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A Hybrid Adaptively Modified Firefly and Differential Evolution in DG Integration Optimization for Improving the Radial Power Distribution Networks

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Abstract: This paper discusses optimizing DG location and size to reduce power loss and bus voltage deviation index in a 51-bus radial distribution network. Optimization of DG placement uses the firefly algorithm, and optimization of DG size uses the differential evolution (DE) algorithm. The results showed that the optimal locations were on buses 16, 45, and 15, with the highest sensitivity indices of 0.6667, 0.0612, and 0.0601. DG at a lagging power factor of 0.95 gives optimal results with sizes of 358.5157, 500.0000, and 499.9781 kW. Active and reactive power loss reduction is 44.6948% and 66.7038% of the system's power loss without DG. In optimizing DG placement, AMFA converges faster than DE, GA, and ICA. In the case of DG size optimization, the DE algorithm converges quicker and gives the most optimal results with a fitness value of 0.12385 which is smaller than the FA, GA, and ICA algorithms.

Keywords: Distributed generation, Modified firefly, Differential evolution, Optimal capacity, Loss reduction, Voltage deviation.

NOMENCLATURE

$R_{i,j}$	line resistance connecting bus *i* and *j*
$X_{i,j}$	line reactance connecting bus *i* and *j*
$I_{i,j}$	line current connecting bus *i* and *j*
$P_{loss\ i,j}$	line active power loss from bus *i* and *j*
$Q_{loss\ i,j}$	line reactive power loss from bus *i* and *j*
P_{loss}^{wDG}	active power loss in a system with DG
P_{loss}^{noDG}	active power loss in a system without DG
VDI	Voltage Deviation Index
V_i^{wDG}	the voltage at bus *i* of the system with DG
V_i^{noDG}	the voltage at bus *i* of the system without DG
V_{min}	minimum limit of bus voltage
V_{max}	maximum limit of bus voltage
S_k	sensitivity index
kVA_i	kVA load at bus *i*
ΔV_k^{max}	the maximum change in bus voltage when installing DG on bus k
$P_{L\,i}$,$Q_{L\,i}$	active and reactive power load at bus *i*
P_{ss} , Q_{ss}	active and reactive power from a substation
$P_{DG\ i}$	active power supplied from the DG-*i*
$Q_{DG\ i}$	reactive power supplied from the DG-*i*
$P_{L\,j}$, $Q_{L\,j}$	active and reactive power load at bus *j*
$P_{loss\ k}$	active power loss at line-*k*
$Q_{loss\ k}$	reactive power loss at line-*k*
n_b	number of buses
n_l	number of lines
n_{DG}	number of DG
V_j	the voltage at bus *j*
P_{DG}^{min}	min of DG active power generation
P_{DG}^{max}	max of DG active power generation
Q_{DG}^{min}	min of DG reactive power generation
Q_{DG}^{max}	max of DG reactive power generation
X_i	*i*-th solution variable (position of firefly *i*)
X_j	*j*-th solution variable (position of firefly *j*)
X_i^t	the *i*-th solution at the *t*-th iteration

Table 1. Comparison with the reviewed literature

Key literature	Considered parameter				Algorithm
	Power loss	Sensitivity Index	Voltage deviation	Power factor of DG	
[8][9][17]	√	X	√	X	GA
[10]	√	X	√	X	DE
[11][12]	√	X	X	X	ICA
[13]	√	X	√	X	FA
This paper	√	√	√	√	A hybrid of AMFA and DE

1. Introduction

The generating unit supplies power to the load via a long-distance transmission line. The resistance and reactance of transmission lines over long distances will cause a non-negligible amount of power losses. In addition, the length of the transmission line will cause poor voltage regulation [1].

Power generation near the load center by utilizing renewable energy sources is the right solution to the problem of power loss and voltage regulation in distribution networks. This type of power generation system is called distributed generation (DG). Integrating DG into the distribution network has several advantages, including clean, green, low complexity and risk, and low operational costs. The ability of DG to supply local load requirements also reduces power flows on transmission lines, which can delay the need to adjust transmission line capacity to load growth [2]. Getting the benefits of DG requires the proper integration of distributed generation. Improper DG integration will worsen the condition of the network. Determining the exact DG location and size of DG can be done through optimization using an analytical approach or by applying artificial intelligence algorithms.

