International Journal of Electrical and Computer Engineering (IJECE)
Vol. 12, No. 6, December 2022, pp. 5765~5774
ISSN: 2088-8708, DOI: 10.11591/ijece.v12i6.pp5765-5774

Modified sunflower optimization for network reconfiguration and distributed generation placement

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Article Info

Article history:

Received Aug 16, 2021
Revised Jun 17, 2022
Accepted Jul 10, 2022

Keywords:

Distributed generation
Electric distribution system
Modified sunflower optimization
Network reconfiguration
Power loss

ABSTRACT

This paper proposed modified sunflower optimization (MSFO) for the combination of network reconfiguration and distributed generation placement problem (NR-DGP) to minimize power loss of the electric distribution system (EDS). Sunflower optimization (SFO) is inspired form the ideal of sunflower plant motion to get the sunlight and its reproduction. To enhance the performance of SFO, it is modified to MSFO wherein, the pollination and mortality techniques have been modified by using Levy distribution and mutation of the best solutions. The results are evaluated on two test systems. The efficiency of MSFO is compared with that of the original SFO and other algorithms in literature. The comparisons show that MSFO outperforms to SFO and other methods in obtained optimal solution. Furthermore, MSFO demonstrates the better statistical results than SFO. So, MSFO can be a powerful approach for the NR-DGP problem.

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1. INTRODUCTION

The combination of network reconfiguration and distributed generation placement (NR-DGP) is one of the most effective approaches to reduce power loss of the electric distribution system (EDS). Network reconfiguration (NR) exchanges power among the system's lines meanwhile distributed generation (DG) placement provides power at load demand site. However, NR-DGP is a nonlinear and discrete problem, wherein its candidate solution includes open switches (OS), locations and power of distributed generations. Furthermore, the NR-DGP solution has to satisfy the constraints such as radial topology guard, voltage and current limits. Therefore, studying on the solving approaches for the NR-DGP should be encouraged to provide more effective methods for this problem.

While the only NR problem can be solved by a number of heuristic methods [1], [2], the metaheuristic algorithms are mainly used to search the optimal solution for the NR-DGP problem. In [3], equilibrium optimization (EO) algorithm has been applied for the NR-DGP to reduce the EDS's power loss. In [4] whale optimization algorithm (WOA) has been used for the NR, DGP and NR-DGP problem for power loss reduction. Furthermore, in [5] WOA is also used for the NR problem to find the network configuration with minimization of power loss. In [6], thief and police algorithm has been applied for the combination of NR-DGP and capacitor placement problem to reduce of power loss, operational cost and improve voltage stability. In [7], butterfly optimizer has been applied for the NR-DGP problem to satisfy the multi goals consisting of load ability, power loss and loading margin. In [8], tabu search algorithm (TSA) is applied successfully for the NR-DGP problem to reduce the cost of power loss and switching. Wherein, the efficiency of TSA is compared to particle swarm optimization (PSO). In [9] binary PSO (BPSO) is presented for the NR-DGP and capacitor placement to reduce the EDS's power loss. In addition, in [10] another improved version of BPSO called Chaotic BPSO has been also applied to the NR problem for power loss reduction. In addition, some of recent algorithms have been successful proposed for the NR-DGP problem such as water cycle algorithm [11], firefly algorithm (FA), gravitational search algorithm (GSA) [12], sine cosine algorithm (SCA) [13], moth flame optimization [14], salp swarm algorithm [15], and three-dimensional group search algorithm (3DGSO) [16].

