum voltage amplitude of 0.9092 pu. Because of lack of rated current of branches, it is assumed that implementing REC and REC-DGP does not influence on the system overload. The control parameters of WGA, PSO and PFA are set similar to those of the 33-node system.

The results of REC and REC-DGP of WGA, PSO and PFA for the 69-node system are presented in Table 3. By performing REC and REC-DGP, the loss power is reduced to 98.5875 and 35.1537 kW respectively corresponding to the reduction of 56.16% and 84.37% compared to the original network. The smallest voltage amplitude in the system gained by implementing using REC and REC-DGP has also increased from 0.9092 to 0.9495 and 0.9813 pu, respectively corresponding to the increase of 4.43% and 7.93% compared to the original structure. In comparison between REC and REC-DGP, the power loss reduction and minimum voltage improvement achieved by the latter is 28.21% and 3.5% respectively higher than those of the former. The voltage profile after performing REC and REC-DGP in Figure 7 shows a significant improvement, wherein REC-DGP has a much better improvement than REC.

In comparison with PSO, PFA and other methods, the results in Table 3 also show the high performance of WGA for the large-scale REC and REC-DGP problems. For the REC problem, the results obtained by GWA are similar to those of PSO, PFA, ESCA [9] and MWOA [1] in both terms of power loss and lowest voltage amplitude. The loss reduction and voltage improvement obtained by WGA is 0.02% and 0.03% respectively higher than those of SSA [7]. For the REC-DGP case, the results obtained by GWA are also similar to those of PFA in both power loss and lowest voltage amplitude while the power loss reduction obtained by PSO is 2.14% lower than WGA. In comparisons with the implemented methods, the power loss reduction of WGA is 0.29%, 0.8%, 0.91% and 0.55% higher than SSA [7], ESCA [9], MWOA [1] and IEO [8], respectively. This result shows that WGOA can reach the higher performance compared the above methods for the REC-DGP problem.

Table 3. The REC and REC-DGP optimal results for the 69-node system of WGA over PSO, PFA and other methods

Case	Method	Optimal OS	DG's location and size in MW	Power loss (kW)	Loss reduction (%)	V_{min} (p.u)	Voltage enhancing (%)	V_{max} (p.u)
Initial REC	-	69-70-71-72-73	-	224.8871	-	0.9092	-	1.0000
	WGA	69-70-14-57-61	-	98.5875	56.16%	0.9495	4.43%	1.0000
	PSO	69-70-14-57-61	-	98.5875	56.16%	0.9495	4.43%	1.0000
	PFA	69-70-14-57-61	-	98.5875	56.16%	0.9495	4.43%	1.0000
	SSA [7]	69-14-71-61-58	-	98.63	56.14%	0.9492	4.40%	-
	ESCA [9]	14-55-61-69-70	-	98.60	56.16%	0.9495	4.43%	-
	MWOA [1]	70-69-61-57-14	-	98.5875	56.16%	-	-	-
REC-DGP	WGA	69-70-14-57-61	61 (1.43399); 11 (0.537415); 64 (0.490203)	35.1537	84.37%	0.9813	7.93%	1.0000
	PSO	10-70-12-57-63	21 (0.768452); 61(1.46703); 21 (0)	39.9562	82.23%	0.9804	7.83%	1.0000
	PFA	69-70-14-56-61	11 (0.537447); 64 (0.490178); 61 (1.43401)	35.1537	84.37%	0.9813	7.93%	1.0000
	SSA [7]	69-14-70-63-58	11 (0.650); 27 (0.490); 61 (1.4675)	35.81	84.08%	0.9808	7.88%	-
	ESCA [9]	12-19-69-63-57	11 (0.436); 61(1.300); 65 (0.4616)	36.95	83.57%	0.9774	7.50%	-
	MWOA [1]	70-69-61-58-14	11 (0.5413); 65 (0.5536); 61 (1.724)	37.20	83.46%	-	-	-
	IEO [8]	12-57-63-69-70	12 (0.362); 26 (0.518); 61 (1.400)	36.39	83.82%	-	-	-

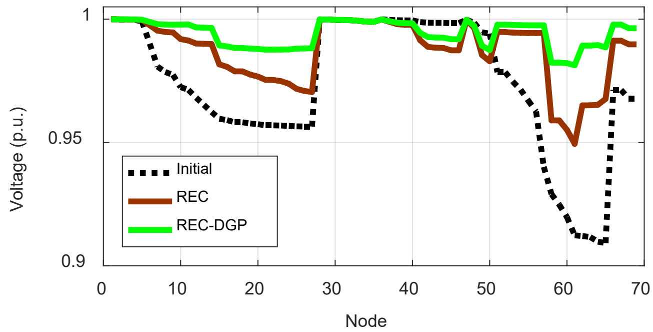
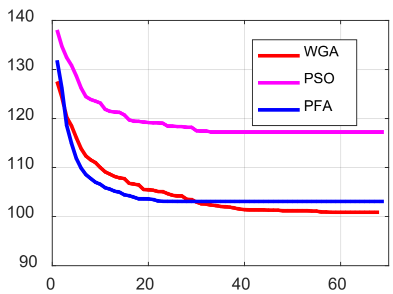


