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Optimal placement of distributed generations on distribution network for reducing power loss and improving feeder balance

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ABSTRACT

The suitable placement and power of distributed generation (DG) can bring technical benefits to the distribution network. This paper applies the Coot optimization algorithm to the DG placement problem with the goal of minimizing power loss and feeder balancing load (LBF). The weight method is used to combine the membership objectives. The evaluation results on the network of 70 nodes for different weight values of the objective function show that the optimal power and installation location of DGs significantly reduces power loss and improves LBF index. In this study, eleven cases were considered. As the weight of power loss part w_1 increases from 0 to 1, the power loss gradually decreases, the LBF index gradually increases, the maximum current gradually decreases, and the minimum voltage amplitude gradually improves. Comparing the results of Coot with particle swarm optimization (PSO) shows that the indicators are improved. In the three cases where w_1 is 0, 0.5, and 1, power loss gained by Coot compared to PSO is less than 47.2663 kW, 73.2725 kW, 30.8708 kW, respectively. LBF index of Coot compared to PSO is less than 98.2%, 88.2%, 81.9%, respectively. The maximum, minimum, average, standard deviation, and CPU time of Coot are smaller than those of PSO. So, Coot is one of the promising methods for this problem.

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1. INTRODUCTION

The distributed generation (DG) is small generators linked to the distribution grid or near loads [1]. DG is divided into two different groups based on the primary energy source. The first group is the green energy group including solar, wind, and small hydroelectric generators, which do not emit greenhouse gases. For this group, installing DG has environmental benefits. The second group of greenhouse gas emissions includes diesel generators and gas [2]. Installing DG in the distribution grid has many technical benefits like reducing power loss, improving voltage [3], improving power quality [4]. However, improper installation of DG increases losses and costs [5]. Thus, optimal DG placement is one of the issues that needs to be considered by the researchers.

There are many problems associated with the installation of DG. Yao *et al*. [6] proposed the problem with the objectives of reducing power loss and enhancing the benefits of users and the grid. The optimal installation of DG in Sellami *et al*. [7] is considered to reduce power loss, improve minimum voltage and stabilize voltage. The DG placement problem solved in Montoya *et al*. [8] is minimum power loss with power, voltage constraints. Mahdad and Srairi [9] presented the problem of reducing power loss, reducing voltage deviation considering costs of loss. Mustaffa *et al*. [10] provided a mathematical model to reducing peak voltage and reducing power loss.

From the above works, it can be shown that the installation of DG can bring many technical benefits. Therefore, the DG installation problem can be extended further into a multi-objective problem.

Optimization algorithms are often used to solve optimization problems in distribution power networks. Strength pareto evolutionary algorithm 2+ (SPEA 2+) is applied to solve the multi-objective problem of social welfare [11]. The differential evolution algorithm (DEA) is applied to the problem with the objective function of minimizing power loss and taking that as the condition to optimize the shunt capacitor size [12]. The fuzzified RAO-3 algorithm is used to solve a four-objective problem considering the impact of electric vehicle charging stations [13]. Optimal network reconfiguration problem using an algorithm based on heuristics [14]. The optimal placement of DG with the objective of reducing voltage deviation using the self-adaptive Lévy flight-based Jaya algorithm [15]. The crow search algorithm (CSA) is used in the problem of optimal network reconfiguration when installing DG and electric vehicle charging stations [16].

