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Optimal placement and sizing of photovoltaic power plants in power grid considering multi-objective optimization using evolutionary algorithms

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Abstract

During the past decade, the effect of renewable and non-renewable Distributed Generation (DG) sources of production has grown all over the world. Also, it has enhanced by national and international policies aimed at increasing the share of renewable energy sources and combining small high efficient heat and power plants to reduce greenhouse gas emissions, and global warming have been encouraged. Although the installation and operation of DGs have discussed for solving network problems in distribution networks, the fact is that in most cases, Distribution System Operator has no control or influence over DG placement and size. In this article, a meta-heuristic algorithm for management and decision-making for optimal selection is presented, and in choosing the optimal solution, the impact factor is suggested in the best case. Inappropriate DG placement may increase system losses, network investment, and operating costs. This paper determined the optimal capacity and placement of photovoltaic sources to reduce losses, improve the voltage profile, and increase the active power to reactive power lines in MATLAB software by the second version of the genetically engineered algorithm with unstable Non-dominated Sorting Genetic Algorithm (NSGA-II).

Keywords: Multi-objective optimization, Optimal DG placement, Decision on the placement, Reliability in evolutionary algorithms, Improve the voltage profile

Introduction

One of the significant problems in distribution networks is the inappropriateness of the voltage profile. The effect of DG units on voltage regulation can be positive or negative. This may depend on the distribution system, characteristics of DG units, and their installation location. As voltage quality is one of the most important yardsticks in terms of power quality in the provision of services by electricity companies, in recent years, with the presence of DG units in distribution networks, great attention has been paid to the effect of these units on the voltage. Moreover, in the distribution systems, loss reduction is of the topics always considered. In [1], the optimal placement and sizing of DGs in distribution networks are considered with a new concept to simultaneously minimize the total energy cost along with the total energy loss and average voltage drop.

In [2], Improvements to the existing multi-objective for PV measuring and site location in radial distribution systems are presented based on reducing power loss and node voltage limiting deviation. In [3], the optimal size and placement of shunt capacitors are modeled in order to minimize line loss. The derivative load bus voltage has calculated to determine the sensitive load buses which further being optimum with the placement of the shunt capacitor. A new mathematical optimization algorithm for maximizing Hosting capacity (HC) by continuous network reconfiguration and placement of open points is proposed [4]. The optimal placement and sizing of DSTATCOM are investigated by considering different residential, commercial and industrial loads in [5]. The placement and sizing of a distribution solar photovoltaic plant (DSPP) are presented using historical time series historical climatic data [6]. The combined Ant Colony Optimization (ACO) configuration with an artificial bee colony algorithm called the ACO-ABC hybrid algorithm for optimal location and measurement of distributed energy sources (DER) is presented in [7]. In [8], a comparison between nonlinear optimization and genetic algorithms for the optimal location and the size of the distributed generation in a distribution network is presented and shows the importance of installing the right amount of DG in the best place. In [9], an improved malfunction sorting genetic algorithm is proposed to optimize the scheduling of several DG units. Three evolutionary algorithms for fog service placement have been compared in [10], the weighted genetic algorithm (WGA), (NSGA-II), and the decomposition-based multi-objective evolutionary algorithm (MOEA/D). In [11], genetic algorithm (GA) and ACO optimization techniques have proposed to find the optimal size and location for distributed generation in electrical networks. In [12], the AC multi-temporal alternating current (AC) algorithm has been presented to uses the convex relaxation of current equations to ensure accurate and optimal solutions with high algorithmic performance. In [13], for placement and sizing with appropriate height, maximum cosmic ray detection, and comparison have used of atmospheric and solar radiation parameters. A reactive power source allocation strategy have proposed in [14], which distinctive feature of this strategy is that, by considering the control scheme in the allocation process, the optimal allocation achieved in a dynamic context. The optimal location and size of DGs in radial distribution networks have been analyzed using a master–slave hybrid meta-innovative method [15]. In [16], a collectible formula has been developed for the optimal placement and measurement by inverter-based renewable systems in multiphase distribution networks. A new metacognitive algorithm in [17] is proposed, the Crow Search Algorithm (CSA) for calculating the optimal size and placement of PV units to diminish power loss and improve voltage characteristics. To optimally measure the energy storage system in a microgrid, determining the size and location of energy storage systems has been proposed along with a new method based on cost–benefit analysis [18]. The Whale Optimization Algorithm (WOA) is a new meta-heuristic algorithm for determining the optimal size of DG. This algorithm gives better results when combined with the voltage sensitivity index method [19]. In [20], a two-phase method is proposed to maximize the penetration of DGs in accordance with mass grid constraints such as voltage harmonics and relay coordination constraints by inverter-based distributed generations (IDGs) and synchronous distributed generations (SDGs), respectively. In [21], a review is provided of the placement, sizing, and optimum performance ESS. In [22], a hybrid approach to solve the problem allocation of protection devices in the power distribution system offers. An improved method for solving the locating problem and measuring posts in [23] is presented based on geographic information and supervised learning. In fact, in a distribution network, the power loss curve with a power generation change in a particular placement on a network is similar to a quadratic function. Given that, I is the line current, R is the line resistance, and S is the surface power of the line, the line losses are directly related to $RI2$, and I has a direct relation with S. Thus, if DG production capacity increases in each node from the distribution network, the total system losses will be reduced. Furthermore, with the further increase in DG production, network losses again start to increase. The displacement loss curve is displayed by changing the capacity of the installed DGs. As can be seen, PDG2 capacity is the optimum rate of DG production to reduce losses. It can also be stated that the shaft voltage profile has a linear relationship with power generation changes in a specific placement so that as the power output from a DG in a particular shaft increases, the voltage of all shins (A bar or a conductor called a bus bar) also increases.

