Journal of Electrical Engineering & Technology (2022) 17:1487–1497
https://doi.org/10.1007/s42835-021-00978-0

ORIGINAL ARTICLE

A New Design of the Objective Function for the Optimal Allocation of Distributed Generation with Short-Circuit Currents

Seung-Wan Son[1] · Dong-Hyeon Lee[1] · Insu Kim[1] · Chang-Hyeon Jung[2] · Hyoungkwon Kim[2] · Dong-Jin Yoon[2] · Joohan Lee[2]

Received: 27 October 2021 / Revised: 25 November 2021 / Accepted: 28 November 2021 / Published online: 7 March 2022

Abstract

Renewable energy sources reduce irresponsible carbon emissions and have the advantage of being located close to the load as a distributed generation (DG). Thus, various studies have examined the optimal placement and capacity of DG to maximize their effect on power grids. However, there was no paper that considered the normalized cost including the fault current in the process of the optimal allocation of DG. The reason that the normalized fault current cost should be included in objective function is that the more DG is connected to the network, the higher fault current will flow. Thus, this paper presents a method of optimizing the DG placement and capacity from a novel perspective using normalized costs that minimize the fault current. For this purpose, this study incorporates the particle swarm optimization method to the Newton–Raphson power-flow calculation and the sequence network decomposition methods. The proposed normalized cost function includes not only voltage variations determined by the power-flow method, installation costs, and power losses but also fault current determined by the sequence method. As a result, the objective function of the new design, adding the normalized fault current cost, enables the solution set to be more optimal than the previous solution set.

Keywords Distributed generation · Fault current · Objective function · Optimal allocation · Particle swarm optimization

Acronyms

DG	Distributed generation
EF	Evaluation function
FC	Fault current
HC	Hosting capacity
IBDG	Inverter based distributed generation
IC	Installation cost
OF	Objective function
PL	Power loss
PSO	Particle swarm optimization
SLG	Single line to ground fault
VSI	Voltage source inverter
VV	Voltage variation

✉ Insu Kim
insu@ac.kr

Seung-Wan Son
22201310@inha.edu

Dong-Hyeon Lee
22201313@inha.edu

Chang-Hyeon Jung
ch.chung@kopri.re.kr

Hyoungkwon Kim
clew21@kopri.re.kr

Dong-Jin Yoon
dj_yoon@kopri.re.kr

Joohan Lee
joohan@kopri.re.kr

[1] Department of Electrical Engineering, InhaUniversity, Incheon, Korea

[2] Korea Polar Research Institute, Incheon, Korea

1 Introduction

The increase in electricity demand cannot be replaced by simply increasing the size of power generation and transmission facilities. The introduction of distributed power sources that inject new and renewable energy into the power grid is the key to realizing Net-Zero [1]. DG has an advantage in that it can inject power near the load [2]. Selecting a distributed power source with optimal placement and capacity is an important issue of optimal allocation. Previous studies are introduced while conceptually expanding the problem of DG optimal allocation.

The power quality can be degraded because of harmonics and the increased use of the power electronically switched inverters of DG [3]. However, DG based on power electronics is modeled as an inverter as a simple voltage source and impedance in this paper. In [4], when considering the loss and voltage impact, the position of the capacitor is selected to minimize the reactive power flowing through the feeder. The optimal allocation problem for a single DG considering two costs was approached by an analytic method. A guideline for considering capacitors as DG (2/3 of the capacitor capacity and the feeder distance, called the two-third rule) was proposed. More various influences needed for optimization should be added. In addition, multiple DG's are also considered, and the use of analytic methods has limitations (e.g., solving the optimal allocation problem by the analytic method).

The various effects of DG installation on grids should be designed as an objective function. Thus, it is necessary to optimize DG in the consideration of the positive and negative effects of DG on the grid (e.g., not only a decrease in losses and voltage magnitude variations but also an increase in installation costs and fault currents). In other words, it takes to the trade-offs resulting in the use of DG into account. For example, as DG is added, the loss is usually reduced because of the reverse power flow (however, the loss can increase if installing the relatively large amount of DG compared to the base rating). Another influence of DG is to improve the voltage profile [5]. But, the installed capacity increases the installation and maintenance costs. Therefore, the various aspects of optimization (e.g., injected power, power flows, and power losses) were proposed [6]. In standpoints of the utility and market, on the one hand, the influence of DG is further subdivided into scheduling and dispatching problems, which can be solved by the optimal power-flow method [7, 8].

After the specified capacity was installed as a single DG or multiple DG's, their impacts on the grid were investigated in the previous various studies. For example, the key problem is to select the bus location that maximizes the positive impact on the grid. However, it is difficult to find a comprehensive solution to determine the placement of DG without specifying the number and capacity of DG. In other words, it is difficult to find the placement and capacity because of the infeasibility of the enumeration of all the possible combinations. Thus, as the dimension of an optimization problem grows, the metaheuristic method has been applied. For example, particle swarm optimization (PSO) is programmed to solve such an optimization problem (e.g., the location and capacity of DG) [9]. This method tries to find a global solution with an efficient way to search the space. The particle swarm optimization algorithm example is presented in [10, 11]. Other metaheuristic methods include the genetic algorithm [12, 13] and the ant bee colony optimization [14]. In [15], various kinds of optimization techniques have been reviewed, which can be classified by tabu search, simulated annealing, and ant colony optimization algorithms.

Recently, the effect of DG on reactive power support (e.g., Volt/Var control and management) was examined in [16, 17]. The fault current and installation costs were added to the optimization problem [18]. However, [18] is normalized without considering the maximum cost, but this paper adopts min–max normalization. Since the previous method considered a general DG type, the optimization problem was solved for PV systems in [19].