The DG installation optimization problem is a nonlinear and discrete problem, so a suitable solution is needed. The type of meta-heuristics algorithm that can solve the problem of installing DG. This type of algorithm can approximate optimization with appropriate time and can solve complex problems [17]. These methods can be divided into four groups [18]. The first group is a group of evolutionary algorithms that have been developed for a long time, including genetic algorithm [19], [20], differential evolution [21], and stochastic fractal search [22]. The second group is a group of swarm based algorithms developed based on the movement of different animals such as particle swarm optimization (PSO) [2], Bat algorithm [23], Coyote algorithm [24], adaptive Cuckoo search [25], Salp swarm algorithm [26], ant lion optimization algorithm [27], firefly algorithm [28], [29], crow search algorithm [30], honey bee mating optimization [31], and whale optimization algorithm [32]. The third group is the human-based algorithms group wherein, the modified teaching–learning-based-optimization [1] is one of them. The last group is a group of algorithms based on physical phenomena such as intelligent water drop algorithms [33]. Algorithms have a variety of ideas. But new algorithms still need to work to bring them into practice step by step.

The Coot algorithm is a recent algorithm introduced in 2021 that simulates the movement behavior of Coot birds to find prey [18]. The algorithm has shown high performance for several test functions. Furthermore, the algorithm has been used to some practical problems such as: welded beam design, multiplate disc clutch brake, cantilever beam design, step-cone pulley problem and reducer design problem. The results show that the algorithm responds well and has many superior indicators compared to the compared algorithms. In this paper, the Coot algorithm is first applied to the DG placement problem with the two objectives of reducing power loss and balancing the loads among feeders. The contributions of the paper can be listed as follows:
- The Coot algorithm has been successfully applied to the multi-objective DG problem.
- The influence of the objective function weights on the problem results is investigated.
- The efficiency of the problem is compared to the PSO.

The rest of the paper is arranged as follows: the problem formular is shown in the next section. The details of Coot algorithm for the DG placement problem are presented in section 3. The results and conclusion are shown in sections 4 and 5.

2. THE DG PLACEMENT PROBLEM FORMULAR

Because of installing at the customer site, the DG can help to reduce power loss and reducing the power from the feeders. Thus, the power loss reduction and feeder load balancing improverment are considered as the main goals of the DG placement problem in this work. The details of them are as follows.

2.1. Power loss reduction

Reducing power loss is often the priority goal considered in operation of the electric distribution system. It is determined as (1).

$$P_{loss} = \sum_{k=1}^{H} \frac{P_k^2 + Q_k^2}{U_k^2} R_k \tag{1}$$

Where H is the branch number of the electric distribution system. P_k, Q_k, U_k, R_k are the active power flow, reactive power flow, the ending voltage and the resistance of the kth branch, respectively.

2.2. Load balance among the feeders

DG is installed in the optimal position to balance the load between feeders. The LBF is described as (2).

$$LBF = var[P_{F1}, P_{F2}, \dots\ P_{Fk}, \dots, P_{FN}] \tag{2}$$

2.3. Constraints of the considered DG placement problem

The installation of DGs on the distribution system study has to ensure two constraints consisting of voltage and current limits.

– Voltage constraint

$$U_{min} \leq U_k \leq U_{max} \tag{3}$$

Where U_k is the voltage amplitude of node $k.$ $[U_{min}, U_{max}]$ is the allowable voltage limit. $U_{min} = 0.95\ p.u$, $U_{max} = 1.05\ p.u.$

– Current constraint

$$I_k \leq I_{rate,k} \tag{4}$$

The current limit represents the load carrying capacity of the power transmission lines. Where I_k is the current on the kth branch, $I_{rate,k}$ is the rated current on the kth branch.

– The computations tie required for solving this problem are constraints on power balance, capacity limits and location of DGs.

$$P_T = P_{Load} + P_{DG} + P_{Loss} \tag{5}$$

$$P_{min,k} \leq P_{DG,k} \leq P_{max,k} \tag{6}$$

$$i_{min,DG} \leq i_{DG,k} \leq i_{max,DG} \tag{7}$$

Where P_T, P_{Load}, P_{DG} is active power of main grid, load, DG, respectively. P_{Loss} is power loss. $P_{DG,k}$ is the power of the kth DG, $[P_{min,k}, P_{max,k}]$ is the kth DG power limit. $i_{DG,k}$ is the position of, the kth DG, $[i_{min,DG}, i_{max,DG}]$ is the position limit of DGs.