Materials and methods

Evolutionary algorithms are a collection of modern discoveries that have succeeded in many applications of great complexity. This success in solving difficult motor drive problems is known as Evolutionary Computation (EC). Optimal placement and sizing, minimizing the losses, bus voltage profile stability, and improvement of power quality and reliability of feed are considered as the fitness functions for the placement of the optimal sizing of this research work. The following power loss curve according to DG capacity change for system evaluation is shown in Fig. 1. The proposed method is presented on IEEE 33 and 69-buses DS. The IEEE 33-buses test system is depicted in Fig. 2.

Index of lines loss

Power losses in a distribution network depend on factors such as the resistance of distribution lines, the losses transformer core, and the engine. The ratio of dielectric and rotary losses to the losses lines is very small, so in this study, only the type of lines losses has been considered. The combined power of S_{ij} is from node I to node j, and S_{ji} from node j to node i.

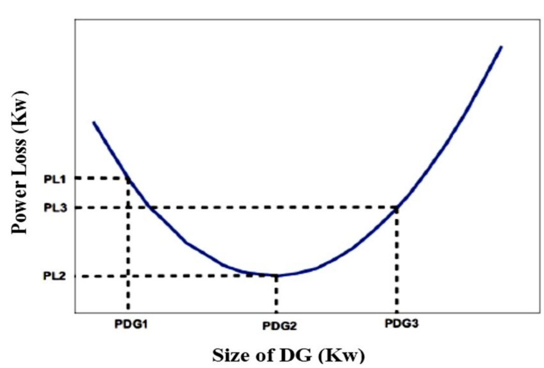


Fig. 1 Power loss curve according to DG capacity change [2]

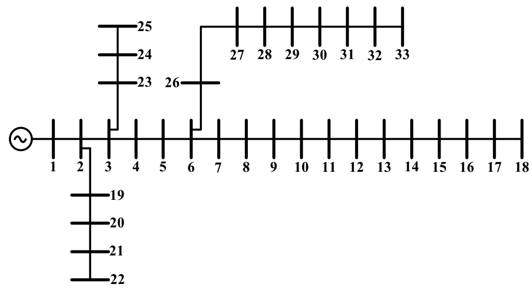


Fig. 2 The IEEE 33-bus DS

$$S_{ij} = V_i I_{ij}^* \tag{1}$$

$$S_{ji} = V_j I_{ji}^* \tag{2}$$

In Eqs. (1) and (2) [4], V_i and V_j, respectively, are the voltages of i and j nodes. The current of the line I_{ij} is the current measured in the direct direction from the shin i to j and the current of the line I_{ji} is measured in the direct direction from j to i. Therefore, the power losses in each line between the shins i and j can be written as the algebraic sum of the relations (1) and (2) in the form (3):

$$S_{L_{ij}} = S_{ij} + S_{ji} \tag{3}$$

After each load transfer, the power losses per line can be obtained using Eqs. (1–3) [4], and by calculating the losses of all lines, the power losses of the entire network are obtained by Eq. (4).

$$\text{Power Loss} = \sum_{k=1}^{n} S_L(k) \tag{4}$$

$$\text{Minimize Ploss (F1)} = \sum_{\text{i=1}}^{\text{nbr}} Ii^2 Ri \tag{5}$$

In Eq. (4), total loss of the network losses and n is the number of network lines. Ii and Ri are the current magnitude and resistance corresponding to the circuit branch.

Shins voltage profile index

The system voltage profile index is also defined as follows:

$$\text{Voltage Profile} = \sum_{i=1}^{m} (1 - |V_i|)^2 \tag{6}$$

where V_i is the i0th voltage in the distribution network based on Perionite and m is the number of network shins. It should be noted that in simulating typical systems, the shaft voltage is calculated in terms of a Perionite based on 12.66 kV.

Index of line capacity

Index or third purpose the optimization in this paper is the ratio of active power to reactive network lines, which is called the capacity occupancy index. This goal should be maximized and defined as follows [6]:

$$\mathrm{PQR} = \sum_{j=1}^{k} \left(\frac{P_j}{Q_j} \right) \tag{7}$$

where P_j is the active power passing through j-th line, Q_j is the reactive power of the j line and k is the number of network lines.