As a result of the literature review, this study found that none of the previous studies took the min–max normalized voltage variations, power losses, installation costs, and fault currents into account for DG optimal allocation. If the larger capacity of DG is connected to the grid, the higher fault currents flow in balanced [20] and unbalanced conditions [21]. Thus, the objective of this study is to present a method of optimizing the DG capacity and placement using normalized costs to minimize fault currents. For this purpose, the PSO is incorporated to the Newton–Raphson power-flow and the sequence network decomposition methods implemented in MATLAB. The proposed objective function includes voltage variations determined by the power-flow method, installation costs, power losses, and fault current determined by the sequence method.

1.1 Contributions and Findings

When DG is added to a power system, if DG is modeled as a current source, the Norton equivalent impedance is added in parallel to the system, [22]. Thus, the fault current changes. In optimizing DG, it should be considered the effect of the fault current. However, the installation costs, voltage variations, and power losses in the previous studies were not added to the fault current cost. Thus, to effectively optimize DG, the effect of normalized fault currents on the objective function of the DG allocation problem is examined in this study. As a result, the addition of the normalized fault current is valid for the DG allocation problem. In particular, the proposed objective function becomes more influential in complex models. The introduction of normalized fault currents is better than the previous solution set.

1.2 Paper Outline

This is organized as follows: Sect. 2 describes the problem statement; Sect. 3 summarizes the existing methods; Sect. 4 proposes the proposed methods; Sect. 5 defines case studies. Finally, Sect. 6 presents the conclusion.

2 Problem Statement

By connecting DG to the P-Q bus, the voltage drop can be alleviated and power losses can be mitigated. However, the installation cost increases as the capacity of DG increases, and DG contributes to an increase in the fault current. Thus, the positive and negative effects of DG on the system should be quantified. For this purpose, this study solves an optimal allocation of DG (e.g., location and capacity) using the PSO method, which is incorporated by the Newton–Raphson power-flow calculation and the sequence network decomposition methods. Then, this study presents the objective function that applies the normalized fault current cost to installation costs, power losses, and voltage variations. Finally, the effect of the normalized fault current cost on the DG optimization problem is examined.

3 Existing Methods

3.1 DG Modeling

DG is analyzed based on an inverter. Inverter-based distributed generation (IBDG) operates as a voltage or current source. A voltage source inverter (VSI) is modeled as Thevenin's equivalent circuit, the impedance of which and the voltage source are connected in series. The Kirchhoff voltage law is as follows:

$$E_a = I_a Z_s + V_a \tag{1}$$

E_a = internal voltage of DG, Z_s = equivalent source impedance of DG, I_a = current of DG, V_a = terminal voltage of bus in Fig. 1.

3.2 Sequence Method and Short-Circuit Current

When a single line-to-ground (SLG) fault occurs only in phase *a*, the current flowing in phase *a* is the fault current(short-circuit current). In the phase domain, no current flows in phases *b* and phase *c* in (2). The fault current is calculated from the voltage of phase *a* and the impedance of the Thevenin equivalent circuit viewed from the faulted point in (3). In the sequence domain, the zero-, positive-, and negative-sequence currents are equal in (4). And each sequence circuit is connected in series in (5) in Fig. 2.

$$I_b = I_c = 0 \tag{2}$$

$$V_{ag} = Z_F I_a \tag{3}$$

$$I_0 = I_1 = I_2 \tag{4}$$

$$I_F = I_a = I_0 + I_1 + I_2 = 3I_1 = \frac{3V_F}{Z_0 + Z_1 + Z_2 + 3Z_F} \tag{5}$$

The fault current is usually calculated by dividing the pre-fault voltage by the Thevenin impedance. The pre-fault voltage is calculated based on the normal (ideal) voltage without considering load currents. The fault current is equal to the sum of the fault currents injected from each generator and DG according to the principle of superposition.

Thus, in Sect. 5, we approach the DG allocation problem by ignoring Z_F, using V_F as $1\angle 0°$ p.u, and limiting the fault point to the bus. And the IEEE models (the IEEE 14- and 30-bus test feeders) modified to 1 p.u. for both slack and P–V buses were used.

3.3 Newton-Rapson Power-Flow Analysis Method

The power-flow analysis problem has high-order nonlinear terms. One of the iterative solutions is the Newton-Rapson method. The *x* and *y* are defined as follows.

$$x = \begin{bmatrix} \delta_2 \\ \vdots \\ \delta_N \\ V_2 \\ \vdots \\ V_N \end{bmatrix}, \quad y = \begin{bmatrix} P \\ Q \end{bmatrix} = \begin{bmatrix} P_2 \\ \vdots \\ P_N \\ Q_2 \\ \vdots \\ Q_N \end{bmatrix}. \tag{6}$$

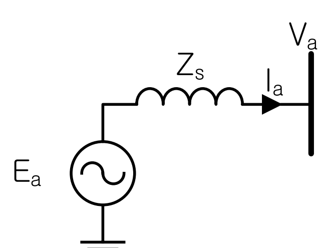

Fig. 1 DG model as a voltage source inverter

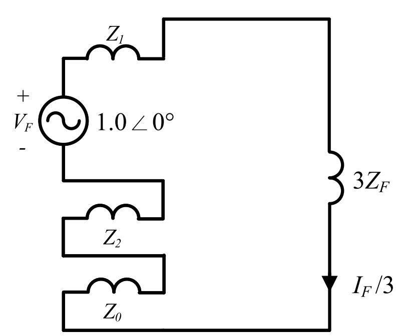

Fig. 2 SLG fault sequence circuit

The y element is as follows.

$$y_k = P_k = P_k(x) = V_k \sum_{n=1}^{N} Y_{kn} V_n \cos\left(\delta_k - \delta_n - \theta_{kn}\right), \tag{7}$$

$$y_{k+N-1} = Q_k = Q_k(x) = V_k \sum_{n=1}^{N} Y_{kn} V_n \sin\left(\delta_k - \delta_n - \theta_{kn}\right). \tag{8}$$

The Jacobian matrix is as follows.