Various studies present DG capacity optimization, deployment, and penetration rates in radial distribution systems (RDS). Optimizing DG capacity for mitigating the loss of power and strengthening the bus voltage profile on the RDS has been done by implementing the Accelerated Particle Swarm Optimization (PSO) [2, 3], Backtracking Search [4], Binary PSO and shuffled frog leap (SLFA) [5], Stud Krill herd algorithm [6], a hybrid of the grasshopper optimization algorithm (GOA) and cuckoo search (CS) technique [7], and a genetic algorithm (GA) and ant colony algorithm (ACO) [8], a combined of GA and PSO [9], differential evolution (DE) [10], imperialist competition algorithm (ICA) [11, 12], and firefly algorithm (FA)[13]. In [14] presents optimizing DG to increase the Voltage Stability Index and reduce power losses using the Bat Algorithm with variations in loudness and pulse. Paper [15] discusses DG optimization for changes in system load using the voltage stability margin index and continuation power flow methods. The effect of residential and industrial load types on optimizing DG size and location for reducing power loss, DG cost, and the deviation of voltage has been studied with the multi-objective shuffled bat [16] and a combination of GA and NSGA II [17], dragonfly algorithm [18], and whale optimization algorithm [19]. DG optimization by considering load fluctuations and the availability of renewable energy to reduce power loss, line load, and DG investment costs has been carried out with the genetic algorithm (GA) [20].

This paper presents the optimization of DG placement and capacity in distribution networks with a hybrid metaheuristic algorithm. Optimization uses two stages. In the first stage, optimization of DG placement by applying an adaptively modified firefly algorithm (AMFA) to maximize the sensitivity index (*Sk*). Changing the firefly algorithm by reducing the random motion coefficient (α) along with iterations aims to make it converge faster. Optimization of the DG placement location uses a penetration rate of 10% of the total active power at load. DG size optimization uses a differential evolution (DE) algorithm to minimize active power loss and voltage deviation index in the second stage. This paper also discusses the influence of the DG power factor to obtain the most optimal conditions. The power factor used includes pf=1 and pf=0.95 lagging. DG optimization is also performed by applying other metaheuristic algorithms consisting of genetic algorithm (GA) and imperialist competitive algorithm (ICA) to compare and validate the proposed method's results and effectiveness.

The organization of the papers is as follows. Section 2 is the problem modeling which consists of distribution line loss, voltage deviation index, sensitivity index, and optimization objective. Section 3 is the proposed method. Section 4 is the results and discussion. Section 5 is conclusions and future research.

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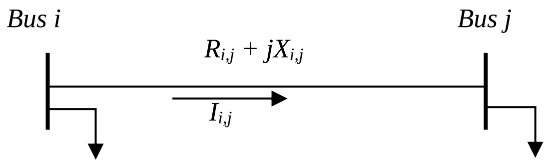

Figure. 1 The line connects bus i and j

2. Problem modeling

2.1 The distribution line loss

The connecting line from bus i to j with an impedance $R_{i,j} + jX_{i,j}$ and a current of $I_{i,j}$, is shown in Fig. 1. The active power loss (P_{loss}) and reactive power loss (Q_{loss}) on the line with current $|I_{i,j}|$ can be stated as Eq. (1) and Eq. (2).

$$P_{loss\ i,j} = R_{i,j} \cdot \left|I_{i,j}\right|^2 \tag{1}$$

$$Q_{loss\ i,j} = X_{i,j} \cdot \left|I_{i,j}\right|^2 \tag{2}$$

The total loss of P_{loss} and Q_{loss} in a system with n_l lines can be written as Eq. (3) and Eq. (4).

$$Total\ P_{loss} = \sum_{k=1}^{n_l} R_k \cdot |I_k|^2 \tag{3}$$

$$Total\ Q_{loss} = \sum_{k=1}^{n} X_k \cdot |I_k|^2 \tag{4}$$

R_k , X_k , and I_k are the resistance, reactance, and current of the line-k, respectively.

DG integration into the power distribution network will impact the power balance. The line current in the distribution network will also change in value and direction. These changes will determine the amount of power loss on the transmission line in the system as a whole. The DG integration aims to reduce the power losses in the distribution network. The percentage reduction in P_{loss} and Q_{loss} due to the installation of DG can be expressed as follows:

$$\%\ Reduction = \frac{P_{loss}^{noDG} - P_{loss}^{wDG}}{P_{loss}^{noDG}}\ x\ 100\ \% \tag{5}$$

2.2 Voltage deviation index

The voltage deviation (VD) is the accumulated square of the difference between the bus voltage and the minimum (V_{min}) and maximum (V_{max}) voltage for all buses except the substation. Voltage deviation index (VDI) is the ratio of VD for a system with DG to without DG, which can be expressed as follows:

$$VDI = \frac{\sum_{i=2}^{NB}\left\{\left(V_i^{wDG} - V_{min}\right)^2 + \left(V_i^{wDG} - V_{max}\right)^2\right\}}{\sum_{i=2}^{NB}\left\{\left(V_i^{noDG} - V_{min}\right)^2 + \left(V_i^{noDG} - V_{max}\right)^2\right\}} \tag{6}$$

V_{min}=0.95 p.u and V_{max}=1.05 p.u are the bus voltage limits.