Objective function

The objective function considered determining the optimal placement and capacity of PV sources in the distribution network is in the form of Eq. (8) combination of the three indicators or the above objective:

$$\text{Objective Function} = \{\text{Power Loss, Voltage Profile, Cost}\} \tag{8}$$

Discussion

Constraints and of the problem

The constraints for placement and allocation of PV units in the distribution network are:

- **Shine voltage constraint**

Network bush voltage must be within the allowed range.

$$V_i^{\mathrm{Min}} \leq V_i \leq V_i^{\mathrm{Max}} \tag{9}$$

In this equation, V_i is the value of the voltage of each shin, and V_i^Min and V_i^Max, respectively, are the lowest and the maximum permissible voltage for the shins. In this paper, these values are considered to be ± 10% nominal voltages.

- **Photovoltaic sources output power constraint**

For the output power of PV sources, a maximum value is considered. In this paper, the maximum value for this purpose is equal to 4 MW.

- **The limitations of the number of PV sources**

In this paper, for the number of PV sources studied in each distribution network 33 and 69 bus, the limit is $0 < \mathrm{nPV} < 5$. In other words, the maximum number of photovoltaic sources is set to 5. The current chart of the NSGA-II algorithm is shown in Fig. 3. In addition, the IEEE 69-buses system is shown in Fig. 4 This method is special for radial distribution networks. In this method, the grid-solving continues from one line to the next systematically, so that all lines in the grid are computed. First, the voltage at all nodes, except for the reference node (whose size and phase it turns out to be), is assumed to be equal to the base voltage value. Based on these voltages

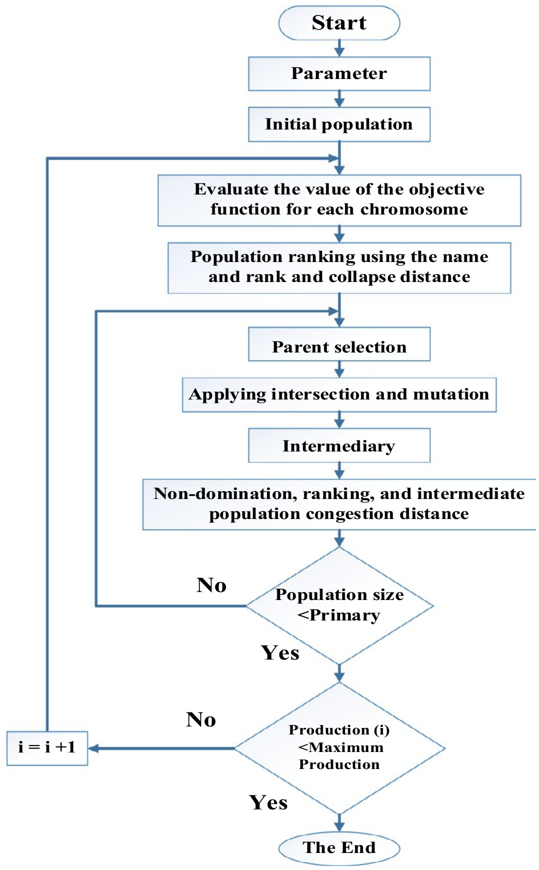


Fig. 3 Proposed flowchart design compatible with NSGA-II algorithm

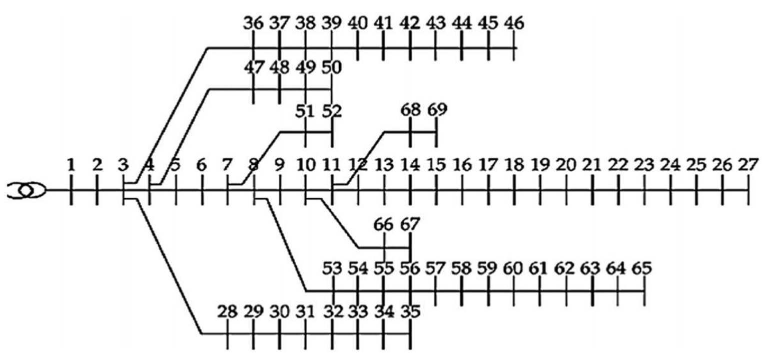


Fig. 4 IEEE 69-bus distribution system

and the voltage-dependent dependence, the active and reactive power voltages of the nodes are we consider the following relationships:

$$\mathrm{P_i} = P_i^{\mathrm{sch}}\left(\frac{|V|_i^{\mathrm{calculate}}}{V_i^{\mathrm{base}}}\right)^{\alpha} \tag{10}$$

$$Q_i = \mathrm{QischVicalculateVibase}\beta \ Q_i = Q_i^{\mathrm{sch}} \left(\frac{|V|_i^{\mathrm{calculate}}}{V_i^{\mathrm{base}}} \right)^{\beta} \tag{11}$$