$$J = \begin{bmatrix} \frac{\partial P_2}{\partial \delta_2} & \cdots & \frac{\partial P_2}{\partial \delta_N} & \frac{\partial P_2}{\partial V_2} & \cdots & \frac{\partial P_2}{\partial V_N} \\ \vdots & & \vdots & \vdots & & \vdots \\ \frac{\partial P_N}{\partial \delta_2} & \cdots & \frac{\partial P_N}{\partial \delta_N} & \frac{\partial P_N}{\partial V_2} & \cdots & \frac{\partial P_N}{\partial V_N} \\ \frac{\partial Q_2}{\partial \delta_2} & \cdots & \frac{\partial Q_2}{\partial \delta_N} & \frac{\partial Q_2}{\partial V_2} & \cdots & \frac{\partial Q_2}{\partial V_N} \\ \vdots & & \vdots & \vdots & & \vdots \\ \frac{\partial Q_N}{\partial \delta_2} & \cdots & \frac{\partial Q_N}{\partial \delta_N} & \frac{\partial Q_N}{\partial V_2} & \cdots & \frac{\partial Q_N}{\partial V_N} \end{bmatrix}. \tag{9}$$

If x and y are defined in (6), the power mismatch equation is iteratively calculated and Δy is also determined. The well-known Newton–Raphson method is incorporated into the proposed method, which is presented in the next section.

4 Proposed Methods

4.1 Min–Max Normalization

The DG installation cost is a factor that measures the negative effect of DG installation on the system. Connecting DG to the grid affects voltage variations, installation costs, power losses, and fault current. To determine these effects, it is necessary to express numerically in which aspect the DG installation is profitable or costly. Thus, if each cost is formulated in its own proportional quantity, each unit can be removed, normalized as possible. And Each bus is assumed to have the same impact for the same cost.

$$C_{\cos t,DG,i} = \frac{\cos t_{DG,i} - \cos t_{DG,i,\min}}{\cos t_{DG,i,\max} - \cos t_{DG,i,\min}}. \tag{10}$$

The voltage variation (VV) is the cost calculated as the difference between the nominal voltage and the voltage obtained by power-flow analysis determined by the Newton–Raphson method. The minimum value is determined by the nominal voltage. For example, the voltage normal operating point is set as follows:

$$V_{\min} \le V \le V_{\max}, \tag{11}$$

where

$V_{\min}$ = minimum of voltage (e.g., – 10%), $V_{\max}$ = maximum of voltage (e.g., + 10%).

The normalized cost of VV is defined as follows,

$$C_{VV} = \frac{\sum_{n=1}^{N_{bus}} \left| V_{n,nom,} - V_n \right|}{0.1 \times N_{bus}}, \tag{12}$$

where

C_{VV} = normalized cost of voltage variation, N_{bus} = number of buses, $V_{n,\text{ nom}}$ = nominal voltage of the nth bus, V_n = voltage of the nth bus.

The installation cost (IC) is an additional cost (in a dollar) per capacity (in kW) to install DG. The hosting capacity is calculated by power-flow analysis. The bus to which DG is connected is modeled with a Petri net approach [23]. If the DG exceeding the hosting capacity is connected to the system, the Q of the P–V buses could exceed $Q_{\max}$, thereby not converging to the solution set. The capacity at the boundary value is defined as the hosting capacity.

The normalized cost of IC is defined as follows,

$$C_{IC} = \frac{P_{DG}}{P_{HC}}, \tag{13}$$

where

C_{IC} = normalized cost of the installation cost, P_{DG} = generation amount of DG, P_{HC} = the hosting capacity.

The power loss (PL) is calculated by impedance and current determined by the Newton–Raphson method. Since the PL constraint must be satisfied, the normalized cost of PL is defined as follows,

$$C_{PL} = \frac{\sum_{k=1}^{N_{br}} \left| S_{PL}(k) \right|}{0.1 \times S_{base} \times N_{br}}, \tag{14}$$

where

C_{PL} = normalized cost of power losses, S_{PL} = complex power of the kth branch, N_{br} = number of branches, S_{base} = base MVA of power.

In the following case study, the case where 10% of the base power is lost in the branch is set to have the largest power loss cost.

The fault current(FC) depends on the placement of DG that works as a VSI. If DG is not connected to the slack bus, in other words, DG is connected to as much as ($N_{\text{bus}-}$ 1), the FC is the highest because every DG may inject its power during the fault at the limited value. Conversely, if DG is not connected, the FC is the lowest, so the following normalization is derived,

$$C_{FC} = \frac{I_F - I_{F,\text{ min}}}{I_{F,\text{ max}} - I_{F,\text{ min}}}, \tag{15}$$

where

C_{FC} = normalized cost of the fault current, $I_{F,\ \min}$ and $I_{F,\ \max}$ = minimum and maximum of the fault current.

4.2 Objective Function

An objective function (OF) that minimizes the sum of the proposed several normalized costs is defined. Since the installation of DG affects VV, PL, IC, and FC, the four normalized cost terms are in (16). Thus, the proposed problem is now to find the optimal method to install DG by minimizing the following OF,

$$OF = \min\left(\sum w_{VV}C_{VV} + w_{IC}C_{IC} + w_{PL}C_{PL} + w_{FC}C_{FC}\right), \tag{16}$$

where

w_{VV}, w_{IC}, w_{PL}, and w_{FC} = weights of voltage variations, installation costs, power losses, and fault currents.

4.3 Particle Swarm Optimization

Particle swarm optimization called PSO, a kind of metaheuristic method is an algorithm created by focusing on the regularity of social behavior patterns such as birds living in colonies. So, PSO is an optimization algorithm that finds the optimal value through self-learning. Each particle searches the search-space and remembers the optimal allocation of DG.

Initial values are as follows. x_0 is the 1 by n bus location matrix with the same random number as an element from 0 to 100. v_0 is x_0 multiplied by 0.1. P_{best} and G_{best} is the initial value of x. Equation (17) defines the momentum. As the number of iterations increases, the initial weight is reduced.

$$w = w_{\max} - (w_{\max} - w_{\min}) \times \frac{ite}{ite_{\max}}, \tag{17}$$

where

w = inertial weight, $w_{\max}$ and $w_{\min}$ = maximum and minimum weights (e.g., 0.9 and 0.4), ite = number of iterations, $ite_{\max}$ = maximum of iterations.