2.3 Sensitivity index (*Sk*)

The sensitivity index (*Sk*) is a parameter commonly used to measure the influence of the location of DG placement on a particular bus on the voltage of the overall bus in the system [21]. Based on these considerations, *Sk* is an important reference for determining the location of DG. Mathematically, the sensitivity index can be expressed in the following:

$$S_k = \sum_{i=2}^{n_b} V_{i,k}^{wDG} kVA_i + \Delta V_k^{max} \tag{7}$$

Where:

$$\Delta V_k^{max} = max\left|V_{i,k}^{wDG} - V_{i,k}^{noDG}\right|\ ,\ \text{i=2,3,...,nb} \tag{8}$$

$$kVA_i = \sqrt{(PL_i)^2 + (QL_i)^2} \tag{9}$$

$V_{i,k}^{wDG}$ and $V_{i,k}^{noDG}$ are voltage at bus i after and before DG is installed at bus k.

2.4 Objective of DG optimization

The optimization of DG includes the placement and size of DG. DG's location is optimized using the AMFA to maximize S_k in Eq. (7), which can be expressed as follows:

$$F_{obj-1} = max(S_{\mathrm{k}}) \tag{10}$$

DG size optimization applies the DE algorithm intending to decrease the total P_{loss} according to Eq. (3) and the accumulated VDI according to Eq. (6), combined using the weighted sum method. This method is carried out by adding up each part of the objective after multiplying it by the weight factors w_1 and w_2. Mathematically it can be expressed in Eq. (11).

$$F_{obj-2} = min(w_1.P\_loss + w_2.VDI) \tag{11}$$

Optimization is carried out by taking into account the following constraints:

- *Power balance constraint*

For n_{DG} optimization on a radial network system with n_b and n_l line, the power balance constraint can be expressed as follows:

$$P_{ss} + \sum_{i=1}^{n_{DG}} P_{DG\ i} = \sum_{j=1}^{n_b} P_{L\ j} + \sum_{k=1}^{n_l} Ploss_{\ k} \quad (12)$$

$$Q_{ss} + \sum_{i=1}^{n_{DG}} Q_{DG\ i} = \sum_{j=1}^{n_b} Q_{L\ j} + \sum_{k=1}^{n_l} Qloss_{\ k} \quad (13)$$

- *Bus voltage constraint*

$|V_j|$ as the voltage of bus j must be between $|V_{min}|$ and $|V_{max}|$.

$$|V_{min}| \leq |V_j| \leq |V_{max}| \text{ , j = 1,2,....,nbus} \quad (14)$$

- *DG generation capacity constraints*

DG power generation must be between the minimum and maximum limits.

$$P_{DG}^{min} \leq P_{DG\ i} \leq P_{DG}^{max} \text{ , i=1,2, … ,nDG} \quad (15)$$

$$Q_{DG}^{min} \leq Q_{DG\ i} \leq Q_{DG}^{max} \text{ , i=1,2, ... ,nDG} \quad (16)$$

3. Proposed method

3.1 Adaptive modified firefly

For the first time, Xin She Yang introduced an algorithm that refers to the behaviour of fireflies. The behaviour of individual fireflies is initially in their scattered positions. Fireflies have an attraction to move toward other fireflies that are brighter and have better fitness. Eventually, all fireflies in the population will converge at the exact position of the brightest and best fitness firefly [22].

The first step in applying the AMFA algorithm to optimize the placement of 3 DG units is to determine the initial location randomly. From each initial location and a DG penetration level of 10% of the total load power, the power flow is calculated using the backward/forward sweep (BFS) method to obtain the bus voltage value and sensitivity index (*Sk*). The value of *Sk* is used as a fitness that expresses the urgency of each initial DG placement location. The highest fitness value indicates the most appropriate bus for DG placement. For DG locations with lower fitness, an adjustment is made like a less bright firefly moving towards a brighter one using Eq. (17).

$$X_i = X_i + \beta\left(X_j - X_i\right) + \alpha . \varepsilon_i \quad (17)$$

ε is a number between 0 and 1. α is a random movement coefficient. The value of β represents the attractiveness influenced by brightness (β_o), the distance between fireflies (r), and the absorption coefficient (γ), as stated in Eq. (18). The value of r is expressed in Eq. (19).

$$\beta = \beta_O . e^{(-\gamma . r^m)} \text{ , } m \geq 1 \quad (18)$$

$$r_{ij} = \sqrt{(X_i - X_j)^2 + (Y_i - Y_j)^2} \quad (19)$$

In Eq. (17), the random movement coefficient (α) can potentially reduce the iteration’s convergence rate. The firefly algorithm is modified by adapting to the iteration by decreasing the value of α. In the (k+1)-th iteration, the value of α^{k+1} is calculated based on its value in the previous iteration using Eq. (20) [23].

$$\propto^{k+1} = \propto^{k} \ \left(\frac{1}{2} k_{max}\right)^{\left(\frac{1}{k_{max}+1}\right)} \quad (20)$$

The process of optimizing DG placement with AMFA can be described in the following Algorithm 1:

3.2 Differential evolution

The differential evolution (DE) algorithm stages consist of initialization, mutation, crossover, and selection, carried out sequentially [24]. Initialization is the first process to determine the initial solution of the optimization problem. Mutation is the process of generating mutants from randomly selected mutation targets. Crossover is the crossing between mutants and targets to create new derived solutions. Selection is selecting the initial and derived solutions to maintain the number of solutions.