In the above equations [8], the values of α and β are determined by the type of load. Here, it can be seen that this algorithm, the load distribution, it does not matter what model is our load. After calculating active power and reactive power, it should obtain the values of the current drawn by the load:

$$I_i = \frac{P_i - jQ_i}{V_i^*} \tag{12}$$

At this stage, it is necessary to calculate the currents of the lines. However, this needs a logical method for tracking network nodes. For this purpose, it is better to use the triangular cross-sectional matrix of lines, and denote each line with respect to its end node. First, it should be started to sweep to calculate the current of the lines from the end node so that after calculating the current of the *i*-th node, according to Eq. (11), this current is equivalent to the linear current with the same number, and if in the triangular cross-sectional matrix Z_{ij} is opposite to zero; the current of the *i*-th line joins with the current of the *j*-th line and is in the current of the *i*-th line. For example, the upper triangular cross-sectional matrix of the above figure is given below. According to this matrix, it is possible to extract the power, current and configuration of the network for power transmission. Moreover, due to the network's radicalness, the volumes of this matrix are zero. This factor is a weakness for this method due to occupation of a large value of computer memory.

Given the above-mentioned points, the current of the lines is calculated during a sweep stage. Now the sweep starts. During this step and according to the following equation, it is better to calculate the voltage of the nodes:

$$V_j = V_i - I_i Z_{ij} \ (1 - 12) \tag{13}$$

when this cycle is completed, the voltages obtained at this stage are compared with the corresponding voltages in the previous step, and if the difference in the two consecutive cycles is less than the tolerance level, the operation is repeated, and eventually the result is desirable.

$$\mathrm{abs}\left(V_n^{k-1} - V_n^k \right) \leq \varepsilon \ (1 - 13) \tag{14}$$

As shown in Fig. 3, this method, in addition to its limitations in terms of execution (Kahn and Tucker conditions), also faces problems in weighting, and the output answer depends on the input weights. In addition, in these methods, in order to obtain a set of effective solutions, it is necessary to solve the algorithm many times and a new solution must be obtained in each execution. In weighting methods after solving, there are no problems caused by weighting, which were stated in the mentioned method. Also, by using evolutionary algorithms in these methods, solving a problem once will lead to a set of effective solutions. In the same way, these algorithms work with an emphasis on moving toward the optimal solution, and by defining the cost function in it, the optimality conditions can be defined. On the other hand, in these algorithms, there is no emphasis on Kahn and Tucker's conditions, like what was in the pre-solution weighting methods.

In the backward and forward load distribution algorithm in Fig. 5, there are two basic steps, which are very easy to learn, and these two steps are used for all radial networks. First, the voltage of all bus bars of the studied network is equal to 1. And two sweepers are used to find the new voltage and current values of the branches.

Modeling result

In this section, the placement and optimal amount of PV sources will be obtained in distribution networks of 33 and 69 bus. The proposed system with a capacity of 3.72 MW and 2.30 MVAR for total network losses, the voltage level of the network is 12.66 kW, the real network losses are 209.913 kW, and the reactive losses are 142.52 kVAR for single power factor, 0.85 post-phase and 0.85 prophase, respectively.

The optimal placement and sizing of PV sources for the 33-bus distribution network

- **Output unit power factor**

The chart of the amount of the objective functions (including total system power losses as the first target, deviation of the shins as the second target, and the ratio of reactive power to active lines as the third objective). (a) The optimization algorithm has been shown in three dimensions for the 33 bus and the output power factor of the unit, (b) Voltage profile is showed in a range of variations, and (c) total power losses of network including active and reactive losses under the output power factor of the unit resulting is shown Fig. 6. The optimal response is obtained using the fuzzy

