Power Loss Minimization by Optimal Placement of Distributed Generation Considering the Distribution Network Configuration Based on Artificial Ecosystem Optimization

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Abstract. *Power loss in the Distribution System (DS) is often higher than that of other parts of the power system because of its low voltage level. Therefore, reducing losses is always an important task in design and operation of the DS. This paper aims to apply a new approach based on Artificial Ecosystem Optimization (AEO) for the Distributed Generation Placement (DGP) and combination of DGP and network REConfiguration (DGP-REC) problems to reduce power loss of the DS to satisfy the technical constraints including power balance, radial topology, voltage and current bounds, and DG capacity limit. The AEO is a recent algorithm that has no special control parameters, inspired from the behaviours of living organisms in the ecosystem including production, consumption, and decomposition. The efficiency of the AEO is evaluated on two test systems including the* 33*-node and* 119*-node systems. The numerical results validated on the* 33*-node and* 119*-node systems show that DGP-REC is a more effective solution for reducing power loss compared to the DGP solution. In addition, evaluation results on small and large systems also indicate that AEO is an effective approach for the DGP and DGP-REC problems.*

Keywords

Artificial Ecosystem Optimization, Distributed Generation, Distribution System, power loss, radial topology, REConfiguration.

1. Introduction

Reducing power loss is one of the top priorities in the operation of the DS due to its low voltage operating characteristics. Reasonable installation of DG is one of the effective solutions to improve the operating efficiency of the DS. The advantage of this technique is the ability to supply electricity at the load side. This way, the DG Placement (DGP) reduces the losses on the lines significantly. Despite costly equipment, in the context of the robust proliferation of renewable energies and the support of governments, the DGP solution is attracting a lot of attention from the managing and operating companies of the DS.

To maximize the efficiency of DG, the choice of capacity and installation location for DG is one of the main concerns of researchers. This problem with a huge number of possible solutions has attracted a lot of attention from researchers. Recent works include metaheuristic-based approaches, such as Particle Swarm Optimization (PSO) [1], adaptive PSO [2], Symbiotic Organisms Search (SOS) [3], modified SOS [4], monarch butterfly optimization [5], differential evolution [6], hybrid elephant herding and PSO [7], spring search algorithm [8], quasi-oppositional chaotic SOS [9], Salp Swarm Algorithm (SSA) [10], ant colony algorithm [11], manta ray foraging optimization [12].

In addition, choosing the optimal radial topology is also one of the most effective ways to enhance the DS's performance. In terms of definition, this process is called network REConfiguration (REC) due to its characteristic of finding a new radial topology to replace the existing one of the DS. This technique does not require any additional equipment but it is accomplished through the selection of the open/close state of the electric switches available on the DS.

The target of the REC process is transmission loads among branches in the system to ensure an optimal load carrying of the lines and reduce losses in the system. However, choosing the optimal structure is a challenge for the operators since there are 2 powers of z structures for systems with z switches. Therefore, study on finding optimal structure is one of the issues being solved by many researchers.

Previously, the REC problem was mainly solved by heuristic methods that rely on the knowledge of the power system. The typical methods are the branch-and-bound method [13] and [14] and branch exchange approach [15]. However, in the recent years, the metaheuristic methods are used for their strengths such as flexibility in the process of changing target function and handling constraints. Thus, these methods are not only widely used in power systems like shunt capacitors placement [16] and [17] estimation of transmission line parameters [18] and [19], phasor measurement unit [20], reactive power planning [21], [22], [23] and [24], but they are also widely applied for the REC problem such as firework algorithm [25], SOS [26], binary PSO [27], modified PSO [28], enhanced binary cuckoo search algorithm [29], improved whale optimization approach [30], combination of wild goats and exchange market algorithms [31].

Since both DGP and REC approaches are performed on the DS, the result of implementation of one approach is completely affected by the other one. Therefore, implementing two approaches at the same time is one of the techniques to ensure that the obtained radial structure and DG parameters are optimal. However, when combining two problems, the DGP and REC (called DGP-REC), the discrete and continuous combination problem becomes more complicated with discrete control variables representing switches and DG installation positions and continuous variables representing the capacity of the DG. Then, the search of the optimal DGP-REC solution becomes a significant challenge.

In recent years, with the problem has been solved by methods such as enhanced Sine-Cosine Algorithm (SCA) [32], Adaptive Modified Whale Optimization Algorithm (AMWOA) [33], Thief and Police Algorithm (TPA) [34], Moth-Flame Optimization (MFO) [35], Tabu Search (TS) [36], Equilibrium Optimization (EO) [37] and SSA [38]. In [32], SCA algorithm has been adjusted for the DGP-REC problem to minimize power loss and operating costs. In [33], AMWOA has been successfully applied to the DGP-REC problem to minimize power loss and improve voltage stability. In [34], the DGP-REC method based on TPA is considered to reduce the power loss, operating costs, and voltage stability. In [35], MFO has been applied to the DGP-REC problem with the considered target function including reducing power loss, improving reliability and voltage. In [36], the efficiency of TS is compared with PSO for the DGP-REC problem to reduce switch costs and power loss. In [37], EO has been improved to successfully solve the DGP-REC problem for reducing power loss and enhancing the voltage stability of the DS. Similarly in [38], SSA has also been successfully applied to the DGP-REC problem for reduction of power loss and improvement of the voltage of the DS.

The summary above shows that for the DGP-REC problem, for most studies, loss reduction is of considerable interest in the process of determining the optimal solution. It is considered as the main module of the DGP-REC problem because reducing power loss will lead to improvement of some other technical factors such as voltage configuration, voltage stability or load balancing.