This paper applies the DE algorithm to optimize the size of 3 DG units integrated into the distribution network. According to the number of DGs, the 3-dimensional solution variable at the t-th iteration can be expressed as Eq. (21):

$$X_i^t = (X_{i,1}, X_{i,2}, X_{i,3}) \text{ , } i=1,2,...,nP. \quad (21)$$

nP is the number of the population.

The minimum and maximum limits for the value of each solution element are defined in Eqs. (22) and (23).

$$X_{min} = (X_{min\ 1}, X_{min\ 2}, X_{min\ 3}) \quad (22)$$

$$X_{max} = (X_{max\ 1}, X_{max\ 2}, X_{max\ 3}) \quad (23)$$

The initial value for the DG size is randomly assigned as the initial solution. The value must meet the minimum and maximum limits and the population size. Mathematically, initialization can be expressed by Eq. (24).

Algorithm 1: DG placement using AMFA

```
Start
 %Set parameters of firefly and boundary
 α ← set 0.25 as a random motion coefficient;
 βo ← set 1 as a brightness;
 γ ← set 1 as absorption coefficient;
 m ← set 2;
 ε ← set 0.5;
 ub ← set upper limit [51];
 lb ← set lower limit [2];
 nff ← set number of populations 30;
 max_iter ← maximum iteration 100;
 nDim ← set 1 as the dimension of solution
            variable1
 %Initial population
 For i1=1:nff
   ff(i1) ← create an initial solution using :
            lb+(ub-lb).random(1,nDim)
 Next i1
 %Main iteration
 For iterFF=1:max_iter
   %calculate the fitness of the solution variable
   For i=1:nff
     Pos_DG ← ff(i)
     Vbus_withDG ← run power flow to provide
                   bus voltage
     Sk ← Calculate sensitivity index using
          Eq. (7-9)
     Fit(i) ← calculate (1/Sk) as a fitness
   Next i
   best_fit ← find a max of fitness as the best
fitness
   best_ff ← find firefly with the best fitness
 %update firefly as a new solution variable
   For i = 1:nff
     For j = 1:nff
       If Fit (i)>Fit (j)
         r1 ← calculate distance using Eq. (19)
         β ← calculate attractiveness using Eq. (18)
         ff(i) ← update position using Eq. (17)
       End if
     Next j
   Next i
   %ceck boundaries
   For ii=1:nff
     if ff(ii)>ub then ff(ii) ← replace with ub
     if ff(ii)<lb then ff(ii) ← replace with lb
   Next ii
   %modified alpha
   α ← calculate α for the next iteration using
       Eq. (20)
 Next iter_FF
 %best DGs position
 Pos_DG ← get best_ff as the optimal DG location
End
```

$$X_i = X_{min\ j} + rand.(X_{min\ j} - X_{max\ j}) \quad (24)$$

i=1,2,...,nP; j=1,2,3; and $rand$ is a random real number between 0 and 1.

After the initial solution is formed, the next step is a mutation to generate mutants (Y_i) based on randomly selected targets from X_i. Mathematically, the mutation is expressed by Eq. (25).

$$Y_i = X_{r_1} + F(X_{r_2} - X_{r_3}) \quad (25)$$

r_1 is the index of the target; r_2 and r_3 are the indices of the selected solutions to create the mutants, $r_1, r_2, r_3 \in [1, nP]$ and $r_1 \neq r_2 \neq r_3 \neq i$; X_{r_1} is the selected individual as the mutation target, and F is the mutation factor with a value between 0 and 1.

Crossover is a cross between a target and a mutant to produce a trial solution or offspring (Z_i). The generation of a trial solution is mathematically expressed as follows:

$$Z_{i,j} = \begin{cases} Y_{i,j} & if\ rand[0,1] < CR\ or\ j = k \\ X_{i,j} & otherwise \end{cases} \quad (26)$$

CR is the rate of crossover, $rand[0,1]$ is a random value between 0 and 1, and $k \in \{1,2,3\}$.

The selection allows the DE to select the target (parent) or trial solution (offspring) that is retained and used for the next iteration. Mathematically, the selection process can be expressed as follows:

$$X_i = \begin{cases} Z_i & if\ f(Z_i) \leq f(X_i) \\ X_i & Otherwise \end{cases} \quad (27)$$

f(.) is an objective function representing the solution's fitness. That fitness value is determined using Eq. (11) after calculating the power flow using BFS to get Ploss and VDI. The DG size optimization with DE can be described in the following Algorithm 2:

4. Result and discussion

Fig. 2 shows the line configuration of the 51-bus RDS used in the DG optimization simulation. Bus 1 acts as the slack bus. The load's power is 2463 kW and 1569 kVAR, respectively[21].