To increase the performance of the metaheuristic algorithms for the NR-DGP problem, some of works have been improved or modified the algorithms with arming to find the better solutions. In [3], improved EO (IEO) has been also proposed for the NR-DGP problem. The results show that its performance has been higher than that of EO. In [17], the combination of genetic algorithm (GA), WOA and PSO has been proposed for the NR-DGP problem. However, in this work the effectiveness of the combination algorithm has not been compared to the original version of the algorithms. In [18], improved sine–cosine algorithm (ISCA) has been proposed for the NR-DGP problem for power loss reduction. In which, ISCA has outperformed to some previous methods. However, its performance has not been compared with the original algorithm. There are many metaheuristic algorithms that have been successfully applied to the NR-DGP problem. However, many methods based on these algorithms have been adapted from the original version for fitting to the NR-DGP problem. The number of studies that improve or modify the original algorithms to enhance the efficiency of the NR-DGP problem is still limited. Thus, the improvement of the original version of metaheuristic algorithms should be consider to give more quality tools for the NR-DGP problem.

Sunflower optimization (SFO) algorithm is a recent algorithm that takes idea of movement of sunflower plant to get sunlight and its reproduction [19]. The sunflower plant population is updated by using three different techniques consisting of pollination, movement and mortality techniques. SFO has been show the higher performance than GA for the problem of damage detection in [19]. In addition, SFO has demonstrated its ability for some problems such as the problem of NR and re-allocating capacitors of the EDS [20] and parameter estimation of battery [21]. In this paper, a modified SFO (MSFO) is proposed for the NR-DGP problem to reduce power loss of the EDS. In MSFO, the pollination and mortality techniques have been adjusted to create candidate NR-DGP solutions that have higher quality than the original SFO. The effectiveness of MSFO is compared with SFO for two test systems. Moreover, the obtained results of MSFO are also compared with the previous algorithms for the NR-DGP problem. The contributions of this work are follows: i) propose modification of pollination and mortality techniques of MSFO for NR-DGP problem, ii) MSFO is first applied for determining the optimal OS, location and size of DGs, and iii) MSFO is better than SFO and other methods in finding the optimal solution for the NR-DGP problem.

The rest paper is arranged as follows: the NR-DGP is shown in the next section. Overview of SFO and MSFO are shown in section 3. Results and discussions are shown in section 4. Conclusion are displayed in section 5.

2. NR-DGP PROBLEM FOR POWER LOSS REDUCTION

The considered goal of the NR-DGP process is to minimize the EDS's power loss (ΔP). It is calculated as (1):

$$\Delta \mathrm{P}\ (S) = \sum_{i=1}^{nbr} \mathrm{P}_{loss,i} \tag{1}$$

where, $\mathrm{P}_{loss,i}$ is power loss of the branch i. S is candidate solution of the NR-DGP problem. It consists open switches, location and size of DGs as (2):

$$S = [OS_1, OS_2, \dots, OS_{nos}, L_{DG1}, L_{DG2}, \dots, L_{DGndg}, P_{DG1}, P_{DG2}, \dots, P_{DGndg}] \tag{2}$$

where, OS, L_{DG}, P_{DG} stands for open switches, location and power of DGs. nos and ndg is number of open switches and DGs, respectively.

The NR-DGP process should satisfy the below constraints:

- Limit of DGs:

$$P_{DG,j} \leq P_{DGmax,j}\ ; j = 1,2, \dots, ndg \tag{3}$$

where, $P_{DG,j}$ and $P_{DGmax,j}$ are power and rated power of the $DG\ j$.

- The radial configuration: It is checked by (4) [22], [23]:

$$|det\ (C)| = 1 \qquad (4)$$

where, $det\ (C)$ is determination of matrix C that describes the connection of the EDS.
– Power balance:

$$\begin{cases} P_s - \sum_{j=1}^{ndg} P_{DG,i} = P_{load} + \Delta P \\ Q_s - \sum_{j=1}^{ndg} Q_{DG,i} = Q_{load} + \Delta Q \end{cases} \qquad (5)$$

where, P_s + jQ_s is complex power of slack bus. $P_{DG,i} + jQ_{DG,i}$ is complex power of the DG i. $P_{load} + jQ_{load}$ is complex load demand of the EDS. $\Delta P + j\Delta Q$ is the complex power loss of the EDS.
– Voltage and current limits:

$$V_L \le V_i \le V_H; i = 1,2, \dots, nbus \qquad (6)$$

$$KI_j \le KI_{H,j}; j = 1,2, \dots, nbr \qquad (7)$$

where, $[V_L, V_H]$ are limits of voltage amplitude. KI_j and $KI_{H,j}$ are the factor of carrying current and its rated value of the branch j.