Furthermore, setting the appropriate value for the control parameters is one of issues suitable for the use of metaheuristic algorithms. For example, using PSO [1], the velocity scale coefficients must be selected before executing the algorithm or the mutation probability of GA has to be set as applying it for the optimization problem [39]. By using SCA [32], the parameters including maximum and minimum weights as well as step length for search orientation have to be selected. As using TPA [34], the percentage of the armature and professional members also have to adjust for finding the optimal solution. In order to simplify the use of algorithms for the DGP-REC problem, selection the algorithms without or less extra parameters should be prioritized. Thus, finding suitable and effective methods for the DGP-REC problem should be also encouraged to diversify methodological choices for the designers and operators of the DS.

In this study, an AEO-based approach is suggested for the DGP and DGP-REC problems. AEO is the recent optimization algorithm taken the idea of energy flow in the ecosystem including production, consumption and decomposition [40]. AEO has been applied successfully in a number of problems such as maximum power from photovoltaic array [41], optimal configuration of the renewable energy system [42], DG placement [43], determining parameters of proportional-integral-derivative controller [44], or photovoltaic parameter estimation [45]. An outstanding advantage of AEO compared to many previous algorithms is that there is no demand to set special parameters in the calculation process. Therefore, AEO promises to be an efficient and easy-to-use tool for the designers and operators of the distribution system in their work once it has been successfully applied to the DGP and DGP-REC problems.

The novelty of this study is that the AEO is adjusted to successfully solve the DGP and DGP-REC problems to reduce power loss and satisfy the equality binding conditions of radial structure and power balance and inequality binding conditions such as voltage, current and DG power limits. The 33- and 119-node DSs are used to evaluate the effectiveness of the proposed approach. The results are compared to other methods including Cuckoo Search Algorithm (CSA) [46], Heuristic Technique of the Exact Loss Formula (HTELF) [47], Stochastic Fractal Search (SFS) [48], SSA [38], hybrid of Grey Wolf Optimization (GWO) and PSO (GWO-PSO) [49], SCA [32], AMWOA [33], EO [37] and COyote Algorithm (COA) [50]. The contributions of this work can be listed as follows:

- The method based on AEO for the DGP and DGP-REC problems is proposed.
- The proposed method has been successfully applied for determining the optimal DGP and DGP-REC solutions on 33-node and 119-node power systems.
- The effectiveness of DGP and DGP-REC approaches in reducing power loss for distribution system is validated.
- The effectiveness of the AEO-based approach is compared with the previous approaches to prove the effectiveness of AEO for the DGP and DGP-REC problems.

2. Problem of Power Loss Reduction of the Distribution System

Power loss of a distribution system is determined as follows:

$$\Delta P_s = \sum_{i=1}^{n_{\mathrm{br}}} k_i \Delta P_i, \tag{1}$$

where ΔP_s is the system's loss. ΔP_i is the i-th branch's loss. k_i is a binary variable that represents the participation of the i-th branch in the DS and n_{br} is total number of the DS's branches.

During the process of DGP-REC, equality binding conditions for the obtained solution must be ensured including radial-shaped structure and power balance as well as inequality constraints including voltage, current and DG capacity as follows:

Radial-shape structure: The radial-shape structure is maintained and all of loads are served if the following condition is met [51] and [52]:

$$|\det(\mathbf{M})| = 1, \tag{2}$$

where $\mathbf{M}$ is a connected-matrix with 0 and 1 values that show the connections between branches and nodes in the system.

Power balance:

$$\begin{cases} P_{\mathrm{gr}} + \sum\limits_{i=1}^{n_{\mathrm{DG}}} P_{\mathrm{DG},i} = \sum\limits_{i=1}^{n_{\mathrm{bu}}} P_{l,i} + \Delta P_s, \\ Q_{\mathrm{gr}} + \sum\limits_{i=1}^{n_{\mathrm{DG}}} Q_{\mathrm{DG},i} = \sum\limits_{i=1}^{n_{\mathrm{bu}}} Q_{l,i} + \Delta Q_s, \end{cases} \tag{3}$$

where P_{gr} and Q_{gr} are active and reactive power of the transmission system supplying for the distribution system. $P_{\mathrm{DG},i}$ and $Q_{\mathrm{DG},i}$ are the active and reactive capacity of the i-th DG. $P_{l,i}$ and $Q_{l,i}$ are the active and reactive loads at the i-th node. ΔQ_s is reactive power loss of the DS, n_{DG} and n_{bu} are the number of DGs and nodes of the DS, respectively.

Voltage limits:

$$\begin{cases} V_{\mathrm{lo}} \leq V_i \leq V_{\mathrm{hi}}; \quad i = 1, 2, \ldots, n_{\mathrm{bu}}, \\ 0 \leq \mathrm{CCF}_i \leq \mathrm{CCF}_{\mathrm{hi}}; \quad i = 1, 2, \ldots, n_{\mathrm{br}}, \end{cases} \tag{4}$$

where V_{lo} and V_{hi} are the allowable voltage limits. $\mathrm{CCF}_{\mathrm{hi}}$ is the allowable current carrying factor of the i-th branch. V_i and CCF_i are voltage at the i-th node and current carrying factor of the i-th branch, wherein CCF_i is defined by the ratio of the current flowing on the i-th branch and its rated current value.

DG capacity:

$$P_{\mathrm{DG},i}^{\mathrm{lo}} \leq P_{\mathrm{DG},i} \leq P_{\mathrm{DG},i}^{\mathrm{hi}}, \tag{5}$$

where i is from 1 to n_{DG}. $P_{\mathrm{DG},i}^{\mathrm{lo}}$ and $P_{\mathrm{DG},i}^{\mathrm{hi}}$ is the capacity limit of the i-th DG. $P_{\mathrm{DG},i}$ is the capacity of the i-th DG.