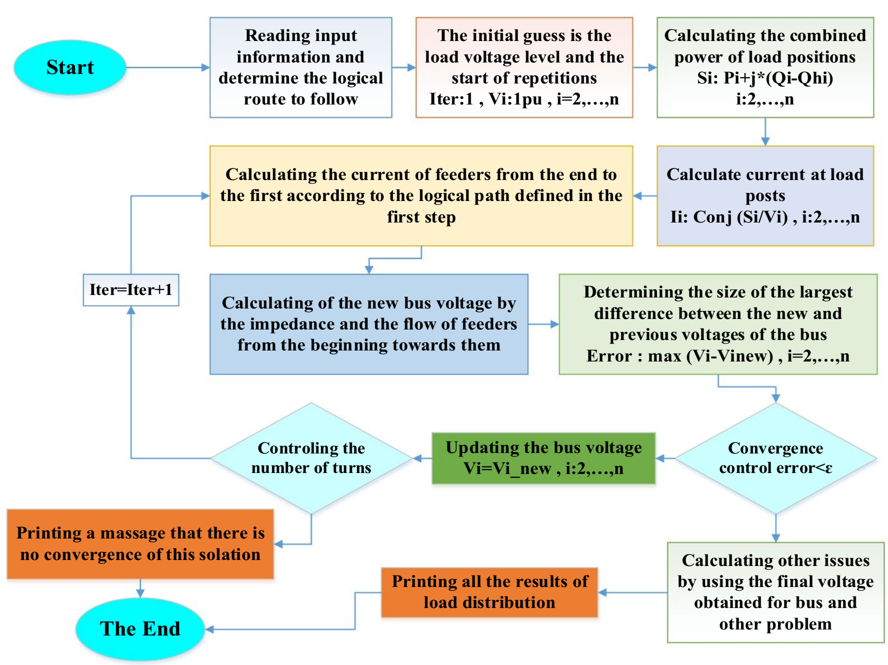


Fig. 5 Flowchart designed to coordinate with backward/forward sweep load flow

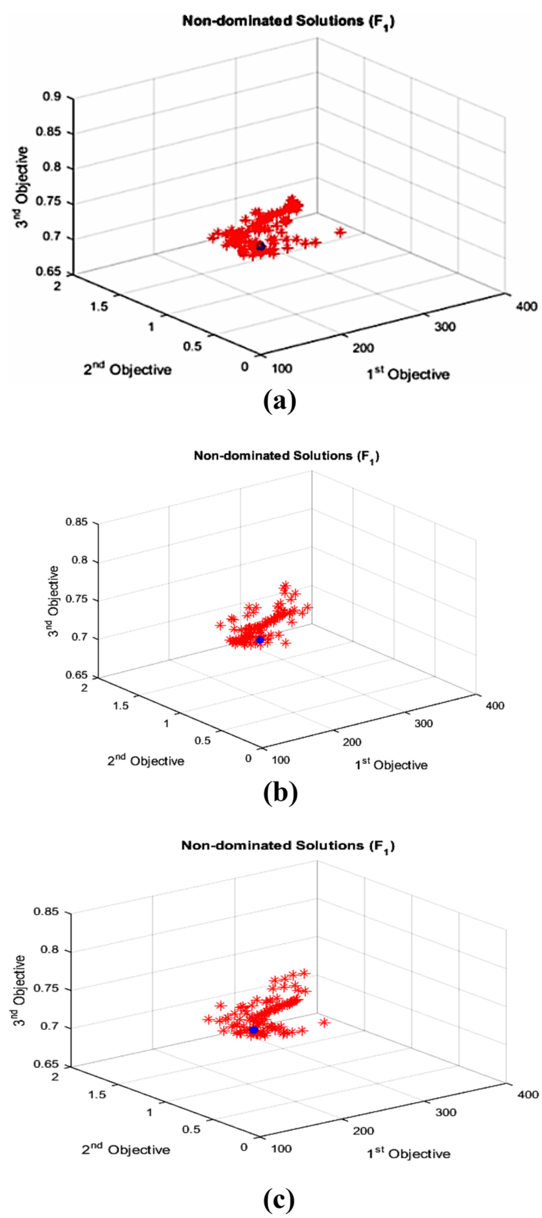


Fig. 6 The graph of the value target functions in the 33-bus network, **a** unit resulting, **b** 0.85 Post-phase, **c** 0.85 pre-phase

Table 1 Parameters of placement and sizing under the output power factor of the unit

Number bus	Power (kW)
5	875
11	487
16	694
24	954
28	746

decision method and is shown in concentrated blue in Fig. 6. Also, the placement and power output of PV sources in this case are shown in Table 1.

- **Output power factor 0.85 Post-phase**

Figure 7 shows (a) The optimization algorithm has been shown in three dimensions for the 33 bus and the output power factor of the unit, (b) Voltage profile is showed in a range of variations, and (c) total power losses of network including active and reactive losses under the output power factor of the unit resulting to 0.85 post-phase. In this figure, the optimal response is also shown as solid. Moreover, the output power of PV sources, along with their placement after optimization, is presented in Table 2.