3. RESEACH METHOD

3.1. The original sunflower optimization

The sunflower plant population is updated by using three different mechanisms consisting of pollination, movement and mortality techniques [19]. The role of pollination technique is exploration of the search space. The movement technique helps SFO to exploit the search by directing solutions to move along with the best one meanwhile the last technique helps to create new solutions in the search space. Details of them as described as follows:
– Generation of new solutions by pollination technique: the sunflower is pollinated by interaction with the plant locating next to it:

$$S_{i,new} = rand(0,1).(S_i - S_{i+1}) + S_{i+1}; i = 1,2, \dots, p.n \qquad (8)$$

where, p is pollination rate. n is population size.
– Generation of new solutions by sunflower movement technique: the sunflowers tend to move to the sun or the best sunflower as (9):

$$S_{i,new} = S_i + rand(0,1).[(S_b - S_i)/(\|S_b - S_i\|)]; i = p.n \div n.(1 - q) \qquad (9)$$

where, S_b is the best solution. $\|S_b - S_i\|$ is the Euclidean length between plants i and best one. q is the mortality rate.
– Generation of new solution by mortality technique: The died plants will be replaced by new random ones as (10):

$$S_{i,new} = L + rand(0,1).(H - L);\ i = n.(1 - q) \div n \qquad (10)$$

where, $[H, L]$ is the boundary of solutions.

3.2. The modified SFO for NR-DGP problem

In this section, The MSFO is proposed for the NR-DGP problem. Wherein, the pollination and mortality techniques are modified to enhance the performance of MSFO. Details of modifications and steps of MSFO for the NR-DGP problem is as follows:
Step 1: Generate the current sunflower plant population

$$S_i = L + rand(0,1).(H - L); i = 1 \div n \qquad (11)$$

For mapping with the NR-DGP, each solution is adjusted as (12).

$$S_{i,j} = \begin{cases} round(S_{i,j}); j = 1,2,\dots,nos + ndg \\ S_{i,j} \quad ; j = nos + ndg, nos + ndg + 1, \dots, nos + 2.ndg \end{cases} \quad ; i = 1 \div n \tag{12}$$

The current population is evaluated the quality by the fitness function consisting of the objective and constraint functions. As shown in (3) is ensured by adjusting the boundaries of new solutions. Meanwhile if (4) and (5) are not maintained, then a high value will be assigned to the fitness value, otherwise, the fitness value is determined as (13).

$$F(S_i) = \Delta\mathrm{P} + \mathrm{z}.[\max(V_L - V_{min}, 0) + \max(V_{max} - V_H, 0) + \max(KI_{max} - KI_H, 0)] \tag{13}$$

Step 2: Generate the new solution by the modified pollination technique

In SFO, the current population will be replaced by new one that is created using pollination, movement and mortality techniques. However, new solutions created by different mechanisms have different characteristics in term of differentiation from the original ones. This results in updating the current population which may be ineffective. For example, a plant with the best quality is at the bottom of the population. Then, comparing its quality with a random solution generated by the mortality mechanism may not be as efficient as a neighboring one generated by the movement mechanism. So, in MSFO, the solutions will be sorted in descending order of the fitness value before implementing mechanisms of creating new solutions.