The quality of each candidate solution is assessed through a Fitness function (F) that includes the objective function and inequality constraints as described in Eq. (6). Meanwhile, if the equality constraints are not met, the fitness function will be assigned to extremely large values.

$$F = \Delta P_s + k_p \left(\max\left(V_{\mathrm{lo}} - V_{\min}, 0\right) + \right.$$
$$+ \max\left(V_{\max} - V_{\mathrm{hi}}, 0\right) + \tag{6}$$
$$\left. + \max\left(\mathrm{CCF}_{\max} - \mathrm{CCF}_{\mathrm{hi}}, 0\right)\right),$$

where k_p is the penalty factor. $V_{\min}$ and $V_{\max}$ are minimum and maximum voltages of the DS. $\mathrm{CCF}_{\max}$ is the maximum current carrying factor of the DS.

3. Application of AEO for the DGP-REC and DGP problems

In the AEO, the ecosystem is examined as a population that contains consumption organisms, one production organism, and one decomposition organism. The organism's energy level is represented by its fitness value. The organism with the highest energy level in the ecosystem is the production one and the best organism is the decomposition organism that has the lowest energy levels. The process of creating and updating organisms in the ecosystem of AEO for the DGP and DGP-REC problems are described in detail below, wherein the main steps are presented for the DGP-REC problem. For the DGP problem, the adjustment will be described in the individual steps.

Step 1: Initialize the ecosystem

To find a solution for the DGP-REC problem, each solution is treated as an organism. Each organism is generated as follows:

$$\vec{O}_i = r\vec{v}_1 \left(\vec{U} - \vec{L}\right) + \vec{L}, \tag{7}$$

where i is from 1 to n. $\vec{O}_i$ is the i-th organism. $r\vec{v}_1$ is a random number vector in $[0, 1]$. n is the size of ecosystem. $\vec{U}$ and $\vec{L}$ are limit vectors of the variables that are defined as shown in Eq. (8), where $[S_i^{\mathrm{lo}}, S_i^{\mathrm{hi}}]$ are the limits of the variable indicating the location of the i-th switch; $[L_i^{\mathrm{lo}}, L_i^{\mathrm{hi}}]$ and $[P_{\mathrm{DG},i}^{\mathrm{lo}}, P_{\mathrm{DG},i}^{\mathrm{hi}}]$ are limits of variables indicating position and capacity of the i-th DG respectively. n_s is the number of opened switches of the DS. For the DGP problem, the limit vectors will consist of two elements $[L_i^{\mathrm{lo}}, L_i^{\mathrm{hi}}]$ and $[P_{\mathrm{DG},i}^{\mathrm{lo}}, P_{\mathrm{DG},i}^{\mathrm{hi}}]$.

To be appropriate for the DGP and DGP-REC problems, the variables corresponding to the opened switch, DG position and capacity of each organism need to be adjusted as follows:

$$\begin{cases} S_{i,j} = f_r\left(S_{i,j}\right); \quad j = 1, 2, \ldots, n_s, \\ L_{i,j} = f_r\left(L_{i,j}\right); \quad j = 1, 2, \ldots, n_{\mathrm{DG}}, \\ P_{i,j} = P_{i,j}; \quad j = 1, 2, \ldots, n_{\mathrm{DG}}. \end{cases} \tag{9}$$

where f_r is the rounding function.

From the solution of the vector $\vec{O}_i$, the parameters of the DS are adjusted and the energy level of the organism $\vec{O}_i$ is determined by using the fitness function (Eq. (6)). The organism with the lowest F value is the best organism ($\vec{O}_{\mathrm{best}}$) in the ecosystem.

Step 2: Update the production organism

To identify production organisms, all organisms in the ecosystem are rearranged in the direction of increasing quality. Then, the first organism is considered as the production organism. The production organism needs to contain new information about the search space to navigate other ones. Hence, it is created as follows:

$$\vec{O}_1^{\mathrm{new}} = r_1 \left(1 - \left(1 - \frac{G}{G_{\max}}\right)\right) \vec{O}_{\mathrm{best}} +$$
$$+ \left(1 - \frac{G}{G_{\max}}\right) \left(r\vec{v}_2 \left(\vec{U} - \vec{L}\right) + \vec{L}\right), \tag{10}$$

where r_1 is a random number in $[0, 1]$, $r\vec{v}_2$ is a random number vector in $[0, 1]$. G and $G_{\max}$ are the current and maximum iteration, respectively.

Step 3: Update the consumption organisms

The consumption organisms may eat herbivores, carnivores with higher energy levels, or both of them. Consequently, the consumption organisms are updated according to three different techniques depending on their classification. The probability of an organism classified as one of the three above categories is equal.

Herbivore will only interact with the production organism as follows:

$$\vec{O}_i^{\mathrm{new}} = \vec{O}_i + \alpha_c \left(\vec{O}_i - \vec{O}_1^{\mathrm{new}}\right), \tag{11}$$

where i belongs to the range of $[2, \ldots, n]$ and α_c is the consumption coefficient determined as follows:

$$\alpha_c = \frac{1}{2}\frac{u_1}{u_2}; \quad u_1 \sim N(0, 1); \quad u_2 \sim N(O, 1), \tag{12}$$

where $N(0, 1)$ is a standard normal distribution.

Carnivore will interact with other carnivore that carries the higher energy level as follows:

$$\vec{O}_i^{\mathrm{new}} = \vec{O}_i + \alpha_c \left(\vec{O}_i - \vec{O}_j\right), \tag{13}$$

where i and j belong to the ranges of $[3, \ldots, n]$ and $j = \mathrm{randi}([2, i-1])$, respectively.