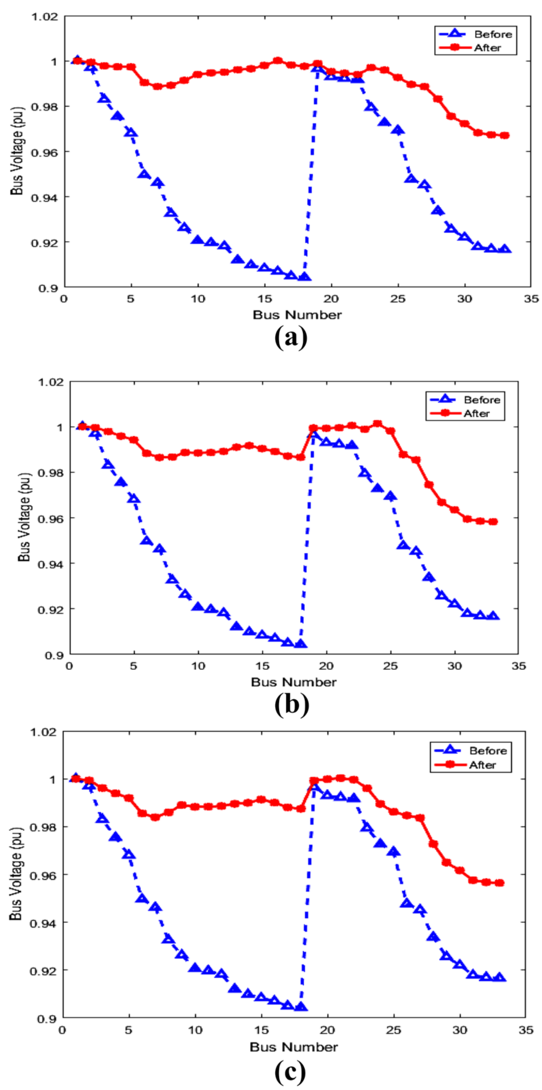


Fig. 7 The graph of voltage Profiles in the 33-bus network, **a** unit resulting, **b** 0.85 Post-phase, **c** 0.85 pre-phase

Table 2 Parameters of placement and sizing under the output power factor of 0.85, post-phase in the 33-bus network

Number bus	Power (kW)
9	632
15	680
21	439
23	1214
27	735

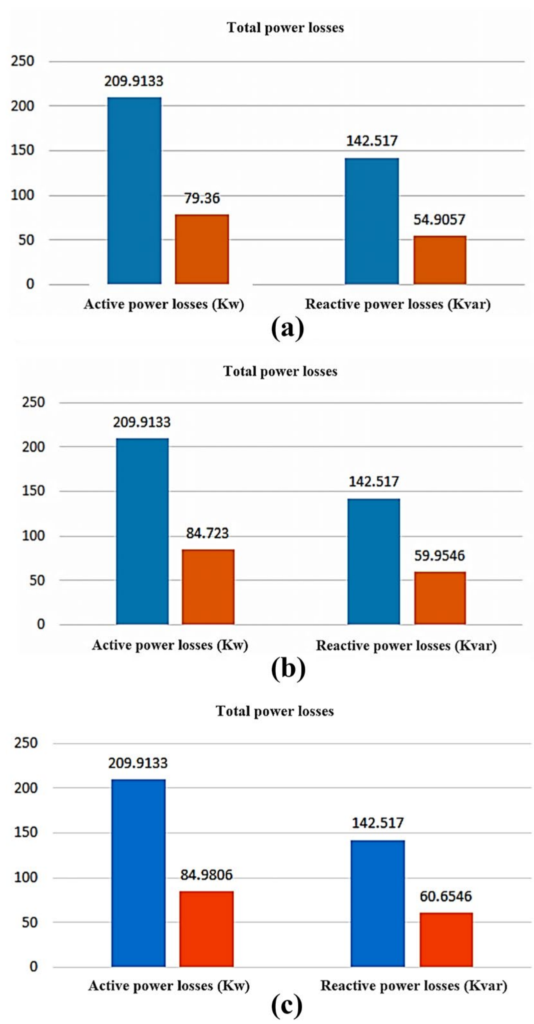


Fig. 8 The graph of total power losses in the 33-bus network, **a** unit resulting, **b** 0.85 Post-phase, **c** 0.85 pre-phase

- **Output power factor of 0.85 pre-phase**

The optimization algorithm has been shown in three dimensions for the 33 bus and the output power factor of the unit (a), Voltage profile is showed in a range of variations (b), and total power losses of network including active and reactive losses

Table 3 Parameters of placement and sizing under the output power factor of 0.85 pre-phase in the 33-bus network

Number bus	Power (kW)
9	632
15	680
21	439
23	1214
27	735

under the output power factor of the unit resulting of 0.85 pre-phase (c) is presented in Fig. 8. The optimal response is obtained with the aid of a fuzzy decision and, as can be seen, the optimal response is shown in solid form. Table 3 also shows the optimal placement and capacity of PV sources in the 33-bus network under the output power factor of 0.85 pre-phase.

Optimal placement and allocation of PV sources in the 69-bus network

- **Unit output power coefficient**

The graph of the value of the objective functions has been shown in three dimensions for the 33 bus and the output power factor of the unit (a), Voltage profile is showed in a range of variations (b), and total power losses of network including active and reactive losses under the output power factor of the unit resulting of 0.85 pre-phase (c) are presented in Fig. 9. In this figure, the optimal response is shown in solid blue. The optimal placement and allocation of output power of PV sources after optimization are shown in Table 4.

- **Output power coefficient 0.85 post-phase**

In Figs. 9, 10 and 11, The graph of the value of the objective functions has been shown in three dimensions for the 33 bus and the output power factor of the unit (a), Voltage profile is showed in a range of variations (b), and total power losses of network including active and reactive losses under the output power factor of the unit resulting of 0.85 pre-phase (c) are presented. In these figures, the optimal response is shown in solid blue. The optimal placement and allocation of output power of PV sources after optimization are shown in Tables 4, 5 and 6. The comparison of the proposed modeling with other valid methods is clearly presented in Tables 7 and 8.