The velocity is updated as the sum of the three components in (18): momentum component (i.e., the previous velocity of the particles), cognitive component (i.e., the velocity from each particle to the best known position), social component (i.e., the velocity from swarm to swarm best known position). The final optimal value is calculated by reflecting the existing value, the particle best value, and swarm best value

$$v(i+1) = w \times v(i) + c_1 \times rand \times \left(P_{best} - x\right) + c_2 \times rand \times \left(G_{best} - x\right), \tag{18}$$

where

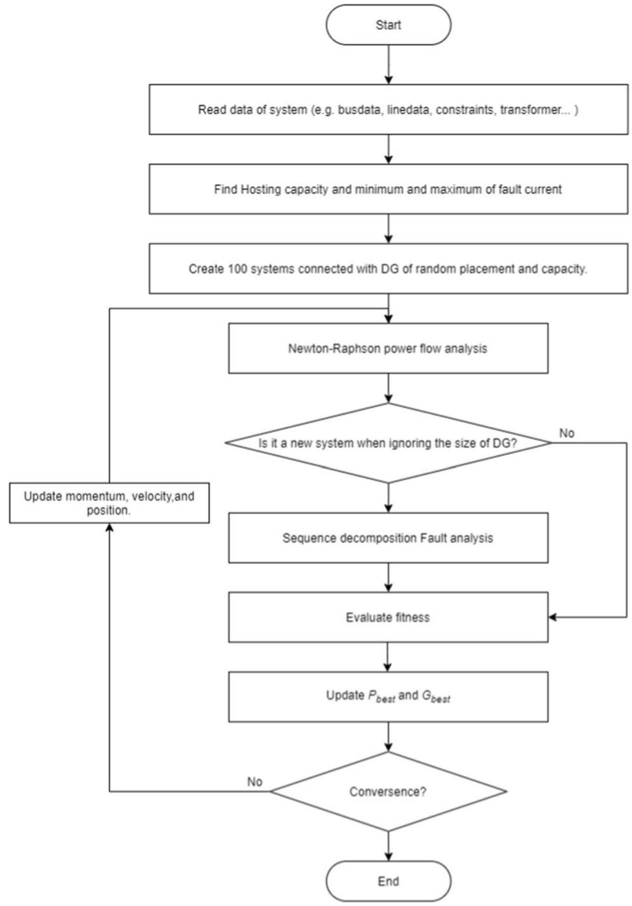

Fig. 3 Flow chart of the proposed method

P_{best} = best particle position, G_{best} = best global position, $rand$ = random number between 0 and 100, c_1, c_2 = accelerator factor (e.g., 2), x = position (1 by n matrix).

When the position and velocity of the previous step in (19) are added, it becomes the position of the next step,

$$x = x_0 + v. \tag{19}$$

The proposed method has a random number from 0 to 100 and generates 100 particles. The momentum, velocity, and position of these particles are updated to find x. P_{best} and G_{best} are selected by calculating the OF value corresponding to the OF value (P_{best}) of the 100 particles and the OF value (G_{best}) of the particles that have been released so far. Again, x and the OF are evaluated. The proposed workflow is shown in Fig. 3. For the evaluation of OF of the particles, this study incorporates the proposed PSO method to the Newton–Raphson power-flow calculation and the sequence network decomposition methods implemented in MATLAB. In short-circuit analysis, unnecessary impedance matrix algorithm operation should be bypassed.

5 Case Study

DG is not installed on the slack and P–V bus in the case study. In other words, DG is connected to the P–Q bus. The weight of each cost has the same proportion, assuming that the OF in the worst case is 1. In this paper, three cases are used for comparisons:

Case 1 Basic system without DG, or denoted as "non-DG;"
Case 2 System allocated with optimal DG using the old OF in (20);
Case 3 System allocated with optimal DG using the proposed OF in (16) and (21).

By comparing Case 1, 2, and 3, the effect of DG on optimization is evaluated as an evaluation function (EF). The EF also indicates the effect of DG on the FC. Therefore, The EF will demonstrate that C_{FC} is necessary for optimization.

$$OF = \min(\sum w_{VV}C_{VV} + w_{IC}C_{IC} + w_{PL}C_{PL}), \tag{20}$$

$$EF = w_{VV}C_{VV} + w_{IC}C_{IC} + w_{PL}C_{PL} + w_{FC}C_{FC}. \tag{21}$$

5.1 Modified IEEE 14 Bus

Figure 4 shows the IEEE 14 bus. Figure 5 indicates the maximum and minimum value of the fault current for normalization. When the fault current is the lowest, the fault current of bus 2 is the largest as 13.4831 p.u. In the case of the lowest fault current, the fault current of bus 4 is the highest at 40.15 p.u.

Optimization is performed using the proposed PSO algorithm using normalized costs. Figure 6 shows the PSO convergence characteristic. As the iteration increases, the OF decreases.

Table 1 presents the optimal values of the placement and capacity of DG. Figure 7 is the voltage on each bus.

Figure 8 is a visualization of Table 2. When the fault current is included in the optimization problem, voltage variation decreases as much as by 66.6048% from 0.0539 to 0.0180 p.u. Power losses decrease by 76.2183% from 0.0513 to 0.0122 p.u. The fault current increases by 10.5317% from 13.4830 to 14.9030 p.u. Finally, the OF value decreases by 28.5171% from 0.1052 to 0.0752 p.u. This result validates the effect of the proposed method on installing DG by showing the decreased OF.