If the consumption organism is omnivorous, it will interact with a producer and a carnivore with higher energy level as follows:

$$\vec{O}_i^{\mathrm{new}} = \vec{O}_i + \alpha_c \left(r_2 \left(\vec{O}_i - \vec{O}_1^{\mathrm{new}}\right) + \right.$$
$$\left. + \left(1 - r_2\right) \left(\vec{O}_i - \vec{O}_j\right)\right), \tag{14}$$

$$\begin{cases} \vec{L} = \left[S_1^{\mathrm{lo}}, \ldots, S_{n_s}^{\mathrm{lo}}, L_1^{\mathrm{lo}}, \ldots, L_{n_{\mathrm{DG}}}^{\mathrm{lo}}, P_{\mathrm{DG},1}^{\mathrm{lo}}, \ldots, P_{\mathrm{DG},n_{\mathrm{DG}}}^{\mathrm{lo}}\right], \\ \vec{U} = \left[S_1^{\mathrm{hi}}, \ldots, S_{n_s}^{\mathrm{hi}}, L_1^{\mathrm{hi}}, \ldots, L_{n_{\mathrm{DG}}}^{\mathrm{hi}}, P_{\mathrm{DG},1}^{\mathrm{hi}}, \ldots, P_{\mathrm{DG},n_{\mathrm{DG}}}^{\mathrm{hi}}\right]. \end{cases} \tag{8}$$

where r_2 is a random number in $[0, 1]$, i and j belong to the ranges of $[3, \ldots, n]$ and $j = \mathrm{randi}([2, i-1])$, respectively.

New organisms are adjusted to fit to the DGP and DGP-REC problems using Eq. (9). Their quality is then assessed using Eq. (6). The ecosystem is updated by using selective technique as follows:

$$\vec{O}_i = \begin{cases} \vec{O}_i^{\mathrm{new}}; & \text{if } F_i^{\mathrm{new}} < F_i, \\ \vec{O}_i; & \text{otherwise}, \end{cases} \tag{15}$$

$$F_i = \begin{cases} F_i^{\mathrm{new}}; & \text{if } F_i^{\mathrm{new}} < F_i, \\ F_i; & \text{otherwise}, \end{cases} \tag{16}$$

where F_i is the fitness function value that is defined in Eq. (6) of the solution $\vec{O}_i$. In addition, the best organism $\vec{O}_{\mathrm{best}}$ is also updated after the ecosystem updated.

Step 4: Update the whole ecosystem by decomposition mechanism

Organisms that die will be decomposed by a decomposition organism. Therefore, in the ecosystem, each organism will interact with the decomposition one as follows:

$$\vec{O}_i^{\mathrm{new}} = \vec{O}_i + 3\alpha_d \left(\beta_1 \vec{O}_{\mathrm{best}} - \beta_2 \vec{O}_i\right), \tag{17}$$

where i is from 1 to n, α_d is the decomposition rate defined by $\alpha_d \sim N(0, 1)$, β_1 and β_2 are weight coefficients that are calculated as follows:

$$\begin{cases} \beta_1 = r_3 \,\mathrm{randi}([1, 2]) - 1, \\ \beta_2 = 2r_3 - 1, \end{cases} \tag{18}$$

where r_3 is a random number in $[0, 1]$.

New organisms are adjusted to fit to the DGP and DGP-REC problems using Eq. (9). Their quality is then assessed using Eq. (9). Selective mechanisms like Eq. (15) and Eq. (16) are used to update the ecosystem again. Similarly, the best organism $\vec{O}_{\mathrm{best}}$ is also updated after the ecosystem updated.

The ecosystem update process from step 2 to step 4 is executed until the number of iterations reaches the maximum value. Then, the best organism $\vec{O}_{\mathrm{best}}$ is considered as the result of the considered problem. The AEO pseudocode for the DGP and DGP-REC problem is depicted in Alg. 1.

Algorithm 1 AEO pseudocode for the DGP-REC and DGP problems.

```
Set the ecosystem size n and maximum iteration G_max.
Generate and adjust the population of solutions by Eq. (7) and Eq. (9).
Determine the fitness value of each solution by Eq. (6) and the best one O_best.
Set G = 1.
while G < G_max do
    Sort the ecosystem in descending order of the fitness value.
    Generate the new production organism using Eq. (8).
    for i = 2 : n do
        if rand ≤ 1/3 then
            Generate new organism O_i^new by Eq. (11).
        else if 1/3 < rand ≤ 2/3 then
            Generate new organism O_i^new by Eq. (13).
        else
            Generate new organism O_i^new by Eq. (14).
        end if
    end for
    Adjust the population of new solutions by Eq. (9).
    Determine the fitness value of each new solution O_i^new by Eq. (6).
    Update the consumption organisms by Eq. (15) and Eq. (16) and update O_best.
    Generate each new organism O_i^new by Eq. (17).
    Adjust the population of new solutions by Eq. (9).
    Determine the fitness value of each new solution O_i^new by Eq. (6).
    Update the consumption organisms by Eq. (15) and Eq. (16) and update O_best.
end while
return the best organism O_best
```

4. Numerical Results

In this section, the effectiveness of each DGP and DGP-REC technique in reducing the system's power loss is assessed. In addition, the obtained results of two problems by AEO are also compared with other works to prove the effectiveness of the DGP and DGP-REC methods based on AEO. The proposed DGP-REC and DGP methods are implemented using the Matlab to search the optimal solution for the DSs consisting of the 33-node and 119-node. The power flow program to calculate the power loss, node voltage, and branch current in the fitness function equation is implemented relied on the Matpower tool [53].