Conclusion

In this paper, the placement and determining the optimal capacity of PV systems in the standard distribution networks 33 and 69 of the IEEE bus are accomplished by the NSGA-II algorithm. The objective function modeling of the problem is also the active power losses and the total reactive power of the system, the voltage profile of the shins, and the ratio of active power to reactive lines. A fine coefficient is also considered within the objective function when the allowed range of $\pm 10\%$ of the shaft voltage is violated. Moreover, due to the radial nature of the distribution networks

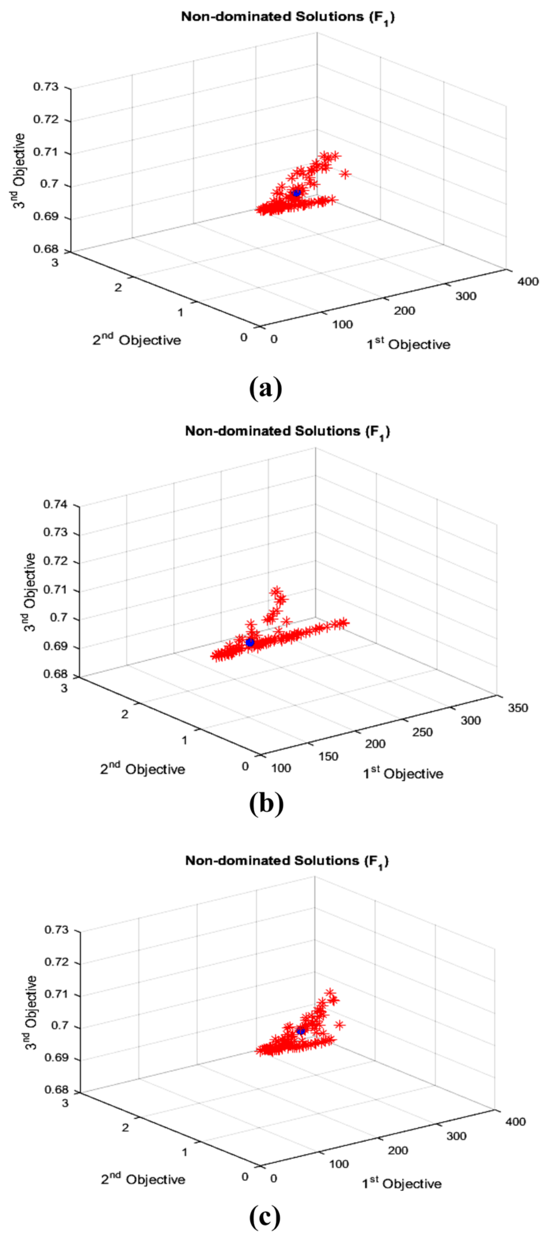
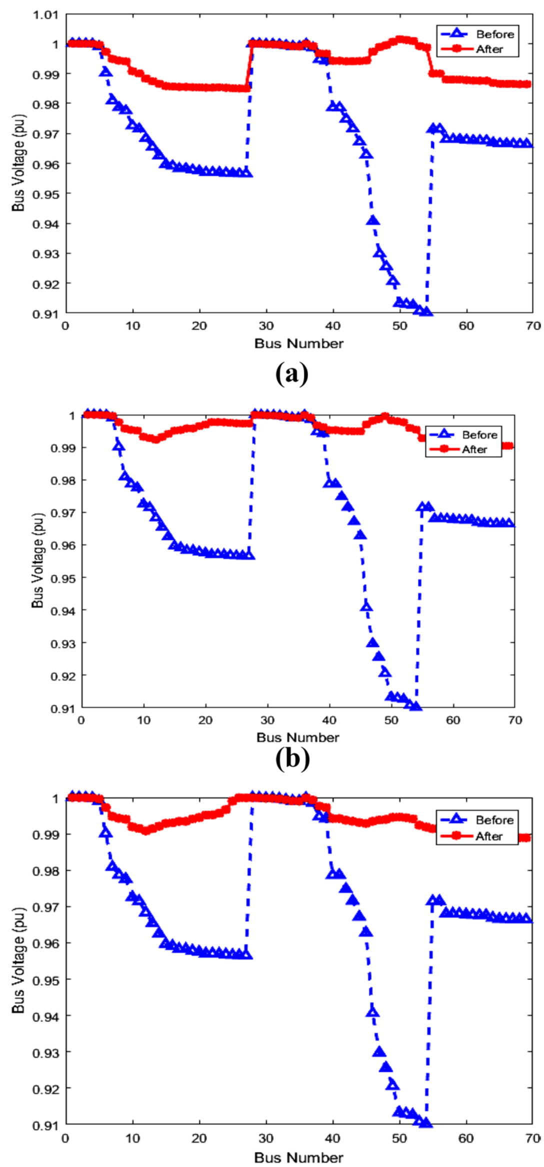