The simulation is carried out with the first stage of optimizing DG placement, then proceeds with optimizing DG size by considering DG's power

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Algorithm 2: DG sizing using DE

```
Start
  %Set parameter and boundary
  F ← set 0.2 as a mutation factor
  CR ← set 0.9 as crossover rate
  w1 ← set 0.6 as weight factor 1
  w2 ← calculate weight factor 2 using (1-w1)
  nP ← set 30 as the number of population
  nDim ← set 3 as a dimension of the solution
  Xmax ← set [51 51 51] as an upper limit
  Xmin ← set [2 2 2] as a lower limit
  max_iter ← set 100 as a maximum iteration
  %Initial population of solution
  For i1=1:nP
     X(i1) ← create an initial solution using Eq.
               (24)
  Next i1
  %Main iteration
  For iter=1:max_iter
     For m=1:nP
        %Mutation
        Y ← generate mutants using Eq (25)
        %Crossover
        Z ← generate trial solution using Eq. (26)
        %Fitness Y and fitness Z
        P_DG ← Set U as a power of DG
        [Ploss, Qloss, VD] ← run power flow to
           get power loss and voltage deviation
        Fit_U ← calculate the fitness of solution U
              using: (w1.Ploss + w2.VD)
        P_DG ← set Z as a power of DG
        [Ploss, Qloss, VD] ← run power flow to
           get power loss and voltage deviation
        Fit_Z ← calculate the fitness of solution Z
              using: (w1.Ploss + w2.VD)
        %Selection for a new solution
        if Fit_U < Fit_Z
           X(m) ← use solution U as a new
                 solution
           Fit(m) ← replace fitness with Fit_U
        else
           X(m) ← use solution Z as a new
                 solution
           Fit(m) ← replace fitness with Fit_Z
        end if
     Next m
     %Best fitness
     best_fit ← find a minimum of fitness as the
              best
     best_X ← find a solution with the best fitness
  Next iter
  % get optimal DGs size
P_DG ← get best_X as an optimal DG size
End
```

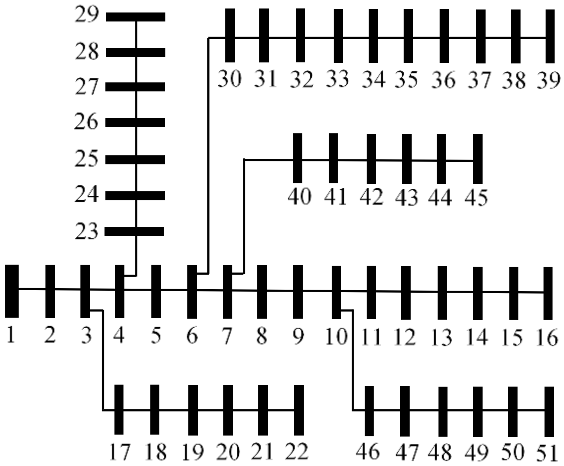

Figure. 2 Single line diagram of the 51-bus radial network

factor (pf). The amount of pf used includes pf=1 and pf=0.95 lagging.

4.1 DG placement optimization

Optimization of DG placements is carried out to maximize the sensitivity index (*Sk*) in Eq. (10). The number of optimized DGs is 10 with a unity power factor, so 10 DG placements have the highest sensitivity obtained. The penetration rate is 10% of the total P_L at the load attached to the system. Table 2 presents the results of optimizing DG placement using the AMFA compared to other metaheuristic algorithms, namely DE, GA, and ICA.

Table 2 shows a bus of DG locations with a sensitivity index arranged sequentially from the highest value. The optimization results of all the algorithms used show that the optimal locations for the first to seventh DGs are the same, namely on buses 16, 45, 15, 44, 14, 43, and 13. For the next 3 DGs, the AMFA algorithm produces optimal locations on buses 12, 22, and 42, while the DE, GA, and ICA algorithms have optimal locations on buses 51, 12, and 50. The top three rankings are used as a location of DG. The optimal results of DG placement are relatively the same. However, the proposed method is more effective with faster convergence, as shown in Fig. 3.

4.2 DG size optimization

Optimization of 3 DG units installed on buses 16, 45, and 15 is carried out to minimize the loss of power and accumulation of voltage deviation according to Eq. (7). It is subject to the constraints according to Eqs. (12-16). The weight factor for active power loss

Table 2. DG location and sensitivity index (*Sk*)

Rank	AMFA		DE [10]		GA [8],[9],[17]		ICA [11],[12]	
	Bus	***Sk***	**Bus**	***Sk***	**Bus**	***Sk***	**Bus**	***Sk***
1	16	0.6667	16	0.6667	16	0.6667	16	0.6667
2	45	0.0612	45	0.0612	45	0.0612	45	0.0612
3	15	0.0601	15	0.0601	15	0.0601	15	0.0601
4	44	0.0597	44	0.0597	44	0.0597	44	0.0597
5	14	0.0567	14	0.0567	14	0.0567	14	0.0567
6	43	0.0548	43	0.0548	43	0.0548	43	0.0548
7	13	0.0542	13	0.0542	13	0.0542	13	0.0542
8	12	0.0520	51	0.0537	51	0.0537	51	0.0537
9	22	0.0503	12	0.0520	12	0.0520	12	0.0520
10	42	0.0498	50	0.0508	50	0.0508	50	0.0508