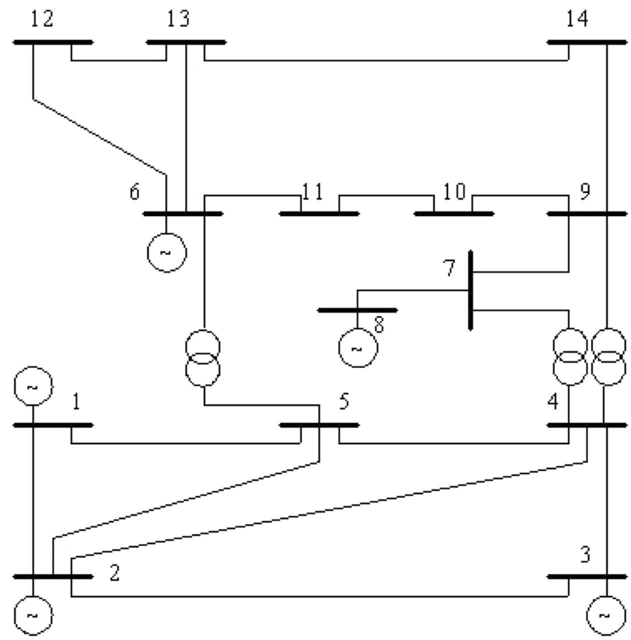

Fig. 4 IEEE 14 bus [24]

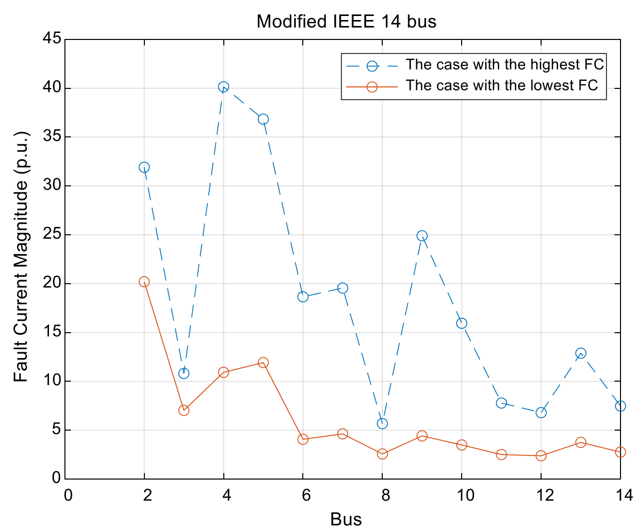

Fig. 5 Min–max fault current candidate (the modified IEEE 14 bus)

In Fig. 6, there is no big difference in the final OFs of Case 2 and 3. The main difference of Case 2 and 3 is whether FC is included or not. Both the OF values reduce compared to when DG was not used (i.e., Case 1). However, the EF of Case 3 in Table 2 was subtly lower than the EF of Case 2. For example, in Case 2, the value of the EF decreases by 23.9543% from 0.1052 to 0.0800 p.u. On the other hand, in Case 3, the value of the EF decreases by 28.5171% from 0.1052 to 0.0752 p.u. Therefore, the proposed method that includes the fault current can be better optimization compared to that excluding the fault current.

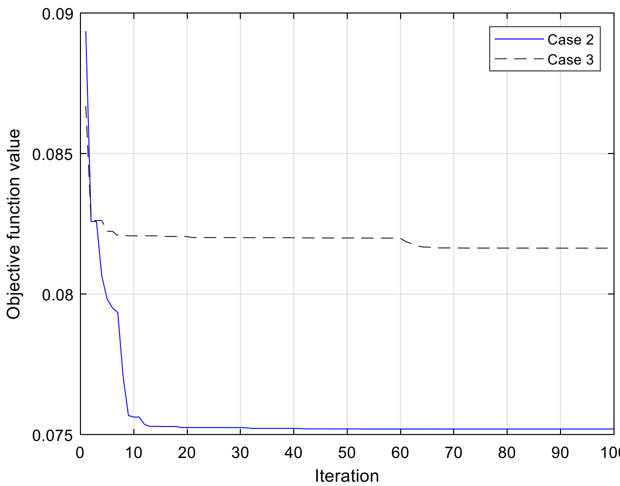

Fig. 6 Convergence curve of PSO (the modified IEEE 14 bus)

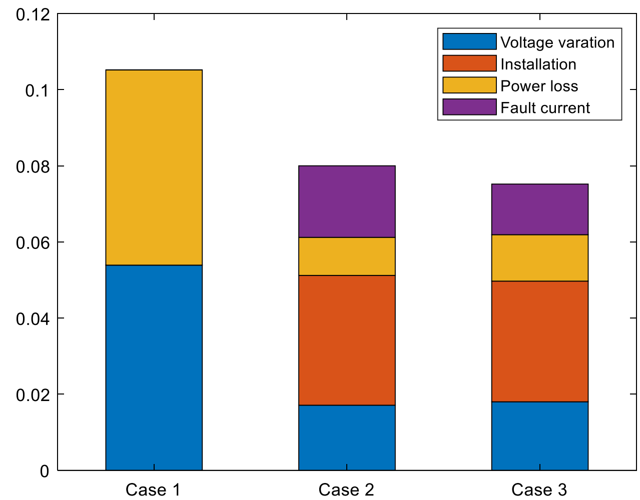

Fig. 8 Evaluation function (the modified IEEE 14 bus)

Table 1 Optimal placement and capacity (the modified IEEE 14 bus)

Case 2		Case 3	
Placement [bus]	Capacity [MVA]	Placement [bus]	Capacity [MVA]
9	15	10	43
10	28	14	37
11	1	–	–
12	7	–	–
14	35	–	–

Table 2 Evaluation elements (the modified IEEE 14 bus)

Evaluation elements	Case 1	Case 2	Case 3
VV	0.0539	0.0171	0.0180
IC	0	0.0341	0.0317
PL	0.0513	0.0100	0.0122
FC	0	0.0188	0.0133
EF	0.1052	0.0800	0.0752