In SFO, a solution interacts with a neighboring one to create a new solution. But the quality of the neighboring solution is not concerned. So, in MSFO, the neighboring solution will be replaced by the best one. In order to avoid tendency of moving to the best one and balance in exploration and exploitation, Levy distribution is used as a scaling factor for the difference between two solutions [24], [25]. The characteristic of the levy distribution is that it is capable of generating steps adjacent to the previous one, and sometimes it produces steps that are much larger than the previous one as depicted in Figure 1.

$$S_{i,new} = S_i + \mu.(S_i - S_b) \otimes Levy\ (\omega); i = 1,2,\dots,p.n \tag{14}$$

Where μ is the step size chosen to 0.3. ω is distribution coefficient selected to 1.5 [25]. $\otimes$ is the entry-wise multiplications. $Levy\ (\omega)$ is the Levy distribution.

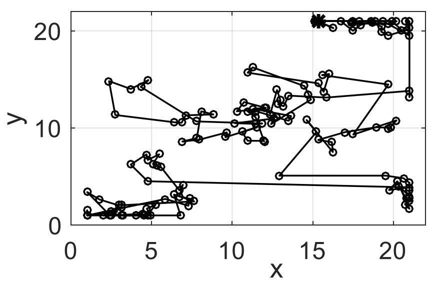


Figure 1. Levy flights path of the (0,0) point over 150 steps

Step 3: Generate new solutions by the sunflower movement technique

The sunflowers tend to move to the sun or the best sunflower as (15):

$$S_{i,new} = S_i + rand(0,1).[(S_b - S_i)/(\|S_b - S_i\|)]\ ; i = p.n \div n.(1 - q) \tag{15}$$

Step 4: Generate new solutions by the modified mortality technique

After sorting the population, the good solutions are located at the bottom of the population. Therefore, the probability that solutions generated randomly by the mortality mechanism of SFO are better than the current ones will be low. So, in MSFO this mechanism will be modified to create new solutions locating around the current solutions. This mechanism works similarly to the mutation of GA or the detection of strange eggs of cuckoo search.

$$S_{i,new} = S_{i,new} + rand(0,1).(S_k - S_h).B;\ n.(1 - q) \div n \tag{16}$$

Where, B is the binary vector that its value is determined as (17):

$$B = \begin{cases} 1; if\ rand > m \\ 0; otherwise \end{cases} \tag{17}$$

where, *m* is the mutation rate selected to 0.2.

Step 5: Update the current sunflower plant population

The new solutions are adjusted if they are out of bounds. Then, they are adapted by (12) for mapping with the NR-DGP and evaluated the quality by using (13). Then, the current sunflower plants are updated if new solutions have the better quality than that of the current ones.

Step 6: Stop searching the best solution

Steps from 2 to 5 are executed in turn until the number of iterations reaches to the maximum value. Then, the S_b is the optimal result of the NR-DGP problem.

4. RESULTS AND DISCUSSION

The method of optimizing open switches, location and size of DGs based on MSFO is built on MATLAB. It is tested on two test systems as shown in Figure 2 with the 33 nodes system in Figure 2(a) and 69 nodes system in Figure 2(b). The data of two EDS are taken from [26], [27]. The rated current of two systems are chosen to 150 A and 100 A. Number of DGs and their powers are limited to 3 MW and 2 MW. To show the efficiency of MSFO, the NR-DGP method based on SFO is also implemented for both systems to compare with MSFO. The number of sunflower plants and the maximum number of iterations are set to 30 and 500, respectively. The pollination and mortality rates are chosen to 0.5 and 0.2, respectively. The control parameters of SFO are chosen similar to them of MSFO.

The optimal results for the first EDS are shown in Table 1. The original system with OS of {33, 34, 35, 36, 37} causes the power loss, the lowest voltage amplitude and the maximum current carrying coefficient of 202.6863 kW, 0.9131 p.u. and 1.4024 p.u., respectively. It is noticed that the system has overloaded branches.