2.4. The fitness function

The fitness function of the problem is determined as (8).

$$F = w_1 \frac{P_{loss}}{P_{loss,o}} + w_2 \frac{LBF}{LBF,o} + k_v\big(max(U_{min} - U_k, 0) + max(U_k - U_{max}, 0)\big) + + k_i(ma\,x(I_k - I_{rate})) \tag{8}$$

Where w_1, w_2 are the weights in the range [0,1], $w_1 + w_2 = 1$, k_v, k_i is voltage and current penalty factor. U_{min}, U_{max} is voltage limit. I_{rate} is rated current.

3. COOT ALGORITHM FOR MULTI-OBJECTIVE DG PROBLEM

Details of calculation steps of Coot algorithm for the considred problem are presented:

– Step 1: population initialization

For solving the optimal problem using Coot algorithm, position of each Coot is conssidered as a solution. To start seaching the optimal result, the random initialization of the population is formulated as (9).

$$C(i) = rand(1, b)(u - d) + d \tag{9}$$

Where $C(i)$ is the position of the individual. b is the number of variables. For the problem with m DGs, the value of b will be $b = 2m$. $d = [d_1, d_2, \ldots, d_b]$ is the lower limit of the search space. Similarly, $u = [u_1, u_2, \ldots, u_b]$ is the upper limit of the variables. d_1 to d_m, is the lower limit of the buses, so this limit is equal to 2 (because node 1 is a select node). d_{m+1} to d_{2m} is the lower power limit of distributed generations and equal to 0. u_1 to u_m is the upper limit of the buses. u_{m+1} to u_{2m} is the upper power limit of DGs. From the newly created population, N_L of individuals are randomly selected to become leaders.

– Step 2: mapping solution of Coot for ploblem

Solution variables have two components. The first component is the position of DGs, this variable has a positive integer value. The second one is the DG power, which is positive. The generated variables are random so they are necessary to modify as (10).

$$C(i,j) = \begin{cases} round(C(i,j))\ if\ j \leq m \\ C(i,j)\ otherwise \end{cases} \tag{10}$$

Where $C(i,j)$ is the jth variable of the ith solution.

After modifying to map with the DG placement problem, these variables are checked and corrected to maintain the permitted limits of $[d, u]$.

– Step 3: evaluating the quality of solutions

From the created new population, the fitness function of each solution is calculated using (8) and the current best solution G_{best} with the best fitness value F_{best} is determined.

– Step 4: generating new positions and updating the location of Coots

Each candidate is updated by three ways including random and chain moverment as well as moverment with leaders. The probability of each way is selected to 50%, 25%, and 25% respectively. Random moverment: this technique is performed randomly as (11).

$$Q = rand(1, d)(u - d) + d \tag{11}$$

This moverment of the candidate solution explores different parts of the search space. This moverment of the candidates will help the Coot algorithm to get out of local optimal. New position of solution is updated by the random moverment is formed as (12).

$$C(i) = C(i) + AR_r Q - C(i)) \tag{12}$$

Where R_r is a random number with a value in the intervale $[0, 1]$. A is calculated as (13).

$$A = 1 - \frac{it}{maxIter} \tag{13}$$

Where it is the current of iterations, $maxIter$ is maximum iteration.

Chain moverment: the new position of the Coot is detemined by the average position of two individuals as (14).

$$C(i) = 0.5(C(i - 1) + C(i)) \tag{14}$$

Where $C(i - 1)$ is the position of the previous candidate Coot.

Moverment with leaders: each candidate has to choose for itself a leader to adjust its position. This movement is expressed by the following formula.

$$k = 1 + mod(i, N_L) \tag{15}$$

Where k is index number of leaders, mod is surplus return function of the division i and N_L.