4.1. The First System

The first DS has voltage level of 12.66 kV, 33 nodes, 37 branches and the total load $3.72 + j2.3$ MVA with the single-line diagram shown in Fig. 1 [54]. The rated current of all branches is assumed as 255 A [55]. The loss of the original structure with Opened Switches (OS) of $\{33, 34, 35, 36, 37\}$ is 202.6863 kW. The number and capacity of DG installed on this system are limited to 3 and 2 MW, respectively. For the penalty factor, if the penalty value is too high compared to the objective value, the algorithm will not converge because the objective function value takes up the small portion of the fitness function value. Conversely, if the penalty value is too small, the constraints might be ignored. Based on the results of many trials, the penalty value for the DS is set to 1000. For the AEO, the population size n is set to 30 for all two cases of DGP and DGP-REC while the maximum number iterations $G_{\max}$ is set to 300 and 500, respectively.

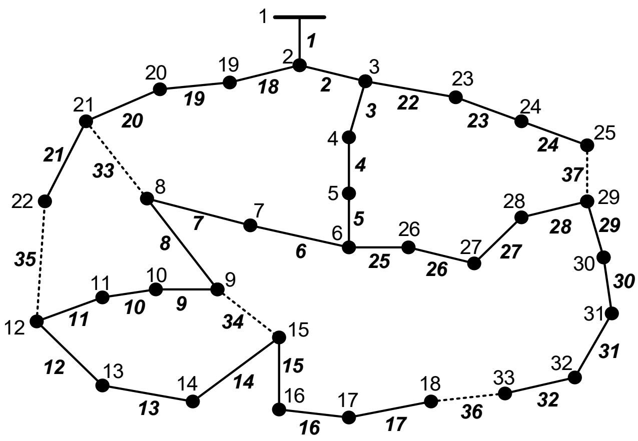
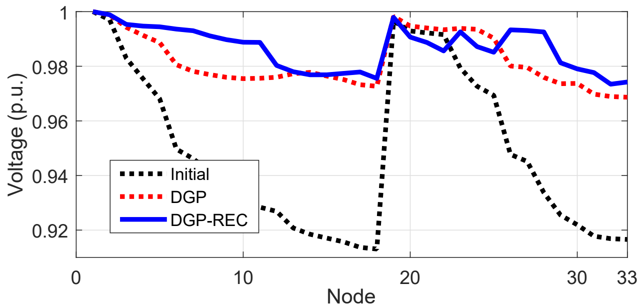


Fig. 1: The 33-node distribution system.

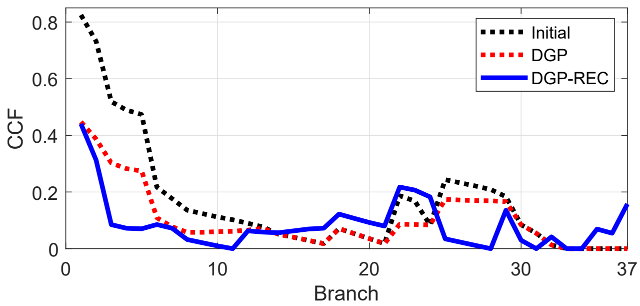
The effectiveness of AEO for the first system is shown in Tab. 1. After implementing the DGP and DGP-REC approaches, the power Loss Reduction (LR) in comparison with that of the initial structure is 64.7 % for DGP and 75.0 % for DGP-REC. The results show that, although implementing DGP approach reduces significantly power loss, DGP-REC method obtained better result than DGP. The decrease of power loss of DGP-REC is 10.3 % higher than that of DGP.

In addition, the DGP-REC approach's node voltage and branch current improvements are higher than that of the DGP approach. Specifically, the lowest voltage has been raised from 0.9131 in the original system to 0.9687 and 0.9734 respectively after performing DGP and DGP-REC. Furthermore, the DGP-REC is the solution that achieves the better results in reducing the highest current carrying factor. Specifically, the maximum current carrying factor has decreased from 0.8250 to 0.4475 and 0.4407 respectively when performing DGP and DGP-REC.

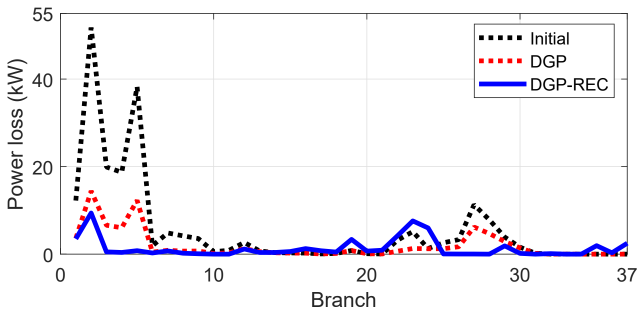
Figure 2 shows an overview of node voltage, current carrying coefficient and line power loss in the DS. The figure shows that the improvement of voltage, current and line power loss profiles is significant after implementing the DGP and DGP-REC approaches, wherein the improvement in ascending order is DGP-REC and DGP respectively.



(a) Voltage profile.



(b) Current profile.



(c) Power loss profile.

Fig. 2: The voltage (a), current (b) and power loss (c) profiles in the 33-node DS obtained by AEO.

