Enhanced sunflower optimization for placement distributed generation in distribution system

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Article Info	ABSTRACT
	Installation of distribution generation (DG) in the distribution system gains many technical benefits. To obtain more benefits, the location and size of DG must be selected with the appropriate values. This paper presents a method for optimizing location and size of DG in the distribution system based on enhanced sunflower optimization (ESFO) to minimize power loss of the system. In which, based on the operational mechanisms of the original sunflower optimization (SFO), a mutation technique is added for updating the best plant. The calculated results on the 33 nodes test system have shown that ESFO has proficiency for determining the best location and size of DG with higher quality than SFO. The compared results with the previous methods have also shown that ESFO outperforms to other methods in term of power loss reduction. As a result, ESFO is a reliable approach for the DG optimization problem. *This is an open access article under the CC BY-SA license.*

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1. INTRODUCTION

Distributed generations (DG) is small power plant connected to the power system at distribution voltage level or installed closed to customers [1]. From the operational perspective, DG installation is able to bring many technical benefits for distribution network such as power loss reduction, voltage improvement and reliability enhancing. However, these maximum benefits are only achieved when DG is installed in the proper position as well as the appropriate capacity, otherwise wrong position and size of DG may cause more technical issues. Therefore, optimization of location and size of DG is the problem that is attracted by many concerns.

For solving the DG optimization problem, there are various methods that have been proposed. In [2], genetic algorithm (GA) is proposed to find the optimal location and size of DG to gain more revenues and reduce imposed costs [2]. In [3], GA is used for solving the DG optimization problem to reduce power loss. Similarly, in [4], GA is also proposed for determining location and size of DG in the smart grid network. In [5], artificial bee colony method (ABC) has been applied to find the appropriate position and size of DG in the distribution system. In [6], power loss reduction is minimized by installing DG based on honey bee mating optimization (HBMO). In [7], particle swarm optimization (PSO) is combined with GA for optimization of DG to reduce power loss and enahnce voltage stability. In [8], PSO is proposed to solve the the DG optimization problem combined with the network reconfiguration.

To solve the DG optimization problem, not only common methods such as GA, ABC, HBMO and PSO are used, but also many recently developed algorithms have been successfully applied such as whale

optimization algorithm (WOA) [9, 10], harmony search (HS) [11, 12], modified crow search (MCS) [13], adaptive cuckoo search (ACS) [14], fireworks algorithm (FA) [15], coyote algorithm [16], uniform voltage distribution algorithm (UVD) [17], hyper cube ant colony optimization (HCACO) [18], runner root [19] and modified plant growth simulation (MPGS) [20]. Compared with classical methods such as dynamic programming [21], linear programming [22] and mixed integer linear programming [23], methods based on general knowledge such as GA, ABC and the aforementioned methods often get better quality results when applied to the DG optimization problem. Therefore, researching new methods to apply to the DG optimization problem is also a matter of concern to supplement the potential methods for solving the problem.

This paper presents a method to optimize location and size of DG in the distribution system to minimize power loss based on enhanced sunflower optimization (ESFO). Wherein, ESFO is enhanced from the original sunflower optimization (SFO) [24]. In [24], the original SFO is taken from an ideal of movement of the sunflower plant to take sunlight. In order to apply for solving the optimization problem, each sunflower plant is considered as solution. The best plant is examined as the sun and all of other plants will move to the best one. Based on the mechanisms of creating new plants of SFO, we proposed to add the mutation technique to create a new plant by mutating the best plant for updating the best sunflower plant.

The effectiveness of the proposed ESFO has been demonstrated on the 33 nodes test distribution system. The calculated result is compared to that of SFO and other previous methods. The contributions of this work can be highlighted as follows:
− A mutation of creating a new plant for updating the best sunflower plant is proposed for ESFO.
− ESFO is first proposed for the DG optimization problem.
− The effectiveness of ESFO is evaluated on the 33 nodes test distribution system.
− ESFO is more effective than SFO as well as the previous methods for the DG optimization problem in terms of the obtained solution quality.