The new position of the Coot is updated with the position of the leader k according to the formula:

$$C(i) = L(k) + 2R_l cos(2R\pi) \times (L(k) - C(i)) \tag{16}$$

Where $L(k)$ is the selected leader. R_l is a random number with a value in the intervale [0, 1]. R is a random number in [-1, 1].

For each created new solution, it is modified to map with the considered problem as describing in the step 2 and its quality (F_i) is determined by using the fitness function as mentioning in step 3. Then, if the quality of the new solution is better than the leader k, the position of the current Coot is updated again as (17):

$$\begin{cases} Temporary = L(k) \\ L(k) = C(i) \\ C(i) = Temporary \end{cases} \tag{17}$$

– Step 5: generating new positions of leaders

Leaders in the population are updated with their positions in the following way: the candidates move towards the optimal area, so the leaders update their position to the target as (18).

$$L(i) = \begin{cases} BR_{l1} \cos(2R\pi) (G_{best} - L(i)) + G_{best} \; R_{l2} < 0.5 \\ BR_{l1} \cos(2R\pi) \left(G_{best} - L(i)\right) - G_{best} \; R_{l2} \geq 0.5 \end{cases} \tag{18}$$

Where G_{best} is the best position found. R_{l1}, R_{l2} is a random number with a value in the intervale [0, 1]. R is a random number with a value in the intervale [-1, 1]. B is defined as (19).

$$B = 2 - \frac{it}{maxIter} \tag{19}$$

For each created new leader, it is modified to map with the considered problem as describing in the step 2 and its quality ($F_{L,i}$) is determined by using the fitness function as mentioning in step 3. Then, if the quality of the new solution is better than the best Coot, the position of the current leader is updated as (20).

$$\begin{cases} Temporary = G_{best} \\ G_{best} = L(i) \\ L(i) = Temporary \end{cases} \tag{20}$$

– Step 6: check search stop condition

If the current iteration is less than the maximum number, the algorithm is returned to step 4 to continue execution, otherwise it will be stopped. Then G_{best} is the optimal solution. The flowchart of Coot algorithm for the considered problem is shown in Figure 1.

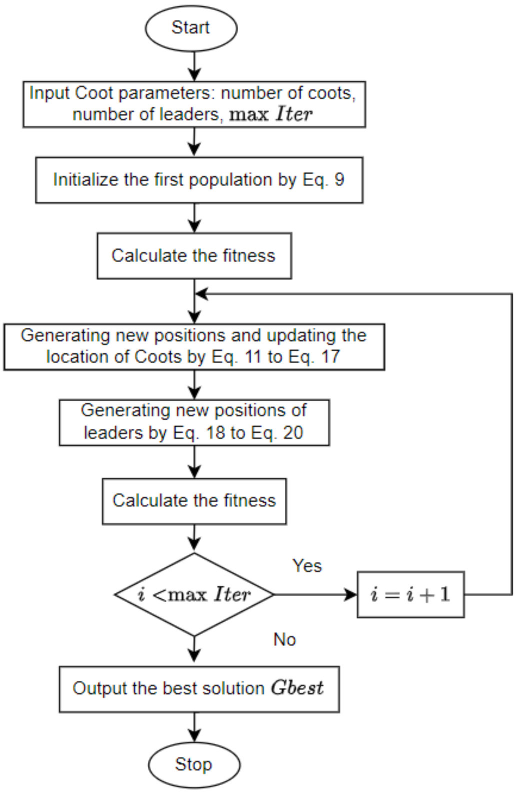


Figure 1. The flowchart of the proposed method

4. RESULTS AND DISCUSSION

The performance of Coot are evaluated on the 70-node system as shown in Figure 2 [34] with 11 cases of different weight values of w_1 and w_2. In this work, the position variables of DGs are limited to the range [2, 70], limiting the DGs capacity to the range of [0, 5] MW. Furthermore, the performance of Coot algorithm is also compared with the well-known PSO algorithm. The control parameters of Coot and PSO algorithms are selected as follows: population $N = 30$, number of iterations $maxIter = 500$. Two approaches are coded in Matlab software and run 30 times independently on the computer with Intel(R) Core (TM) i5-8250U CPU @ 1.80 GHz, 12GB RAM. The best solution over these runs is examined as the result.