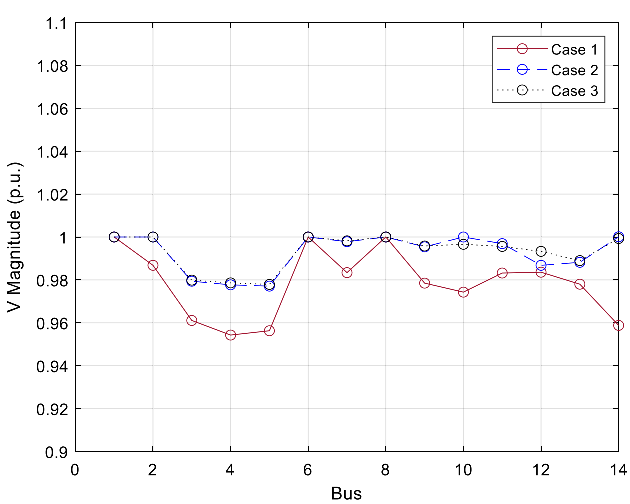

Fig. 7 Voltage variation (the modified IEEE 14 bus)

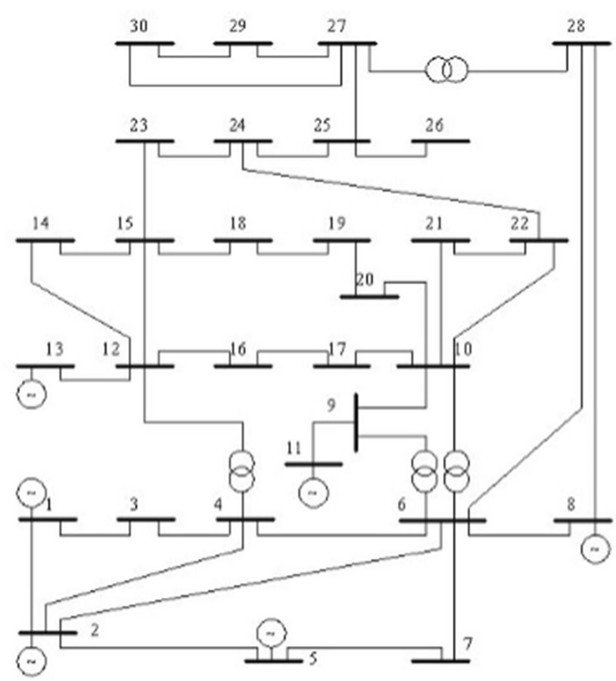

Fig. 9 IEEE 30-bus test system [24]

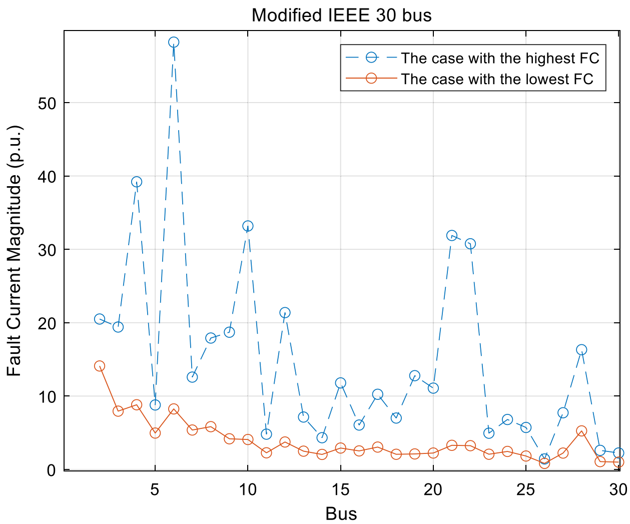

Fig. 10 Min–max fault current candidate (the modified IEEE 30- bus system)

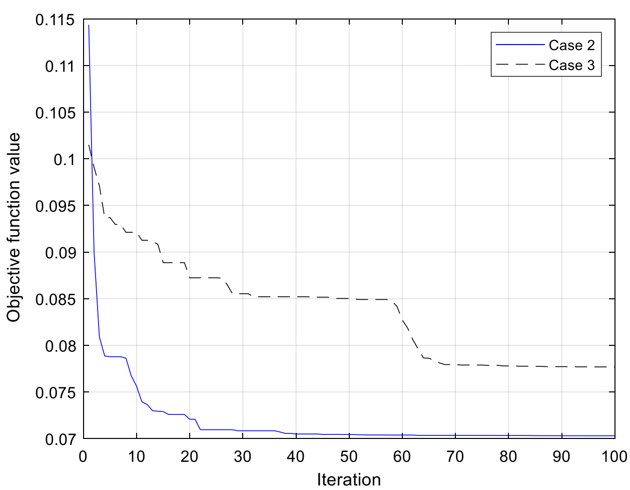

Fig. 11 Convergence curve of PSO (the modified IEEE 30-bus system)

5.2 Modified IEEE 30 bus

Figure 9 shows the IEEE 30-bus test system. Figure 10 indicates the minimum and maximum value of the fault current for normalization. When the fault current is the lowest, the fault current of bus 2 is the largest as 14.1020 p.u. In the case of the lowest fault current, the fault current of bus 6 is the highest at 58.24 p.u.

Figure 11 presents the PSO convergence characteristic when PSO is performed using the proposed normalized costs. As iteration increases, OF decreases. Table 3 shows the optimized values of the placement and capacity of DG. Figure 12 is the voltage profile on each bus.