The rest paper is organized as follows: The following section shows the problem of DG optimization. The section 3 demonstrates the proposed ESFO and its application for the DG optimization problem. The section 4 presents results and discussion. Finaly, the conclusion section is demonstrated.

2. PROBLEM OF DG OPTIMIZATION

One of the biggest benefits of installing DG in the distribution system is power loss reduction. The main goal of the problem is to minimize power loss. It is determined as follows:

$$\Delta P = \sum_{i=1}^{n_l} p_{loss,i} \tag{1}$$

where $p_{loss,i}$ is power loss of the line i. n_l is number of lines in the system.

Installing DG in the distribution system should be maintained the following constraints:
− Voltage and current limits:

$$\begin{cases} \text{V}_{min}^{li} \leq V_i \leq \text{V}_{max}^{li} \; ; \; i \, = \, 1 \div n_b \\ LI_i \leq LI_{max,i}^{li} \qquad ; i \, = \, 1 \div n_l \end{cases} \tag{2}$$

where V_{min}^{li} and V_{max}^{li} are the lower and upper limits of the node voltage. V_i is the voltage amplitude of node i. LI_i and $LI_{max,i}^{li}$ are the load carrying coefficient and maximum coefficient of the line i. n_b is number of nodes in the system.
− DG size limits:

$$s_k \leq s_{k,max} \; ; \; k \, = \, 1 \div n_{dg} \tag{3}$$

where s_k is size of DG k in MW. $s_{k,max}$ is the maximum capacity limit of DG k. n_{dg} is number of DG installed in the distribution system.

3. ENHANCED SUNFLOWER OPTIMIZATION FOR THE DG OPTIMIZATION PROBLEM
3.1. The original sunflower optimization

For solving the optimal problem, the population of sunflower plants is updated by three different techniques. The first one is called pollination technique. A part of the population that is determined by the pollination rate is chosen for pollination and creating new plants for the next generation. The pollination technique to create new plants is done by the combination of two consecutive plants in the population as follows:

$$p_i = rand(0,1).(p_i - p_{i+1}) + p_{i+1} ; i = 1 \div r_p.n \tag{4}$$

where p_i and p_{i+1} are the plant i and $i+1$ in the population. r_p is the pollination rate that is chosen to 0.6 [24]. n is number of plants in the population.

The second one is called the survival technique. In the remainder of the population, a number of plants will survive and maintain over the next generation. The retention of information of a plant through the next generation is determined by the distance from itself to the best plant. The closer to the best one a plant is, the greater probability that it will remain the same over the next generation. The details of creating new plants by the survival technique is described as below:

$$p_i = p_i + rand(0,1).\left((p_{best} - p_i)/(\|p_{best} - p_i\|)\right) ; i = r_p.n \div n.(1 - r_d) \tag{5}$$

where, p_{best} is the best plant. $\|p_{best} - p_i\|$ is the Euclidean length of the $p_{best} - p_i$ vector. r_d is the death rate that is chosen to 0.1 [24].

The last one is called mortality technique. In the remainder of the population, a number of plants that is determined by the mortality rate will be died and replaced by new random plants as follows:

$$p_i = ub + rand(0,1).(ub - lb) ; i = n.(1 - r_d) \div n \tag{6}$$

where ub and lb are the upper and lower bounds of the plants.

The new plants are validated the fitness function and they are used to replace for the corresponding ones in the population if their quality is better than the corresponding ones' quality. In addition, the best sunflower plant is updated until the maximum number of generation is reached.