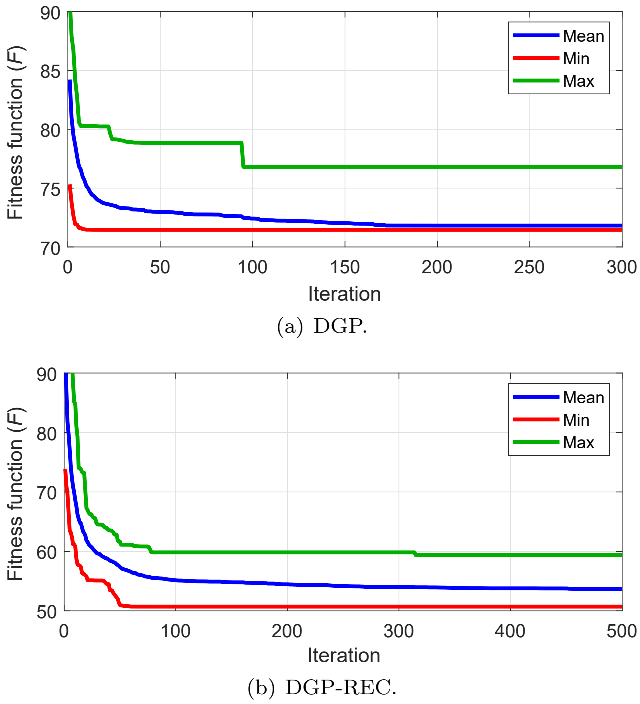
The comparison of the results between AEO and other approaches in Tab. 1 shows the superior efficiency of AEO for all three problems. When performing the DGP, the result obtained by AEO is similar to SFS [48], HTELA [47], SSA [38] and GWO-PSO [49]. Compared with CSA [46], SCA [32] and AMWOA [33], the loss reduction obtained from the AEO is higher by

Tab. 1: The results of DGP and DGP-REC for the 33-node DS.

DGP solution						DGP-REC solution					
Method	OS	P_{DG} (MW) [node]	ΔP (kW)	LR (%)	V_{min} (p.u.) [node]	Method	OS	P_{DG} (MW) [node]	ΔP (kW)	LR (%)	V_{min} (pu) [node]
Initial	33 to 37		202.6863		0.9131 [18]	AEO	33, 34, 11, 31, 28	0.7530 [17] 0.9570 [7] 1.2796 [25]	50.7189	75.0	0.9734 [32]
AEO	33 to 37	0.7540 [14] 1.0994 [24] 1.0714 [30]	71.4599	64.7	0.9687 [33]	CSA [46]	33, 34, 11, 31, 28	0.8968 [18] 1.4381 [25] 0.9646 [7]	53.21	73.7	0.9806
CSA [46]	33 to 37	0.7798 [14] 1.1251 [24] 1.3496 [30]	74.26	63.4	0.9778	SFS [48]	7, 9, 14, 27, 30	0.7753 [22] 0.7356 [33] 1.2858 [25]	53.01	73.8	0.972
SFS [48]	33 to 37	0.7540 [14] 1.0994 [24] 1.0714 [30]	71.47	64.7	0.9687	HTELA [47]	11, 28, 30, 33, 34	0.8997 [7] 0.8651 [18] 1.2956 [25]	51.3	74.7	0.968 [31]
HTELA [47]	33 to 37	0.7406 [14] 1.0094 [24] 1.0542 [30]	71.5	64.7		SSA [38]	6, 14, 11, 17, 28	1.027 [8] 1.180 [24] 0.837 [31]	56.42	72.2	0.9762 [18]
SSA [38]	33 to 37	0.7536 [13] 1.1004 [23] 1.0706 [29]	71.45	64.7	0.9686 [32]	GWO-PSO [49]	11, 28, 30, 33, 34	0.9569 [7] 0.7529 [17] 1.2795 [25]	50.8905	74.9	0.9734
GWO-PSO [49]	33 to 37	1.0717 [30] 1.1003 [24] 0.7540 [14]	71.4571	64.7		SCA [32]	7, 14, 9, 27, 30	0.5672 [12] 0.7125 [18] 1.190 [25]	53.53	73.6	0.9651 [31]
SCA [32]	33 to 37	0.929 [30] 0.789 [13] 0.826 [24]	73.18	63.9	0.9635 [33]	AMWOA [33]	11, 28, 31, 33, 34	0.8299 [8] 1.3412 [17] 0.7109 [31]	50.61	75.0	
AMWOA [33]	33 to 37	1.1066 [24] 1.3383 [30] 0.8086 [14]	71.70	64.6		EO [37]	7, 10, 13, 27, 31	0.399 [8] 0.669 [17] 1.160 [29]	57.40	71.7	

1.3, 0.8 and 0.1 %, respectively. Meanwhile, for the DGP-REC combination problem, only the power loss reduction obtained by AMWOA [33] is equal to that of AEO, all other methods including CSA [46], SFS [48], HTELA [47], SSA [38], GWO-PSO [49], SCA [32] and EO [37] have lower power loss reduction than that of AEO. Specifically, their power loss reduction is 1.3, 1.2, 0.3, 2.8, 0.1, 1.4 and 3.3 % respectively lower than AEO.

The AEO's statistical results including the maximum (F_{max}), minimum (F_{min}), mean (F_{mean}) and STandard Devitation (STD) of the fitness function, the number of converging iterations (G_{mean}) and the average computation time as well as minimum, maximum and average convergence characteristics of 30 runs for a 33-node network are presented in Tab. 2 and Fig. 3. During 30 runs, F_{mean} value in two cases DGP and DGP-REC is 71.8166 and 53.6995, respectively. These values are only 0.3567 and 2.9806 respectively lower than the corresponding F_{min} values. Compared to the EO [37], the F_{max}, F_{min} and F_{mean} values gained by AEO are lower than that of EO method. The mean convergence line is close to the minimum convergence one, the mean convergence value is close to the minimum convergence value and the small STD value shows the efficiency and reliability of AEO for the DGP and DGP-REC problem.



(a) DGP.

(b) DGP-REC.