Table 3 Optimal placement and capacity (the modified IEEE 30-bus test system)

Case 2		Case 3	
Placement [bus]	Capacity [MVA]	Placement [bus]	Capacity [MVA]
14	1	15	30
19	30	18	28
21	32	25	28
23	19	30	19
25	9	–	–
26	7	–	–
28	1	–	–
30	18	–	–

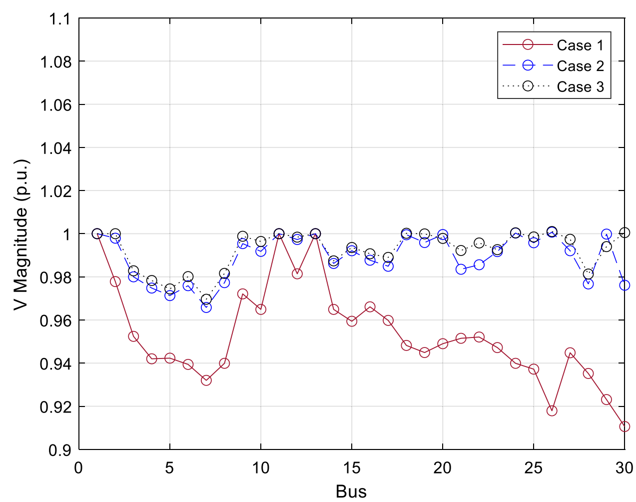

Fig. 12 Voltage variation in the modified IEEE 30-bus test system

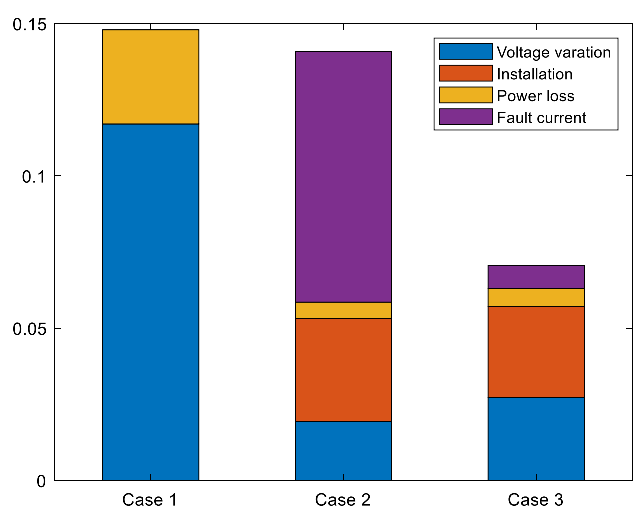

Fig. 13 Evaluation function (the IEEE 30-bus system)

Table 4 Evaluation elements (the IEEE 30-bus system)

Evaluation elements	Case 1	Case 2	Case 3
VV	0.1170	0.0193	0.0272
IC	0	0.0339	0.0299
PL	0.0309	0.0053	0.0058
FC	0	0.0823	0.0077
EF	0.1479	0.1408	0.0705

Figure 13 indicates the EF of each case. In Table 4, when the fault current is included in the proposed optimization algorithm, VV decreases by 76.7521% from 0.1170 to 0.0272 p.u. PL decreases by 81.2297% from 0.0309 to 0.0058 p.u. The EF decreases by 52.3326% from 0.1479 to 0.0705 p.u. In the IEEE 30-bus system, the effect of C_{FC} is evident. In Case 2, the EF decreases by 4.8005% from 0.1479 to 0.1408 p.u. On the other hand, in Case 3 that uses the proposed OF, the value of the EF decreases by 52.3326% from 0.1479 to 0.0705 p.u. Therefore, the proposed OF that includes the fault current can be better optimization compared to that excluding the fault current.

5.3 Validation

[25] selects hosting capacity by evaluating the performance index for various constraints. However, with a few exceptions, several constraints are considered in this paper: Power balance (net load = gross load—P_{DG}); $V_{\min}$ and $V_{\max}$; $Q_{\min}$ and $Q_{\max}$. A detailed discussion should be made in various models including these excluded constraints. However, in the case study, all IEEE model data was used without exception.

Kim 2021, 2019 [20, 21] prove that C_{FC} should be included in the objective function. This principle is reflected in Figs. 5 and 10. By applying the modified IEEE 14 and 30 bus, the results are described in Sects. 5.1 and 5.2. Using EF, Figs. 8, 13, Table 2, and Table 4 prove Case 1, 2, and 3 that C_{FC} should be included in the objective function. In particular, the EF of the modified IEEE 30-bus has been reduced by more than half.

6 Conclusion

This paper has presented a new designed OF for the optimal allocation of DG. The proposed OF includes not only voltage variations determined by the power-flow method, installation costs, and power losses but also fault current determined by the sequence method. In the IEEE 14- and 30-bus feeders, the EF has been compared according to the inclusion of C_{FC}. As a result, the cost of increasing the fault current when DG is connected cannot be ignored. In addition, the optimal allocation problem should be made in consideration of the fault current and its normalized value. Since the EF decreases with the introduction of C_{FC}, it can be a factor that searches for a better solution set. However, when the system is complexly connected or large, the proposed method should be also validated, which is our ongoing work.

Acknowledgements This work was supported by the Korean Ministry of Oceans and Fisheries (Project No. 1525011610, KIMST-20210629).

Declarations

Conflict of interest The authors declare no conflict of interest.

References

1. Pepermans G, Driesen J, Haeseldonckx D, Belmans R, D'haeseleer W (2005) Distributed generation: definition, benefits and issues. Energy Policy 33(6):787–798
2. Ackermann T, Andersson G, Söder L (2001) Distributed generation: a definition. Electr Power Syst Res 57(3):195–204
3. Dugan RC, Mcdermott TE (2002) Distributed generation. IEEE Ind Appl Mag 8(2):19–25
4. Willis HL (2000) Analytical methods and rules of thumb for modeling DG-distribution interaction. In: 2000 power engineering society summer meeting (Cat. No. 00CH37134), vol 3, pp 1643–1644. IEEE
5. Moradi MH, Abedini M (2012) A combination of genetic algorithm and particle swarm optimization for optimal DG location and sizing in distribution systems. Int J Electr Power Energy Syst 34(1):66–74
6. Ghosh S, Ghoshal SP, Ghosh S (2010) Optimal sizing and placement of distributed generation in a network system. Int J Electr Power Energy Syst 32(8):849–856
7. Algarni AA, Bhattacharya K (2009) Utility-owned DG units' impacts on distribution system operation. In: 2009 IEEE/PES power systems conference and exposition, pp 1–6. IEEE
8. Mohan B, Ramesh M (2012) Optimal DG placement under standard market design using GA. In: 2012 international conference on emerging trends in electrical engineering and energy management (ICETEEEM), pp 148–153. IEEE
9. Ghatak SR, Acharjee P (2016) Optimal allocation of DG using exponentential PSO with reduced search space. In: 2016 second international conference on computational intelligence & communication technology (CICT), pp 489–494. IEEE
10. Lalitha MP, Reddy VV, Usha V (2010) OPTIMAL DG PLACEMENT FOR MINIMUM REAL POWER LOSS IN RADIAL DISTRIBUTION SYSTEMS USING PSO. J Theor Appl Inf Technol 13
11. Prakash D, Lakshminarayana C (2016) Multiple DG placements in distribution system for power loss reduction using PSO Algorithm. Procedia Technol 25:785–792
12. Ganguly S, Samajpati D (2015) Distributed generation allocation on radial distribution networks under uncertainties of load and generation using genetic algorithm. IEEE Trans Sustain Energy 6(3):688–697
13. Kim I (2020) The optimization of the location and capacity of reactive power generation units, using a hybrid genetic algorithm