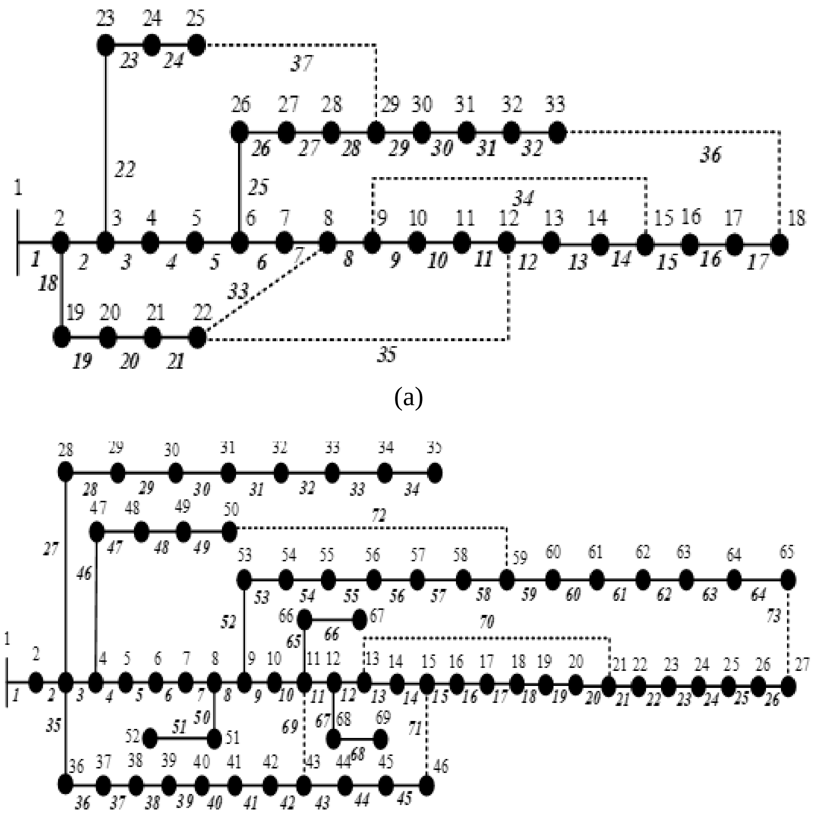


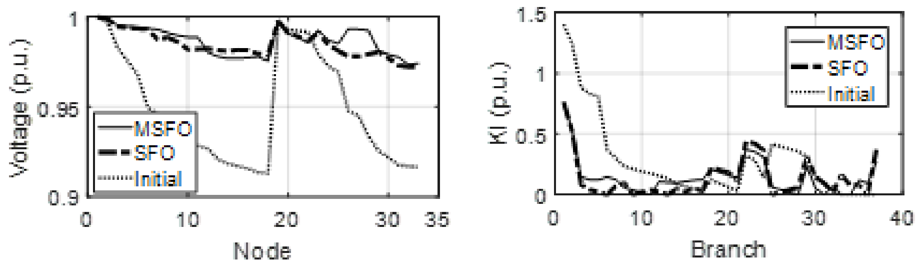
Figure 2. The test systems for (a) 33-nodes and (b) 69-nodes