Fig. 9 The graph of the value target functions in the 69-bus network, **a** unit, **b** 0.85 Post-phase, **c** 0.85 pre-phase

Table 4 Parameters of placement and sizing under the output power factor at unit in the 69-bus network

Number bus	Power (kW)
17	123
23	169
36	879
39	799
50	2257



(a)

(b)

(c)

Fig. 10 The graph of voltage profiles in the 69-bus network, **a** unit resulting, **b** 0.85 Post-phase, **c** 0.85 pre-phase

under study, backward/forward sweep load-flow method is used. The results of the optimization show the improvement of the voltage profile and the significant reduction in total power losses and the improvement of the active-reactive power to reactive ratio lines in the IEEE standard 33 and 69-bus distribution networks. Moreover, the results show that changing the power factor of PV sources will not affect the amount of the above-mentioned objective functions in the distribution networks, and will only change the placement and capacity of the PV resources.

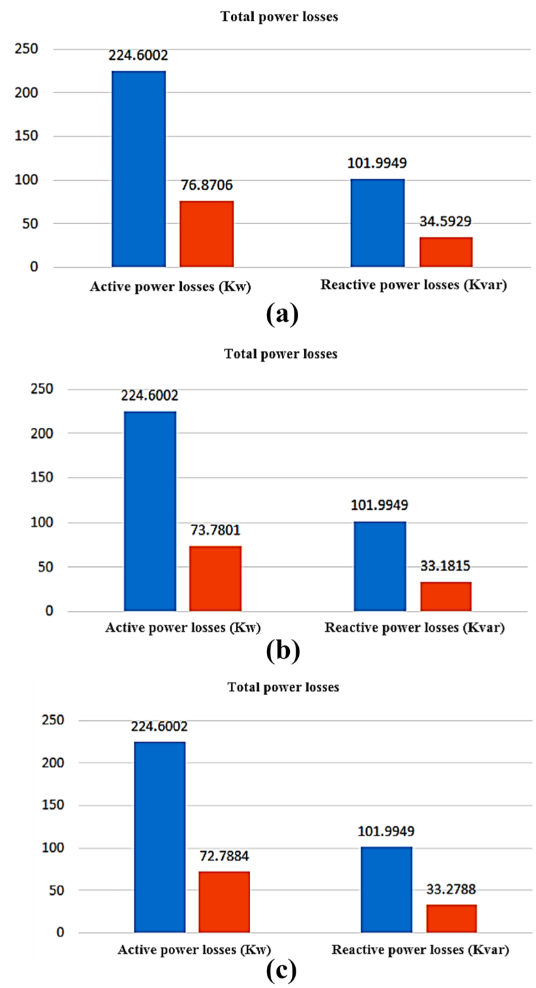


Fig. 11 The graph of total power losses in the 69-bus network, **a** unit resulting, **b** 0.85 Post-phase, **c** 0.85 pre-phase

Table 5 Parameters of placement and sizing under the output power factor of 0.85, post-phase in the 69-bus network

Number bus	Power (kW)
17	123
23	169
36	879
39	799
50	2257

Table 6 Parameters of placement and sizing under the output power factor of 0.85 pre-phase in the 69-bus network

Number bus	Power (kW)
3	136
21	548
28	974
39	831
51	2012

Table 7 Comparison of the results of NSGA-II and SEW algorithms for decision-making by fuzzy logic method

Method	The first bus	The second bus	Value of DG1 for first bus (KW)	Value of DG2 for second bus (KW)	Cost ($)	Total losses (KW)	Mean Voltages (P.U)
Original Network	–	–	–	–	–	210.99833	0.94532
Fuzzy logic for SEW algorithm	15	32	811.3730	497.2931	6801.1768	73.72540	0.97725
Fuzzy logic for NSGA-II algorithm	31	17	622.58300	686.0790	6801.1556	73.87335	0.97673

Table 8 Comparison of computation time of SEW and NSGA-II algorithms for decision-making by fuzzy logic method

Algorithm	Number of Function Evaluations (NFE)	Algorithm computation time (second)	Fuzzy logic computation time (second)
SEW algorithm	2,455,200	23,424.95940	7769.83621
Fuzzy logic for NSGA-II algorithm	23,051	141.53268	0.00069

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Author contributions
MM and SA conceived of the presented idea. SA developed the theory and performed the computations. EG verified the analytical methods. All authors discussed the results and contributed to the final manuscript.

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Availability of data and materials
In this article, the necessary general information has been cited from the reference in the manuscript body, and the system modeling incumbent data have been provided in different parts. Also, if more information and questions are requested in the review process, we are willing to provide data and answer questions.

Declarations

Competing interests
The authors declare that they have no competing interests.

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