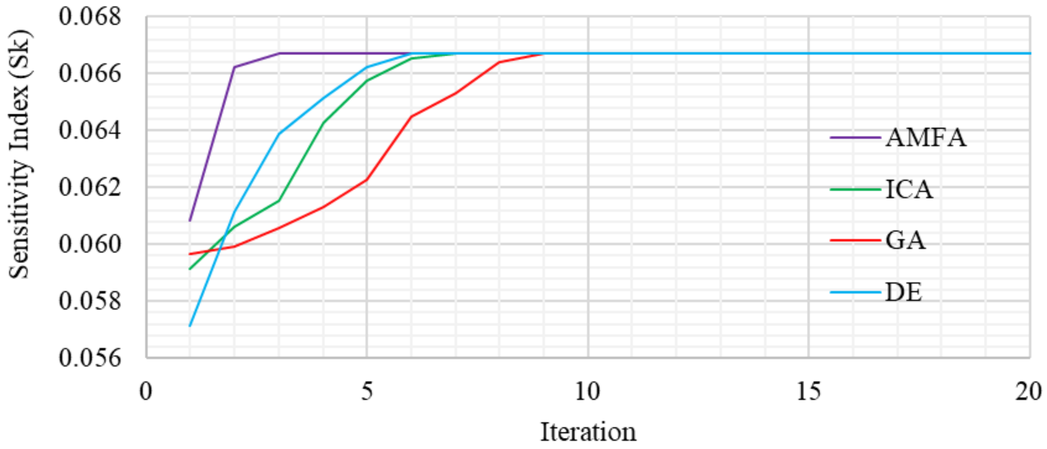

Figure. 3 Convergence properties of the AMFA, ICA, GA, and DE algorithms used in DG placement optimization.

Table 3. DG size optimization results with pf=1

Parameter	Without DG	With optimized DG			
		DE	**FA** [13]	**GA** [8],[9],[17]	**ICA** [11],[12]
Size of DG (kW)	-	308.0097	287.6826	294.1836	287.6332
	-	499.9999	500.0000	488.7974	500.0000
	-	478.9099	500.0000	497.5241	500.0000
The total size of DG (kW)	-	1286.9195	1287.6826	1280.5051	1287.6332
Total P loss (kW)	129.5555	86.4569	86.2623	86.2265	86.2586
Total Q loss (kVAR)	111.6832	54.4044	54.3316	54.4368	54.3313
Lowest bus voltage (p.u)	0.90812	0.95703	0.95705	0.95698	0.95705
Lowest voltage bus	16	51	51	51	51
Voltage deviation	0.57553	0.35940	0.35930	0.35970	0.35930

and voltage deviation is w_1=0.6 and w_2=0.4, respectively.

The impact of the power factor is also studied by simulation for DG with a unity power factor in case-1 and 0.95 lagging in case-2.

Case 1: DG with pf=1

Table 3 presents the optimization results of 3 DGs with pf=1. Optimizing the DG size with the DE algorithm provides P_{loss} and Q_{loss} of 86.4569 kW and 54.4044 kVAR, respectively. The lowest bus voltage is 0.95703 p.u on bus 51. The VD is 0.57553 p.u.