Table 1. NR-DGP results of MSFO for the 33 nodes system

Method	OS	P_{DG} [L_{DG}]	ΔP (kW)	Reduction (%)	V_{min}	V_{max}	KI_{max}
Initial	33, 34, 35, 36, 37	-	202.6863	-	0.9131	1	1.4024
MSFO	33, 34, 11, 31, 28	0.95695 (7), 0.75296 (17), 1.27957 (25)	50.7189	74.9767%	0.9734	1	0.7492
SFO	6, 13, 9, 36, 25	0.99150 (8), 0.21338 (16), 1.67559 (29)	60.6798	70.0622%	0.9720	1	0.7635
EO [3]	8, 27, 33, 34, 36	0.16500 (8), 0.65100 (14), 1.41300 (29)	61.4800	72.1639%	-	-	-
IEO [3]	7, 10, 13,27, 31	0.39900 (8), 0.66900 (17), 1.16000 (29)	57.4000	74.8920%	-	-	-
WOA [4]	11, 28, 31, 33, 34	0.8299 (8) 1.3412 (17) 0.7109 (31)	50.61	69.6674%			
FA [12]	7, 9, 13, 28, 32	0.64500 (31), 0.52000 (32), 0.58000 (33)	72.425	71.6804%	0.9742		
GSA [12]	7, 10, 13, 28, 32	0.67560 (31), 0.51600 (32), 0.63340 (33)	72.361	75.0304%	0.9750		
3DGSO [16]	7, 8, 14, 25, 36	0.63000 (12), 0.60000 (18), 1.19000 (30)	57.97	64.2674%	0.9899		
ISCA [18]	7, 9, 14, 28, 31	0. 62178 (30), 0.72661 (18), 0.43626 (20)	67.57	64.2990%	0.9678		
SSA [15]	6, 14, 11, 17, 28	1.02700 (8), 1.18000 (24), 0.83700 (31)	56.4200	71.3992%	0.9762	-	-
GWO-PSO [28]	11, 28, 30, 33, 34	0.95690 (7), 0.75290 (17), 1.27950 (25)	50.8905	66.6628%	0.9734	-	-

After performing NR-DGP using MSFO, the optimal OS is {33, 34, 11, 31, 28} and the optimal DG power of the three DGs is 0.95695, 0.75296, 1.27957 MW installed at nodes of 7, 17 and 25, respectively. The optimal solution results in power loss of 50.7189 kW that is 151.9674 kW less than that of the original system. This reduction is about 74.9767% compared to that of the original system. Furthermore, the lowest voltage amplitude has been improved to 0.9734 p.u. and the maximum current-carrying coefficient has also been decreased to 0.7492 p.u. Meanwhile, the solution obtained by SFO only helps to reduce 142.0065 kW corresponding to 70.0622% compared to that of the original system. Specifically, the power loss obtained by SFO is 60.6798 kW which is 9.9609 kW higher than that of MSFO. Furthermore, the lowest voltage amplitude and maximum current-carrying factor of the system by using MSFO's solution are also more improvement than that of SFO.

Table 1 has also shown that the high performance of MSFO for NR-DGP problem in term of comparing to other methods. The power loss reduction of MSFO is respectively 5.3092%, 3.2963%, 10.7092%, 10.6776%, 3.5775%, 8.3139%, 2.8128% and 0.0847% greater than that EO, IEO, FA, GSA, 3DGSO, ISCA, SSA and gray wolf optimization-particle swarm optimization (GWO-PSO) methods and it is only lower than WOA about 0.0537%. The node voltage amplitudes and current carrying factors of the solutions of MSFO, SFO and the original system in Figure 3 demonstrate that the voltage ranges in Figure 3(a) and current ranges in Figure 3(b) obtained by MSFO are in the allowed ranges with [0.95, 1.05] p.u. for voltage amplitude and [0, 1.0] p.u. for current carrying factors. Furthermore, the improvement of the system by using the optimal solution of MSFO is better than that of SFO and the original system.



(a) (b)

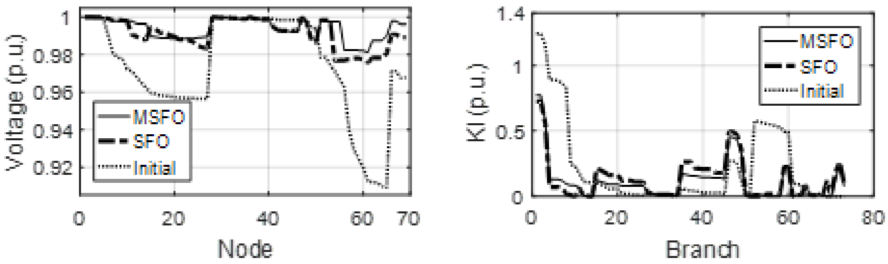
Figure 1. Voltage and current profiles of the 33-nodes system: (a) voltage amplitude and (b) current carrying factor