For the initial 70-node system, the power loss and LBF values are 227.5256 kW and 0.0790 respectively, the maximum current is 93.7062 A. The minimum voltage in the system is 0.9052 p.u. After running the proposed algorithm, the results for different values of w_1 and w_2 are shown in Table 1. When w_1 increases from 0 to 1, the technical indexes of the system also change. Power loss decreased from 259.0288 kW to 116.4946 kW, LBF increased from 6.7308e-12 to 0.0567 and maximum current gradually decreased from 84.8847 A to 57.6859 A. Minimum voltage amplitude increased from 0.9052 pu to 0.9461 pu. In case of $w_1 = 0.5$ that is balanced with the two objectives of the problem, power loss and LBF values are 136.1568 kW, 0.0019 respectively. The maximum power difference between feeders reduced from 0.6129 MW (initial case) to 0.0930 MW ($w_1 = 0.5$ case). The voltage and current profiles of the system compared to the initial case are shown in Figure 3. Figure 3(a) shows that the voltage profile after installing the DG is improved compared to the initial voltage while Figure 3(b) shows that the maximum current value has been decreased after DG placement.

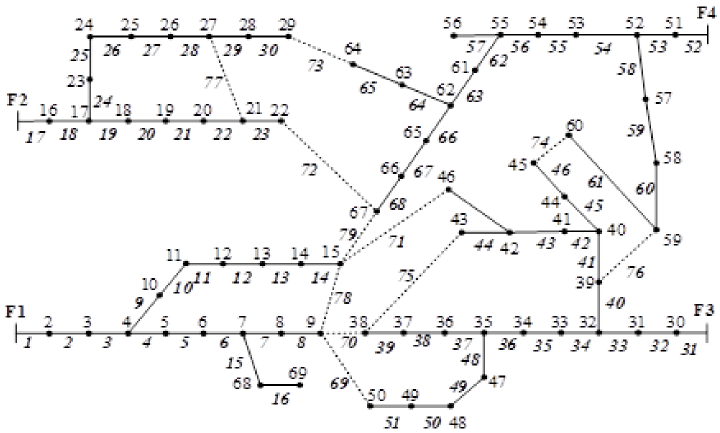


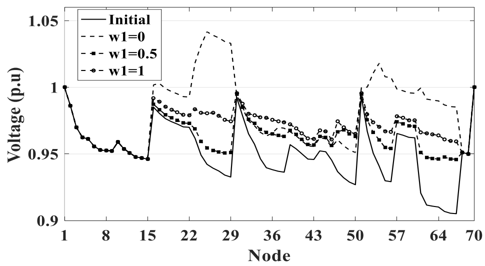
Figure 2. 70-node system

Table 1. The results gained by Coot algorithm for the system of 70 nodes

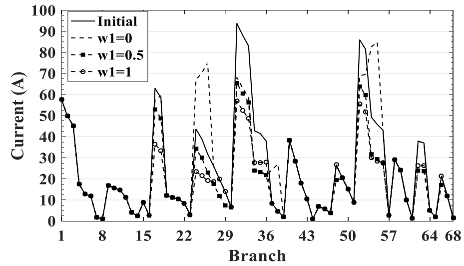
Case	Power of DGs in MW (node)	Ploss (kW)	LBF	Power of feeders (MW)	I_{max} (A)	U_{min} (pu)
Initial	-	227.5256	0.0790	0.8758, 1.0091, 1.4887, 1.3218	93.7062	0.9052
$w_1 = 0$	2.2094 (54), 0.5850 (37), 1.9165 (25)	259.0288	6.7308e-12	0.8758, 0.8758, 0.8759, 0.8758	84.8847	0.9461
$w_1 = 0.1$	0.1455 (29), 0.5980 (48) 0.4346 (66)	143.9030	1.4595e-04	0.8758, 0.8509, 0.8573, 0.8497	67.2874	0.9418
$w_1 = 0.2$	0.6087 (48), 0.1593 (29) 0.4473 (66)	142.2031	3.4925e-04	0.8758, 0.8362, 0.8464, 0.8365	66.8974	0.9427