3.2. The enhanced sunflower optimization

It can be seen that SFO uses three different techniques to renew the population. In the first technique, the method of combining two consecutive plants in the population to create a new plant. The role of this technique is exploration and exploitation the search space. The second technique helps to create new plants that move to the best plant. It helps SFO to exploit the search space. Meanwhile, the final technique generates random plants to explore the search space and prevent the SFO from converging to local optimal solution soon. Based on the above mechanisms of SFO, in this study we propose the enhanced sunflower optimization (ESFO). Wherein, a new technique is suggested to create a new plant by mutating the best one. After the new population of plants has been created from the three above techniques, their fitness function is calculated and the best plant is determined. Before the population is renewed again in the next generation, the new plant is created by mutation of the best plant. If the new plant has better quality than the best one, it is used to replace the best plant, otherwise it will be die if its quality is worse than the best one. The new plant is generated as follows:

$$p_{new,j} = p_{best,j} + rand(0,1).\mu.\rho(0,1) ; j = 1 \div d \tag{7}$$

where, $p_{new,j}$ and $p_{best,j}$ are the control variable j of the new and best plants. d is problem dimension. μ is a constant to determine the maximum change limit of the variable. $\rho(0,1)$ is a function that returns the value of 0 or 1. If the $\rho(0,1)$ is equal to 0, the $p_{new,j}$ is similar to $p_{best,j}$ otherwise the $p_{new,j}$ will be set to new value. The value of $\rho(0,1)$ is determined as follows:

$$\rho(0,1) = \begin{cases} 1 ; if\ rand(0,1) < r_m \\ 0 ; otherwise \end{cases} \tag{8}$$

where r_m is mutation rate that is selected to 0.2. It means that about twenty percent of variables of the p_{best} is renewed. The new plant is validated the fitness function and it will become to the best plant if it has better quality than the best one, it is used to replace the best plant, otherwise it will be die.

3.3. The application of ESFO for the DG optimization problem
Step 1: Initialization

For applying to the DG optimization problem, each sunflower plant is presented as follows:

$$p_i = [l_{i,k}, s_{i,k}] ; i = 1 \div n\ and\ k = 1 \div n_{dg} \tag{9}$$

where l_k and s_k are location and size of DG k. n_{dg} is number of DG installed in the distribution system.

At the beginning, the initial plants are created randomly as follows:

$$p_i = ub + rand(0,1).(ub - lb) ; i = 1 \div n \tag{10}$$

where ub and lb for are determined as follows:

$$\begin{cases} ub = [l_{k,max}, s_{k,max}] \\ lb = [l_{k,min}, s_{k,min}] \end{cases} ; k = 1 \div n_{dg} \tag{11}$$

where $s_{k,max}$ and $s_{k,min}$ are the upper and lower sizes of the DG k. $l_{k,max}$ and $l_{k,min}$ are the highest and lowest nodes in the distribution system.

Then, the variable part indicates the location of DG is rounded to integer value to map with the DG optimization problem and the system data is updated to calculate the fitness function (F) value as follows:

$$Fit = \Delta P + K. \begin{bmatrix} max(V_{min}^{li} - V_{min}, 0) + max(V_{max} - V_{max}^{li}, 0) \\ + max(LI_{max} - LI_{max}^{li}, 0) \end{bmatrix} \tag{12}$$

where, K is penalty coefficient, V_{min} and V_{max} are the minimum and maximum voltage amplitude is the system. LI_{max} maximum load carrying coefficient in the system.

Based on the F value, the best plant p_{best} is determined.

Step 2: Creating of new plants by using the pollination, survival and mortality techniques

The new population of sunflower plants is generated by using the pollination, survival and mortality techniques as described in equations (4-6). Wherein, the variable part indicates the location of DG of new plants is rounded to integer value. The quality of new plants is validated by the fitness function as (12). The new plants are used to replace for the corresponding ones in the current population if their quality is better than the corresponding ones' quality. Otherwise, they will be died. The final procedure of this step is to update the best plant by comparing the plant having the best fitness value with the best plant of the previous generation.