The optimal results for the second EDS are shown in Table 2. The original system with OS of {69, 70, 71 72, 73} causes the power loss, the lowest voltage amplitude and the maximum current carrying factor of 224.8871 kW, 0.9092 p.u. and 1.2413 p.u., respectively. After performing NR-DGP using MSFO, the optimal solution causes power loss of 35.1921 kW that is 189.695 kW lower than that of the original system. The power reduction is about 84.3512% compared to that of the original system. The lowest voltage amplitude has been improved to 0.9813 p.u. and the maximum current-carrying coefficient has also been decreased to 0.7694 p.u. Meanwhile, the solution obtained by SFO only helps to reduce 178.4656 kW that is 11.2294 kW corresponding to 4.9933% lower compared to that of MSFO. Furthermore, the lowest voltage amplitude of the system by using MSFO's solution is also more improvement than that of SFO.

Table 2 has also shown that the reliability of MSFO for NR-DGP problem in term of comparing to other methods. Compared to EO, IEO, WOA, FA, GSA, 3DGSO, ISCA and SSA, the power loss reduction of MSFO is respectively 1.0485%, 0.5327%, 0.0257%, 2.1126%, 2.0921%, 1.3268%, 2.0179% and 0.2748% greater than that of the above methods. Compared to GWO-PSO, power loss reduction of MSFO is only 0.0260% lower than that of these methods. The node voltage amplitudes and current carrying factors of the solutions of MSFO, SFO and the original configuration in Figure 4 show that the voltage ranges in Figure 4(a) and current ranges in Figure 4(b) obtained by MSFO are in the allowed ranges. In addition, the improvement of the 69-node system by using the optimal solution of MSFO is better than that of SFO and the original system.

Table 2. NR-DGP results of MSFO for the 69 nodes system

Method	OS	P_{DG} $[L_{DG}]$	ΔP (kW)	Reduction (%)	V_{min}	V_{max}	KI_{max}
Initial	69, 70, 71 72, 73	-	224.8871	-	0.9092	1	1.2413
MSFO	69, 70, 14, 55, 61	0.52749 (65), 0.53739 (11), 1.43398 (61)	35.1921	84.3512%	0.9813	1	0.7694
SFO	10, 14, 12, 53, 61	1.23929 (61), 1.22993 (15), 0.56539(38)	46.4215	79.3579%	0.9759	1	0.7235
EO [3]	12, 18, 56, 63, 69	0.52200 (27), 1.46300 (61), 0.27800 (66)	37.5500	83.3027%	-	-	-
IEO [3]	12, 57, 63, 69, 70	0.36200 (12), 0.51800 (26), 1.40000 (61)	36.3900	83.8185%	-	-	-
WOA [4]	71, 62, 57, 17, 8	1.69430 (18), 0.95010 (36), 0.43980 (61)	35.25	84.3255%	-	-	-
FA [12]	12, 13, 58, 61, 69	0.53531 (60), 0.99296 (61), 0.48986 (62	39.943	82.2386%	0.98161	-	-
GSA [12]	12, 13, 57, 61, 69	0.54120 (60), 0.99499 (61), 0.47008 (62)	39.897	82.2591%	0.98176	-	-
3DGSO [16]	14, 56, 61, 69, 70	1.3130 (61), 0.4410 (62), 0.7520 (50)	38.1760	83.0244%	0.9823	-	-
ISCA [18]	12, 19, 69, 63, 57	1.0009 (61), 0.4106 (62), 0.4616 (65)	39.73	82.3334%	0.9798	-	-
SSA [15]	69, 14, 70, 63, 58	0.6500 (11), 0.49000 (27), 1.46750 (61)	35.8100	84.0765%	0.9808	-	-
GWO-PSO [28]	14, 55, 61, 69, 70	1.43400 (61), 0.49020 (64), 0.53750 (11)	35.1337	84.3772%	0.9813	-	-