$w_1 = 0.3$	0.1739 (29), 0.4614 (66) 0.6205 (48)	140.4500	6.7052e-04	0.8758, 0.8205, 0.8344, 0.8218	66.4719	0.9436
$w_1 = 0.4$	0.4782 (65), 0.1914 (29) 0.6345 (48)	138.1505	0.0012	0.8758, 0.8019, 0.8202, 0.8041	65.9720	0.9445
$w_1 = 0.5$	0.4968 (65), 0.6494 (48) 0.2094 (29)	136.1568	0.0019	0.8758, 0.7828, 0.8050, 0.7848	65.4448	0.9460
$w_1 = 0.6$	0.2444 (28), 0.5278 (65) 0.6803 (47)	132.5836	0.0036	0.8758, 0.7458, 0.7736, 0.7529	64.3713	0.9461
$w_1 = 0.7$	0.7059 (47), 0.5490 (65) 0.2801 (28)	129.7003	0.0057	0.8758, 0.7081, 0.7476, 0.7311	63.5014	0.9461
$w_1 = 0.8$	0.3354 (28), 0.7451 (47) 0.5872 (65)	125.8293	0.0098	0.8758, 0.6504, 0.7078, 0.6920	62.2103	0.9461
$w_1 = 0.9$	0.8089 (47), 0.4289 (28) 0.6698 (62)	120.7667	0.0201	0.8758, 0.5538 0.6435, 0.6079	60.2296	0.9461
$w_1 = 1$	0.7674 (62), 0.9287 (35) 0.6778 (26)	116.4946	0.0567	0.8758, 0.3017, 0.5233, 0.5097	57.6859	0.9461

The compared results between Coot and PSO for different values of w_1 and w_2 are shown in Table 2. From the table, the performance of Coot is better than that of PSO. For example, in case of $w_1 = 0.5$, Coot's power loss and LBF are 136.1568 kW and 0.0019 meanwhile these indexes gained by PSO are 209.4293 kW and 0.0161, respectively which are higher than those of Coot. The maximum, minimum, standard deviations (STD) and mean of Coot are smaller than those of PSO. They are 0.4513, 0.3142, 0.0353, and 0.3625 respectively for

Coot while their values of PSO are respectively 0.7235, 0.5766, 0.0531, and 0.6813. Figure 4 shows mean and minimum convergence characteristics of both algorithms for different values of w_1 and w_2 wherein, the curver for $\{w_1 = 0, w_2 = 1\}$, $\{w_1 = 0.5, w_2 = 0.5\}$, and $\{w_1 = 1, w_2 = 0\}$ is shown in Figures 4(a)-(c), respectively. They demonstrate that the convergence curves of Coot reach smaller values than PSO. Besides, the minimum convergence curve of Coot is much closer to the mean convergence one. This proves the stability of Coot for the multi-objective DG problem.