Fig. 3: The maximum, minimum and mean convergence curves of AEO for the 33-node DS.

Tab. 2: The results of AEO for the 33-node DS.

Method	F_{max}	F_{min}	F_{mean}	STD	G_{mean}	Time (s)
DGP problem						
AEO	76.8099	71.4599	71.8166	1.3573	216	63.9172
DGP-REC problem						
AEO	59.3672	50.7189	53.6995	2.5796	389	84.4297
EO [37]	71.19	57.4	66.63	0.0452		

Tab. 3: The results of DGP and DGP-REC for the 119-node DS.

DGP solution						DGP-REC solution					
Method	**OS**	P_{DG} (MW) [node]	ΔP (kW)	LR (%)	V_{min} (p.u.) [node]	**Method**	**OS**	P_{DG} (MW) [node]	ΔP (kW)	LR (%)	V_{min} (pu) [node]
Initial	118 ÷ 132		1273.45		0.8676 [77]	AEO	42, 25, 21, 121, 122, 58, 39, 125, 70, 74, 98, 82, 130, 131, 33	2.6382 [50] 3.3265 [109] 3.7533 [91]	569.1325	55.3	0.9552 [99]
AEO	118 ÷ 132	3.1203 [109] 2.9814 [71] 2.8627 [50]	645.98	49.3	0.9505 [99]	COA [50]	42, 25, 21, 121, 122, 58, 39, 125, 70, 74, 98, 82, 130, 131, 33	2.6382 [50] 3.7533 [91] 3.3265 [109]	569.1325	55.3	0.9552 [99]
CSA [46]	118 ÷ 132	3.2664 [71] 3.1203 [109] 2.86267 [50]	648.10	49.1	0.9515	CSA [46]	42, 25, 22, 121, 122, 58, 39, 125, 70, 127, 128, 81, 130, 131, 33	2.5331 [50] 3.6819 [109] 3.7043 [73]	586.24	54.0	0.9644

4.2. The Second System

The system with 11 kV, 119 nodes, 132 branches and total load 22.7097+j17.4051 MVA has a single line diagram in Fig. 4 [56]. The loss of the original structure is 1273.45 kW. The number and capacity of DG installed on this system is limited to 3 and 5 MW, respectively. For AEO, the maximum number of iterations G_{max} for the DGP and DGP-REC problems is set to 800 and 1000, respectively, while the other parameters are selected similar to the first system.

The efficiency of AEO for the 119-node network is shown in Tab. 3. After implementing the DGP and DGP-REC approaches, the reduction of power loss compared to the original structure is 49.3 and 55.3 %, respectively. The power loss decrease of DGP-REC is 6.0 % higher than that of DGP. Furthermore, the voltage improvement of DGP-REC measure is better than that of DGP. Specifically, the lowest voltage has been raised from 0.8678 in the original system to 0.9505 and 0.9552 respectively after performing DGP and DGP-REC. Figure 5 and Fig. 6 show that the improvement of voltage and power line loss is significant after implementing the DGP and DGP-REC approaches, wherein the improvement in DGP-REC is better than that of DGP.

The comparison with the other methods is shown in Tab. 3. For DGP problem, AEO has obtained better results than CSA [46] and SFS [48]. Loss reduction obtained by AEO is 0.2 and 1.7 % higher than that of CSA [46] and SFS [48], respectively. Meanwhile, for the DGP-REC problem, the result obtained by AEO is similar to COA [50] and better than CSA [46]. The loss reduction of CSA [46] is 1.3 % lower than that of AEO. Compared to the SFS [48], the power loss reduction of the AEO is lower by 0.2 %, but the capacity limit of DGs for AEO is only set to 5 MW while this value of SFS [48] is higher because the optimal value obtained by SFS [48] for a DG is up to 8.7132 MW. Thus, AEO is an effective technique to the DGP and DGP-REC problem on the large networks such as the 119-node system.

The statistical results of AEO in 30 runs for the 119-node network are presented in Tab. 4 and Fig. 7. During 30 runs, the F_{mean} value for two cases of DGP and DGP-REC is almost equal to F_{min} value. Note

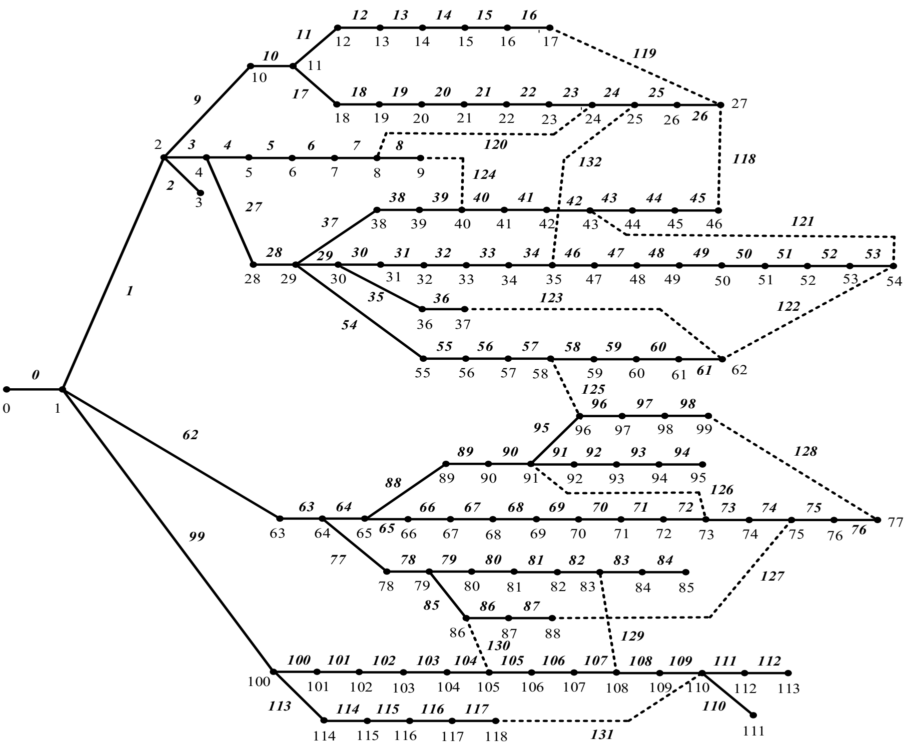


Fig. 4: The 119-node system.