incorporated by the bus impedance power-flow calculation method. Appl Sci 10(3):1034
14. Abu-Mouti FS, El-Hawary M (2011) Optimal distributed generation allocation and sizing in distribution systems via artificial bee colony algorithm. IEEE Trans Power Deliv 26(4):2090–2101
15. Keane A et al (2012) State-of-the-art techniques and challenges ahead for distributed generation planning and optimization. IEEE Trans Power Syst 28(2):1493–1502
16. Lee D, Son S, Kim I (2021) Optimal allocation of large-capacity distributed generation with the volt/var control capability using particle swarm optimization. Energies 14(11):3112
17. Kim I (2017) Optimal distributed generation allocation for reactive power control. IET Gener Transm Distrib 11(6):1549–1556
18. Kim B, Rusetskii N, Jo H, Kim I (2021) The optimal allocation of distributed generators considering fault current and levelized cost of energy using the particle swarm optimization method. Energies 14(2):418
19. Kim I (2018) Optimal capacity of storage systems and photovoltaic systems able to control reactive power using the sensitivity analysis method. Energy 150:642–652
20. Kim I (2021) A calculation method for the short-circuit current contribution of current-control inverter-based distributed generation sources at balanced conditions. Electr Power Syst Res 109:106839
21. Kim I (2019) Short-circuit analysis models for unbalanced inverter-based distributed generation sources and loads. IEEE Trans Power Syst 34(5):3515–3526
22. Zilberdrut S,Cecchi V (2015) Investigating the effects of grid equivalent circuit at a point of common coupling on bus voltage variations due to variable distributed generation. In: 2015 North American power symposium (NAPS), pp 1–6. IEEE
23. Kim I, Xu S (2019) Bus voltage control and optimization strategies for power flow analyses using Petri net approach. Int J Electr Power Energy Syst 112:353–361
24. Khokhlov MV (2008) Test circuit (translated from Russian language: Тестовые схем ы). Accessed 1 Mar 2020. Available: http://energy.komisc.ru/dev/test_cases/
25. Reno MJ, Coogan K, Seuss J, Broderick RJ (2007) Novel methods to determine feeder locational PV hosting capacity and PV impact signatures. Sandia National Lab (SNL-NM), Albuquerque, NM (United States)

Seung-Wan Son received B.S degree in electrical engineering from Inha University. His research interests are distributed generation, fault analysis, and power flow analysis.

Dong-Hyeon Lee received B.S degree in electrical engineering from Inha University. His research interests are distributed generation, volt/var control, and harmonicanalysis.

Insu Kim received the Ph.D. degree from Georgia Institute of Technology, Atlanta, GA, USA, in 2014. He is currently an Associate Professor of electrical Engineering with Inha University, South Korea. His major research interests include 1) analyzing the impactof stochastically distributed renewable energy resources, such as photovoltaic systems, wind farms, and microturbines on distribution networks; 2) examining thesteady-state transient behavior of distribution networks under active and reactive power injection by distributed generation systems; and 3) improving power-flow, short-circuit, and harmonic analysis algorithms.He received B.S degree inelectrical engineering from Inhauniversity. His research interests are distributed generation, fault analysis, and power flow analysis.

Chang-Hyeon Jung received the Ph.D. degree in Mechanical and Environmental Informatics, Tokyo Institute of Technology, Tokyo, Japan in 2013. From 2004 to 2008, he worked as a Senior Research Engineer at Samsung Electronics in Suwon, Korea. From 2013 to 2017, he worked as a Principle Research Engineer at Hanwha Techwin in Seongnam, Korea. He is currently a Senior Research Engineer in the Office of Technology development & Service of Korea Polar Research Institute, Incheon, Korea. His research interests include field robot design, polar exploration and research equipment development.

Hyoungkwon Kim received the M.S. degree in Mechatronics Engineering, Hanyang University, Ansan, Korea in 2009. From 2013 to 2018, he worked as a Senior Research Engineer at Hanwha Corporation in Daejeon, Korea. He is currently an Engineer in the Office of Technology Development & Service of Korea Polar Research Institute, Incheon, Korea. His research interests include polar exploration and research equipment development and Internet of Extreme Things.

Dong-Jin Yoon received the M.S. degree in Intelligent Automobile, Kookmin University, Seoul, Korea in 2013. From 2013 to 2016, he worked as a Senior Research Engineer at Firstec Corporation in Changwon, Korea. He is currently a Senior Research Engineer in the Office of Technology Development & Service of Korea Polar Research Institute, Incheon, Korea. His research interests include polar exploration and research equipment development and Internet of Extreme Things.

Joohan Lee received the Ph.D. degree in Polar Science from the University of Science and Technology, Daejeon, Korea in 2008. He is currently a Principal Research Scientist and Director of Department of Future Technology Convergence of Korea Polar Research Institute, Incheon, Korea. His research interests include mapping of internal layers and subglacial topography of Antarctic ice sheet using radar and its signal processing.