Step 3: Creating the new plant by mutating the best plant

From the best plant determined in step 2, the new plant is created by using equation (7). Then, the variable part indicates the location of DG of new plants is rounded to integer value to map with the DG optimization problem. Finally, its quality evaluated by using (12) is compared with the best plant. The best plant is updated one more time if the quality of the new plant is better than that of the best plant.

Step 4: Checking the stopping condition

The stopping condition is set based on a maximum number of fitness evaluation (MNFE). It means that step 2 and 3 will be executed until number of fitness evaluation reaches to the MNFE value.

4.   RESULTS AND DISCUSSION

In this section, the performance of ESFO is compared with the original SFO in the same personal computer based on Matlab platform. In addition, the effectiveness of ESFO is also compared with previous DG optimization methods in the literature. All of methods are validated on the 33 nodes distribution system as shown in Figure 1 [25]. In which, the load, voltage level and line parameters are taken from [25] and the rated current of all lines are referenced set to 150 A. The number of DG selected for optimization is fixed to 3 and their power limit is set to 2 MW. The parameters of ESFO and SFO consisting of n and MNFE are set to 30 and 9000, respectively. For ESFO, the μ constant in (7) is chosen to 3. The penalty coefficient K in the fitness function equation is selected to 1000.

The calculated results of ESFO are shown in Table 1. From the table, the total losses have been reduced from 202.6863 kW to 72.2671 kW. It means that the power loss reduction is 130.4192 corresponding to reduction of 64.35%. Furthermore, the node voltage and line current as shown in Figure 2 have been also enhanced after installing three DG with power of 1.0945, 1.3162 and 0.8046 MW at the nodes of 30, 24 and 13. In more details, the minimum voltage amplitude in per unit has been raised from 0.9131 to 0.9709 and the maximum LI value has been decreased from 1.4024 to 0.7354. In comparison with SFO, power loss obtained by ESFO is 0.4715 kW lower than that of SFO corresponding to 0.24% reduction higher than that of SFO. In addition, the minimum voltage amplitude obtained by ESFO is 0.003 higher and the maximum LI value is 0.064 lower than those of SFO. The improvement of voltage profile of SFO shown in Figure 2 is also

worse than that of ESFO. These results show that ESFO outperforms to SFO for finding optimal location and size of DG in the distribution system. The optimal location of three DG in the system is shown in Figure 3.
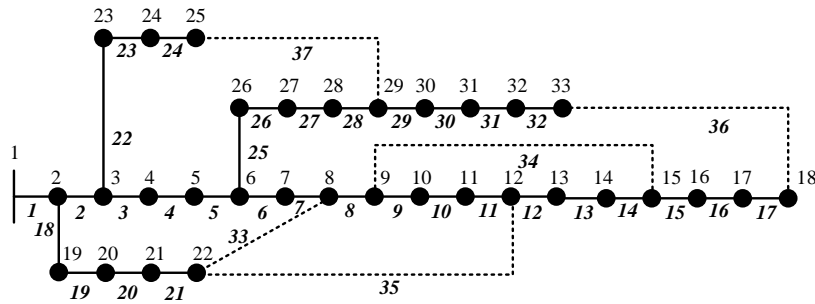