(a)

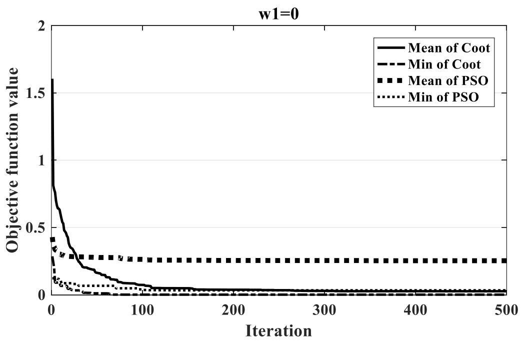


(b)

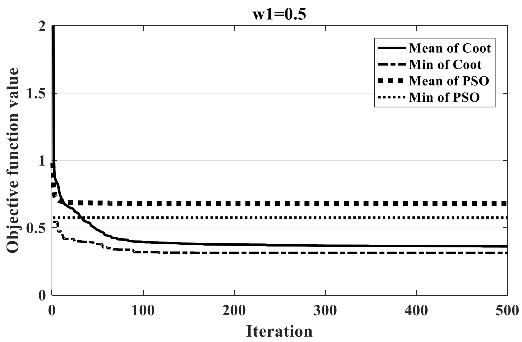
Figure 3. Voltage and current profiled of the 70-node system: (a) voltage and (b) current

Table 2. The comparisons between Coot with PSO with different values of w_1 and w_2

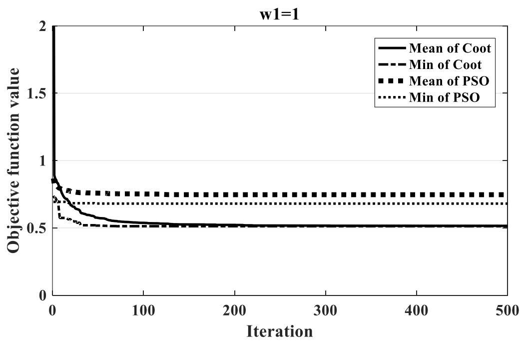
w_1, w_2	$w_1 = 0, w_2 = 1$		$w_1 = 0.5, w_2 = 0.5$		$w_1 = 1, w_2 = 0$	
Method	Coot	PSO	Coot	PSO	Coot	PSO
Ploss (kW)	259.0288	306.2951	136.1568	209.4293	Coot	PSO
LBF	6.7308e-12	3.7880e-10	0.0019	0.0161	116.4946	147.3654
I_{max} (A)	84.8847	114.8064	65.4448	74.0717	0.0567	0.3136
$U_{min}(pu)$	0.9461	0.9052	0.9460	0.9288	57.6859	85.9469
Max of fitness	0.2481	0.4872	0.4513	0.7235	0.9461	0.9052
Min of fitness	9.1014e-04	0.0329	0.3142	0.5766	0.5697	0.8971
Mean of fitness	0.0264	0.2529	0.3625	0.6813	0.5129	0.6806
STD of fitness	0.0503	0.1279	0.0353	0.0531	0.5155	0.7466
CPU times (second)	1866.3688	1903.5474	1865.9460	2488.2533	0.0105	0.0672



(a)



(b)



(c)

Figure 4. Convergence characters of Coot and PSO for values of w_1 and w_2; (a) $\{w_1 = 0, w_2 = 1\}$, (b) $\{w_1 = 0.5, w_2 = 0.5\}$, and (c) $\{w_1 = 1, w_2 = 0\}$

5. CONCLUSION

This paper has proposed a method to solve the multi-objective DG problem based on the Coot algorithm. The objective function considered is to reduce power loss and load balancing among the feeders. The algorithm is applied to a distributed grid of 70 nodes. In the case of only considering power loss reduction, power loss is reduced by 48,7993 % and LBF is reduced by 28,2278 %. In the case of considering only LBF, the power difference between feeders is almost zero. In the case of considering the two targets at the same level of balance, the power loss is reduced by 40,1576%, and the LBF is reduced by 97,5949%. The results compared with the PSO algorithm show that the Coot proposed method is more efficient than the PSO. The matching results show the effectiveness of the method based on the Coot algorithm for the multi-objective DG problem on the distribution grid. Based on the results of this research, the problem can be applied to real distribution network and the Coot algorithm can be applied to other problems.

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