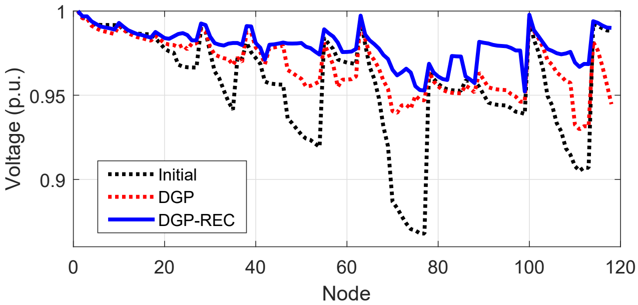


Fig. 5: The voltage profile in the 119-node DS obtained by AEO.

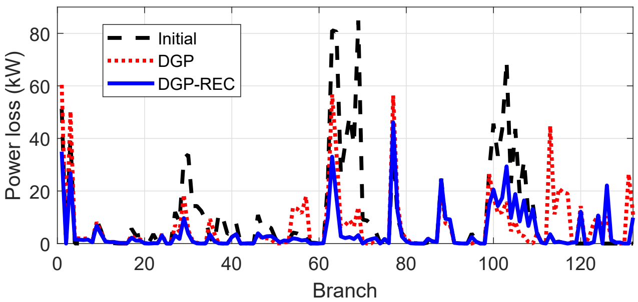


Fig. 6: The voltage profile in the 119-node DS obtained by AEO.

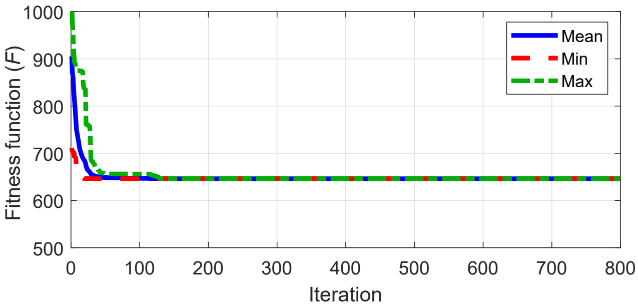
that in DGP problem, the F_{mean} value rounded to two decimal places is equal to the F_{min} value. This shows the stability of the AEO for three problems on large networks. Compared to the COA [50], the F_{max} and G_{mean} gained by AEO are lower than that of COA while the F_{mean} value is 5.24 higher than that of COA method. The convergence curve of the DGP and DGP-REC problems in Fig. 7 shows that DGP-REC is the technique able to reduce the fitness function value better compared to DGP. In addition, the proximity of the average curves to the minimum ones shows high reliability of the AEO in each run for the DGP and DGP-REC problems.

5. Conclusion and Future Research

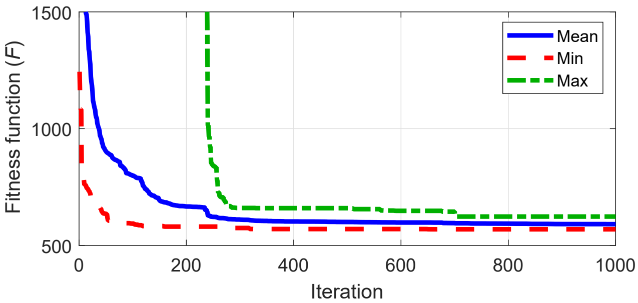
In this paper, the AEO-based method is used to the DGP and DGP-REC problems to reduce power loss on the distribution network. The AEO-based method is applied to find optimal solutions for two problems on the 33-node and 119-node systems. The calculation results demonstrate that for the purpose of power loss reduction, DGP-REC is a better solution than DGP in reducing the power loss in the DS. The power loss reduction in percent for the two systems obtained by DGP-REC is $\{75.0, 55.3\}$ while this value for DGP is $\{64.7, 49.3\}$. The results compared with selected implemented methods also show that AEO is one of the potential options for finding optimal solution of the DGP and DGP-REC problems on the practical distribution networks. Future works should investigate the DGP and DGP-REC considering the uncertainties of loads and the primary energy sources of the DGs.

Tab. 4: Results of statistical analysis of AEO for the 119-node DS.

Method	$F_{\max}$	$F_{\min}$	F_{mean}	STD	G_{mean}	Time (s)
DGP problem						
AEO	645.98	645.98	645.98	$1.1 \cdot 10^{-11}$	497	705.90
DGP-REC problem						
AEO	623.58	569.13	591.00	17.181	858	613.58
COA [50]	828.25	569.13	585.76	46.39	1312	569.13



(a) DGP.



(b) DGP-REC.

Fig. 7: The maximum, minimum and mean convergence curves of AEO for the 119-node DS.

In addition, the efficiency of AEO for the practical DS systems might be addressed in future works.

Author Contributions

Thu.T.N. developed the theoretical formalism, performed the analytic calculations and the numerical simulations. Thu.T.N and Tha.T.N contributed to the final version of the manuscript. Thu.T.N supervised the project.

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