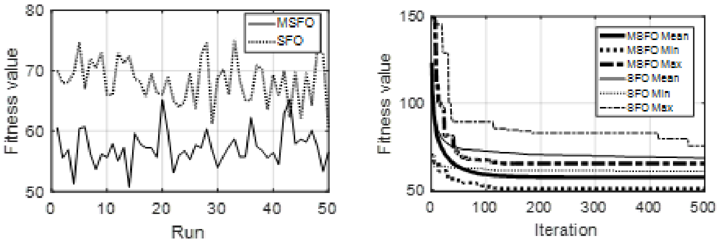
(a) (b)

Figure 4. Voltage and current profiles of the 69-nodes system: (a) voltage amplitude and (b) current carrying factor

The statistical results MSFO and SFO for two systems in 50 runs are displayed in Table 3. The indexes consisting of minimum (F_{min}), maximum (F_{max}), average (F_{aver}) and STD (F_{std}) values of MSFO are lower than that of SFO. These values show that the modifications of MSFO bring the positive results for the NR-DGP problem. The number of convergence iterations ($No.Iter_{aver}$) and executed time (T_{exe}) of MSFO are higher than that of SFO. However, although SFO converges earlier than MSFO, the convergence solution of SFO is worse than that of MSFO. The fitness value and convergence curves over 50 runs for two systems of MSFO and SFO are shown in Figures 5 and 6. Figures 5(a) and 6(a) show that the fitness value in each run of MSFO is often less than that of SFO while Figures 5(b) and 6(b) demonstrate that the mean, maximum and minimum curves of MSFO converge to lower values compared with that of SFO. These evidences indicate that MSFO outperforms to SFO for the NR-DGP problem.

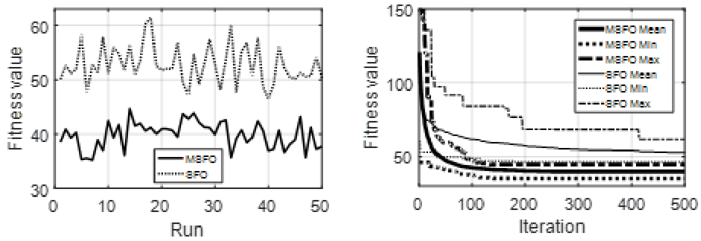
Table 3. Comparisons of MSFO and SFO

System	Method	F_{min}	F_{max}	F_{aver}	F_{std}	$No.\ Iter_{aver}$	T_{exe} (s)
33-node	MSFO	50.7189	65.2285	57.287	2.9578	474	52.0891
	SFO	60.6798	75.3332	68.2843	3.6840	239	31.3706
69-node	MSFO	35.1921	44.7150	39.8546	2.4698	460	155.7653
	SFO	46.4215	61.4485	52.7802	3.5798	267	95.7453



(a) (b)

Figure 5. Convergence character of MSFO and SFO of the 33-node system in 50 runs: (a) fitness value and (b) convergence curve



(a) (b)

Figure 2. Convergence character of MSFO and SFO of the 69-node system in 50 runs: (a) fitness value and (b) convergence curve

5. CONCLUSION

The method of NR-DGP based on MSFO has been proposed in this paper. The goal is to minimize power loss of the EDS considering to voltage and current limit constraints. In MSFO, improvements consisting of arranging the population, using Levy distribution for generating new plants in the pollination mechanism and using mutation mechanism to creating new plants in the mortality technique have been proposed for MSFO. The calculated results for MSFO and SFO for the 33-node and 69-node EDSs have shown that MSFO is more effective than SFO for the NR-DGP problem. The power loss reduction of MSFO for two systems is respectively 4.9144% and 4.9933% greater than that of SFO. The statistical results in several runs also shown the better performance of MSFO compared to SFO for the NR-DGP problem. The compared results with other methods in term of final solution demonstrated that MSFO is a powerful approach for the NR-DGP problem. For future work, MSFO may be applied for NR-DGP problems for optimization of other goals.

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