Figure 1. The 33 nodes test system

Table 1. Optimal solution for the 33 nodes system

| Method	DG size (MW)	DG location (node)	ΔP (kW)	Loss reduction (kW)	Loss reduction (%)	V_{min} (p.u)	LI_{max}
Initial	-	-	202.6863	-	-	0.9131	1.4024
ESFO	1.0945, 1.3162, 0.8046	30, 24, 13	72.2671	130.4192	64.35%	0.9709	0.7354
SFO	0.78392, 0.72531, 1.09894	24, 14, 30	72.7386	129.9477	64.11%	0.9679	0.7994
ACS [14]	0.7798, 1.1251, 1.3496	14, 24, 30	74.26	128.4263	63.36%	0.9778	-
HS [11]	0.1070, 0.5724, 1.0462	18, 17, 33	96.76	105.9263	52.26%	0.9670	-
FA [15]	0.5897, 0.1895, 1.0146	14, 18, 32	88.68	114.0063	56.25%	0.9680	-
GA [7]	1.5, 0.4228, 1.0714	11, 29, 30	106.3	96.3863	47.55%	-	-
PSO [7]	0.9816, 0.8297, 1.1768	13, 32, 8	105.3	97.3863	48.05%	-	-
UVD [17]	0.875, 0.925, 0.931	11, 29, 24	74.213	128.4733	63.39%	0.962	-
MPGS [20]	0.1058, 0.5900, 1.0812	17, 18, 33	95.42	107.2663	52.92%	0.9585	-
HCACO [18]	0.1082, 0.5800, 1.0520	18, 17, 32	96.34	106.3463	52.47%	0.9504	-

(a)

(b)
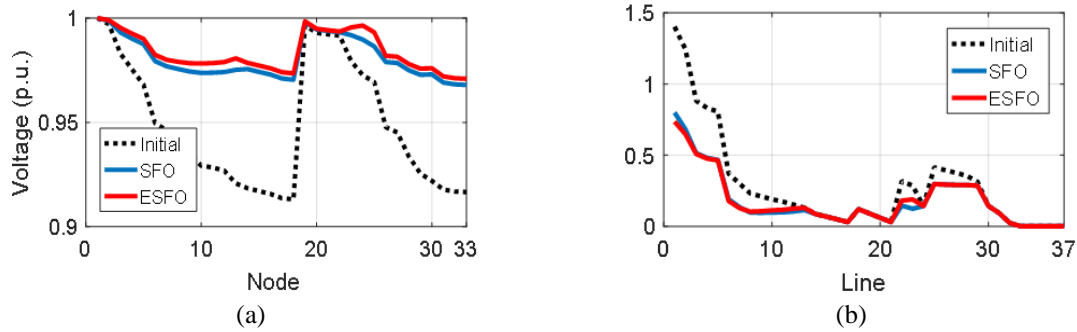
Figure 2. The voltage and current profile after optimizing DG by ESFO and SFO,
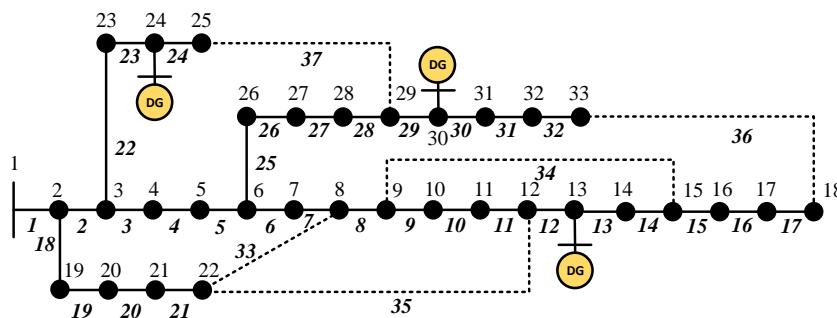(a) Voltage profile and (b) Current profile

Figure 3. Location of DG obtained by ESFO

Compared to results obtained by the previous methods ACS [14], HS [11], FA [15], GA [7], PSO [7], UVD [17], MPGS [20] and HCACO [18], power loss reduction obtained by the proposed method is 0.99%, 12.09%, 8.10%, 16.80%, 16.30%, 0.96%, 11.43% and 11.88% higher than that of the above methods. Table 2 also shows that the minimum voltage amplitude obtained by ESFO is better than that of most of methods except the ACS [14].