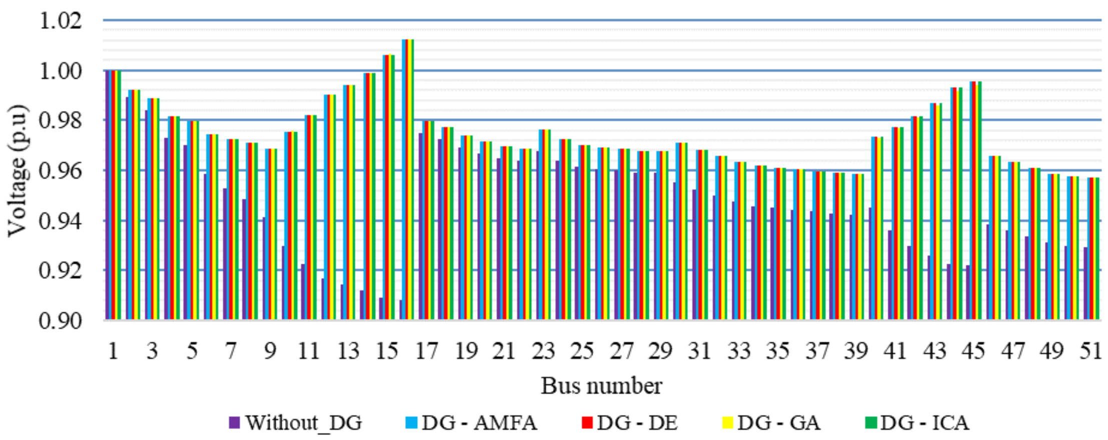

Figure. 4 Bus voltage profile of the system with DG at pf=1

Table 4. DG size optimization results in a power factor of 0.95 lagging

Parameter	Without DG	With optimized DG			
		DE	FA [13]	GA [8],[9],[17]	ICA [11],[12]
The optimal size of DG (kW)	-	358.5157	358.4900	379.0565	358.0000
	-	500.0000	500.0000	488.7974	500.0000
	-	499.9781	500.0000	483.5395	500.0000
The total size of DG (kW)	-	1358.4938	1358.4900	1351.3934	1358.0000
Total P loss (kW)	129.5555	71.6509	71.6502	71.9267	71.6094
Total Q loss (kVAR)	111.6832	37.1862	37.1861	37.4129	37.1836
Lowest bus voltage (p.u)	0.90812	0.96511	0.96511	0.96539	0.96550
Lowest voltage bus	16	39	39	39	39
Voltage deviation	0.57553	0.30855	0.30855	0.30903	0.30855

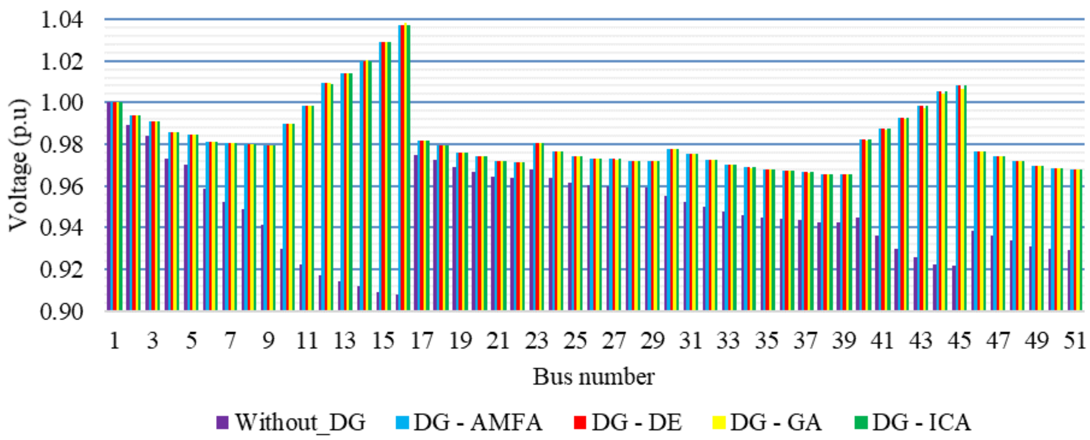

Figure. 5 Bus voltage profile of the system with DG at pf=0.95 lagging

Fig. 4 shows the overall bus voltage of the system. These results are validated by comparing optimization with AMFA, GA, and ICA algorithms.

Case 2: DG with power factor 0.95 lagging

To observe the influence of the DG power factor on the optimization results, the following simulation to be carried out is to set the DG power factor at 0.95 lagging. Load condition, DG penetration level, and objective weight factor remained the same as in case-1. Table 4 presents the optimization results with the DE algorithm and is validated with the AMFA, GA, and ICA algorithms. The optimization results show that the loss of power is 71.6509 kW and 37.1862

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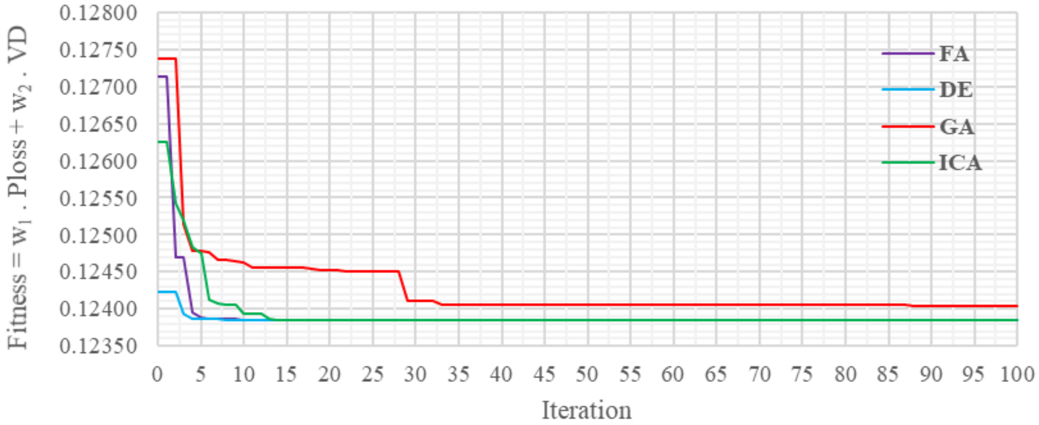

Figure. 6 Convergence properties of the DE, FA, GA, and ICA algorithms used in DG size optimization