Figure 7.Voltage amplitude profile for the 69-node system by REC and REC-DGP

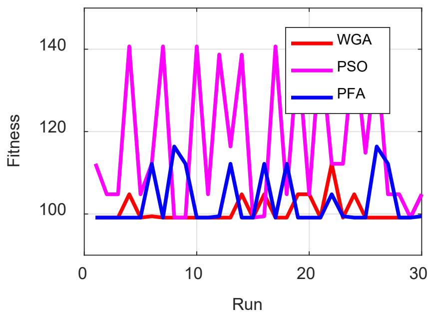
The statistical results of WGA with PSO and PFA for the 69-node system are presented in Table 4. For the REC problem, although all three methods have obtained the optimal results in 30 runs, the ratio of founding out the optimal structure of WGA is 56.67% and 10% higher than that of PSO and PFA, respectively. Furthermore, all of the values of the indexes such as F_{worst}, F_{ave} and std and the run time of WGA are also lower than those of PSO and PFA. The average convergence characteristic over 30 runs and the minimum fitness value in each run for two problems in Figure 8 and Figure 9 show that WGA converges to a lower value than PSO and PFA in each run. These results once again confirm the superiority of WGA over PSO and PFA for REC and REC-DGP problems.

Table 4. The performance of WGA, PSO and PFA for the REC and REC-DGP problems on the 69-node system

Case	Method	Successful rate (%)	F_{worst}	F_{best}	F_{ave}	std	CPU time (s)
REC	WGA	70	112.1841	99.1169	100.8847	3.2252	24.8745
	PSO	13.3333	140.7413	99.1169	117.2604	16.8942	27.774
	PFA	60	116.3852	99.1169	103.1021	6.3702	34.7089
REC-DGP	WGA	3.3333	43.8166	35.1537	38.4488	2.4717	291.0964
	PSO	3.3333	53.7236	39.9562	44.5813	2.9177	304.7312
	PFA	3.3333	44.0419	35.1537	40.0178	2.9603	322.0344

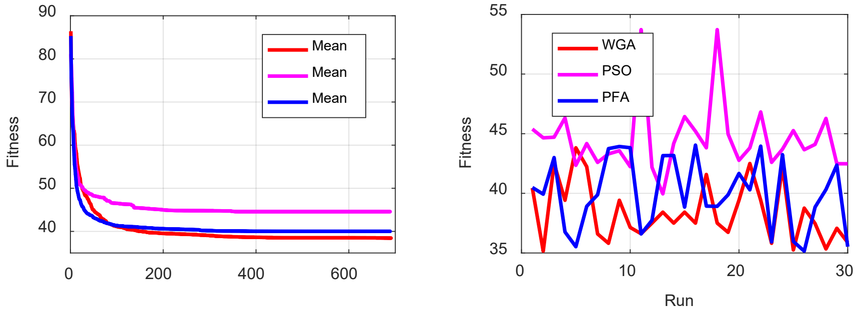


a) Mean convergence curve



b) Optimal fitness value in each run

Figure 8. The convergence curve and value over 30 runs of REC only for the 69-node system



a) Mean convergence curve

b) Optimal fitness value in each run

Figure 9. The convergence curve and value over 30 runs of REC-DGP for the 69-node system

5. Conclusion

In this paper, the swarm intelligence-based WGA algorithm has been adjusted to successfully solve the combination problem of optimal network reconfiguration and DG installation on the DN. The considered objective in the REC-DGP process is to minimize the power loss considering the improvement of voltage and current profiles. In addition, the REC-DGP implementation must maintain the radial structure and ensure the power limit of the DGs as well as the power balance of the DN. The recommended WGA method is compared with two other swarm intelligence-based algorithms including PSO and PFA. The effectiveness of the methods is evaluated on the 33-node and 69-node DNs for both problems including REC and REC-DGP. The main findings of this work can be summarized as follows:

1) The WGA has been successful adjusted for finding the optimal solution of the REC and REC-DGP problem. The solutions gained by WGA have the lower power loss than that of the original network. for the REC problem, the power loss of the 33-node and 69-node DNs has been respectively reduced by 30.94% and 56.16% compared to the original status of the DNs. For the REC-DGP problem, the loss reduction of the two systems are up to 74.98% and 84.37%, respectively. In addition, the voltage and current profiles are also greatly improved compared to the original structure.

2) The improvement achieved by REC-DGP is much greater than that of implementing REC only, wherein power loss reduction achieved by REC-DGP solution is 44.04% for the 33-node DN and 28.21% for the 69-node DN higher than that of REC only.

3) The statistical result comparison shows that WGA outperforms PSO and PFA for both of the problems in indexes of worst, average, standard deviation values of the fitness function and the computation time. In addition, the results compared with the previous performed methods on the two systems also show that WGA is an appropriate method for both of the REC and REC-DGP problems. Based on the achieved results, WGA is one of the effective and reliable methods for the REC and REC-DGP problems.

For future work, the REC and REC-DGP problems can be carried out considering to the uncertainty factors and WGA can be used for the REC and REC-DGP problems for practical DNs to satisfy other technical and economic objectives.

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