Table 2. Comapred results between ESFO and SFO for the DG optimization problem

Method	Fit_{max}	Fit_{min}	Fit_{mean}	STD	G_{mean}	Run times (s)
ESFO	78.6518	72.2671	74.8274	1.6571	172	30.2619
SFO	81.1677	72.7386	76.1131	2.4050	173	29.1834

In order to compare the performance of ESFO and SFO, both of the algorithms are executed in 50 independent runs and the obtained indexes comprising of maximum (Fit_{max}), minimum (Fit_{min}), mean (Fit_{mean}) and standard deviation (STD) as well as the mean of number of convergence generations (G_{mean}) are used to evaluate the effectiveness of two methods. The obtained results are presented in Table 2. From the table, the Fit_{max}, Fit_{min}, Fit_{mean} and STD values obtained by ESFO are better than those of SFO. Wherein, these values of ESFO are 2.5159, 0.4715, 1.2857 and 0.7479 lower than those of SFO, respectively. Meanwhile, the run time value of ESFO is only 1.0785 longer than that of SFO. In addition, the minimum fitness value obtained in each run as shown in Figure 4a shows that the better performance of ESFO compared to SFO. In which, there are 35 runs in total 50 runs, ESFO obtained a better fitness value than that of SFO while SFO has only found a better fitness value than that of ESFO in 15 runs. The maximum, minimum and mean convergence curves of ESFO and SFO in 50 runs are shown in Figure 4b. From all curves obtained by ESFO are much lower than corresponding ones of SFO. This again confirms that ESFO's improvements have yielded more positive results than SFO for the DG optimization problem.
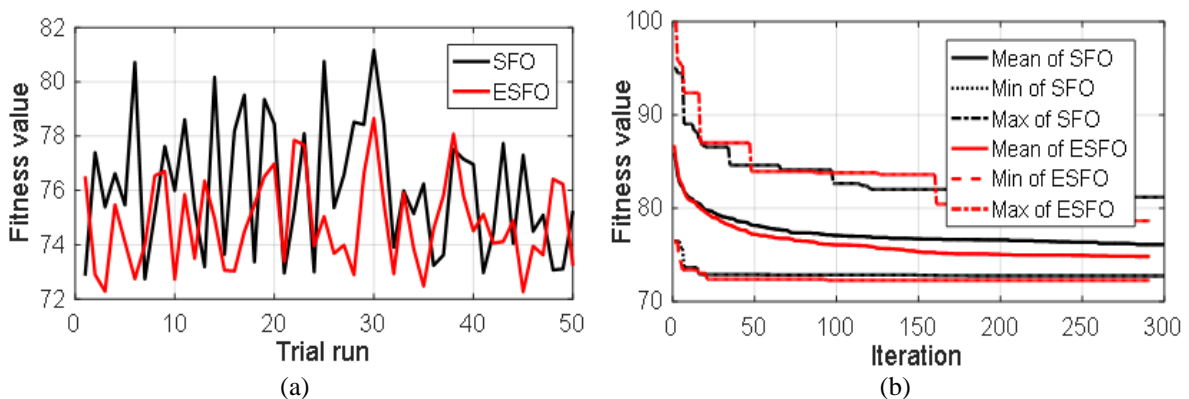

Figure 4. Comparison of performance of ESFO and SFO, (a) Optimal fitness value in 50 runs
and (b) Convergence curves in 50 runs

5.   CONCLUSION

In this paper, ESFO has been successfully proposed for the DG optimization problem to minimize active power loss of the distribution system. In which, ESFO has been added the mutation technique for updating the best sunflower plant. The performance of the proposed ESFO has been evaluated on the 33 nodes test system. The obtained results compared with the original SFO have sent a message that ESFO outperforms to SFO in terms of the minimum power loss as well as indexes related to effectiveness of an optimization algorithm such as maximum, minimum and mean values as well as STD of the fitness function. The compared results with other previous methods have also leaded to the conclusion that ESFO is in one of the effective techniques to the DG optimization problem for power loss reduction. Thus, ESFO can be a potential method for solving the DG optimization problem for practical systems or gratifying other goals.

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