Table 5. Comparison of optimization results for DG with pf=1 and pf=0.95 lagging

pf DG	Parameter	With optimized DG			
		DE	FA [13]	GA [8],[9],[17]	ICA [11],[12]
1	% Reduction in Ploss	33.2665	33.4167	33.4443	33.4196
	% Reduction in Qloss	51.2869	51.3520	51.2578	51.3523
	% Reduction in voltage deviation	37.5532	37.5706	37.5011	37.5706
0.95 lagging	% Reduction in Ploss	44.6948	44.6954	44.4819	44.7269
	% Reduction in Qloss	66.7038	66.7039	66.5009	66.7062
	% Reduction in voltage deviation	46.3885	46.3190	46.3885	46.3885

kVAR, respectively. The lowest bus voltage is 0.96511 p.u on bus 39. The voltage profile of the overall bus is shown in Fig. 5. Table 5 compares the optimization results for DG with pf=1 and 0.95 lagging. The comparison includes the percentage reduction in power loss and voltage deviation as the fitness component of the optimization objective. Fig. 6 shows the convergence properties of the algorithms used in optimization.

4.3 Discussion

Optimizing DG placement with *Sk* as an objective has resulted in the best ten buses for DG placement. The selection of the best bus refers to the *Sk* value of the bus. The bus with the highest *Sk* means that the installation of DG on that bus will provide the most significant improvement in the bus voltage profile. Bus 16, which occupies the top rank, is the priority compared to other buses ranked below.

The results of optimizing DG placement with AMFA as the proposed method are very similar to the comparison method, which consists of DE, GA, and ICA. This similarity indicates that the results obtained from the proposed method are valid. The results of optimizing DG placement with AMFA are similar to the comparison method, which consists of DE, GA, and ICA. This similarity indicates that the results obtained from the proposed method are valid. AMFA can be more effective than DE, GA, and ICA, especially in convergence. AMFA converges faster than the comparison algorithm, whereas it already gives results in the 3rd iteration. In comparison, the algorithms DE, GA, and ICA converge at iterations 8, 11, and 9, respectively. The ability to provide the result faster will significantly benefit when the proposed method is applied to large distribution systems with more buses.

In the case of DG size optimization, the DE algorithm as the proposed method is compared with the FA, GA, and ICA algorithms. The proposed method gives the same optimization results as the FA and ICA algorithms. These three algorithms can provide the most optimal results to minimize the optimization objective, which consists of active power loss and voltage deviation to the lowest value of 0.12385. This similarity shows the validity of the proposed method. In contrast, the GA algorithm can only provide the lowest result of 0.12405. If evaluated from convergence, the proposed algorithm is more effective than the other three. The DE algorithm converges the fastest, wherein the 8th iteration gives results for the optimal DG size. While the FA, GA, and ICA algorithms converge on the 10th, 38th, and 14th iterations, respectively. From the description above, the combination of the AMFA and DE algorithms in optimizing DG placement and size has shown its effectiveness.

The optimized DG installation has been able to improve the system condition. These improvements include reducing the loss of power and voltage deviation and increasing the bus voltage profile in the distribution network. The DG's power factor is also very influential on the results. DG with a power factor of 0.95 lagging gives better results than the unity power factor. The loss of power and voltage deviation decrease, and the bus voltage profile increases most significantly. The description above proves that the integration of DG in the distribution network has solved the problems caused by the length of the transmission line.

5. Conclusion and future works

Installation of DG on RDS aims to improve system conditions by minimizing power losses and improving the bus voltage profile. DG placement and size must be chosen appropriately. The bus sensitivity index is one of the parameters that can be used to optimize DG placement. Meanwhile, power loss and voltage deviation are parameters that can be used to optimize DG size. In this paper, DG optimization has been presented by consolidating the AMFA and DE algorithms. Optimization of DG placement by applying AMFA and sensitivity index as objectives have shown a significant improvement in the bus voltage profile. The effectiveness of AMFA is demonstrated by its ability to converge faster than the DE, GA, and ICA algorithms. Optimization of the DG size by applying the DE algorithm has been able to reduce power losses and bus voltage deviation compared to the system without DG. Compared to the FA, GA, and ICA algorithms, the effectiveness of the DE algorithm is shown by its ability to converge faster and more optimal results with the combined fitness value of power loss and minimum voltage deviation.

Conflicts of interest

The authors declare no conflict of interest.

Author contributions

Conceptualization, Sujono and Mauridhi Heri Purnomo; methodology, Sujono; software, Sujono; validation, Sujono, Ardyono Priyadi, Margo Pujiantara; formal analysis, Sujono and Margo Pujiantara; writing—original draft preparation, Sujono; writing—review and editing, Sujono, Ardyono Priyadi, Margo Pujiantara, and Mauridhi Hery Purnomo; visualization, Sujono; supervision, Ardyono Priyadi, Margo Pujiantara, and Mauridhi Hery Purnomo; project administration, Sujono.

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