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A new method of decision making in multi-objective optimal placement and sizing of distributed generators in the smart grid

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Abstract: One of the most important aims of the sizing and allocation of distributed generators (DGs) in power systems is to achieve the highest feasible efficiency and performance by using the least number of DGs. Considering the use of two DGs in comparison to a single DG significantly increases the degree of freedom in designing the power system. In this paper, the optimal placement and sizing of two DGs in the standard IEEE 33-bus network have been investigated with three objective functions which are the reduction of network losses, the improvement of voltage profiles, and cost reduction. In this way, by using the backward-forward load distribution, the load distribution is performed on the 33-bus network with the power summation method to obtain the total system losses and the average bus voltage. Then, using the iterative search algorithm and considering problem constraints, placement and sizing are done for two DGs to obtain all the possible answers and next, among these answers three answers are extracted as the best answers through three methods of fuzzy logic, the weighted sum, and the shortest distance from the origin. Also, using the multi-objective non-dominated sorting genetic algorithm II (NSGA-II) and setting the algorithm parameters, thirty-six Pareto fronts are obtained and from each Pareto front, with the help of three methods of fuzzy logic, weighted sum, and the shortest distance from the origin, three answers are extracted as the best answers. Finally, the answer which shows the least difference among the responses of the iterative search algorithm is selected as the best answer. The simulation results verify the performance and efficiency of the proposed method.

Key words: backward-forward load distribution, fuzzy logic, iterative search algorithm, multi-objective optimization, shortest distance from the origin, weighted sum

1. Introduction

In developed and developing countries, access to new energy sources is critical for economic and political development. Recent research shows that there is a direct relationship between a country's level of development and its energy consumption. Advanced optimization techniques on the placement and sizing of distributed generation units based on renewable resources can have stabilizing and compensatory effects on environmental, economic, technological, and regulatory factors [1]. In [2], the paper plans to expand a novel compound approach referred to as backtrapping assisted elephant herding optimization (BAEHO), to address the RPD issues in the power system under distortion situations. In [3], the problem of optimal placement is formulated for maximizing the DG owners' revenue and minimizing their allocated costs (production and transmission cost) to achieve the most optimal size and site of DGs from their owners' perspective. In another article, the exponential particle swarm optimization (EPSO) algorithm and voltage stability index (VSI) have been used in an optimization process to improve the voltage profile, save energy costs and reduce losses [4]. In [5], binary particle swarm optimization and shuffled frog leap (BPSO-SLFA) algorithms are used to minimize losses, improve voltage profiles, and enhance cost savings for different distribution systems. Research shows that the linear model combined with GA is efficient in reducing real power losses by finding the optimal location and size of DG units [6]. In [7], using the differential evolution meta-heuristic algorithm, the placement and sizing of distributed generation units has been done to reduce active power losses and it has been compared with the cuckoo search algorithm (CSA), simple genetic algorithm (SGA) and ant-lion optimization algorithm (ALOA). In [8], through the ant-lion optimization algorithm (ALO) and fuzzy technique, optimal DG placement and sizing is carried out to reduce the cost of purchased energy from the upstream network (due to the generation of DGs), improve reliability and buses' voltage deviation.

Considering the minimization of active power losses and maximization of voltage stability, the multi-objective optimization based on a hybrid technique (NSGA-II and fuzzy logic) is used to obtain optimal multi DG location and sizes [9]. In [10], dynamic models for inverter-based distributed generator (IBDG) units, network branches, and loads are used to accurately investigate the effects of small-signal stability constraints on optimal placement and sizing of IBDGs in a radial distribution system (RDS). For optimal allocation of the distributed generator (DG), in [11], a hybrid strategy employing a combination of particle swarm optimization (PSO) and Newton-Raphson flow (NRPF) methods has been developed and validated to minimize the real power loss, reactive power loss, reactive power generation and voltage deviation. Using a combination of genetic optimization (GA) and particle swarm optimization (PSO) algorithms for optimal placement and sizing of DGs leads to combined optimization values and accurate performance [12]. In [13], a multi-objective particle swarm optimization (MOPSO) algorithm is performed to optimally determine the size and location of DGs in coordination with the location and tap setting of the voltage regulator (VR), aiming at voltage profile improvement and the minimum number of tap operations of the voltage regulator. In [14], the loss sensitivity factor (LSF) and invasive weed optimization (IWO) are used to determine the optimal placement and sizing of DGs, respectively. In another research, the fuzzy logic technique is used for placement of DGs to improve the voltage profile and minimize losses in the network [15]. In [16], the multi-objective genetic optimization algorithm (NSGA-II) method is used for optimal placement and sizing of a DG to reduce losses and improve the voltage profile. In [17], in order to achieve the goals of reduction of losses and improvement of the voltage profile in a microgrid, the optimal allocation and sizing of DGs have been considered through using a proposed genetic algorithm (GA). In [18], a new method for optimal placement and sizing is proposed to minimize the total line losses of the radial distribution network. In [19], a novel method based on the coyote algorithm (COA) is proposed for the problem of simultaneous network reconfiguration and distributed generation (DG) placement to reduce real power loss. In [20], the authors suggest a method for determining the optimal sizing and location of the battery energy storage system (BESS) in an independent network while taking into account the unpredictability related to system generation and demand. In [21], an overview of the various methods for DG placement, with the goals of improving the voltage profile, power quality, productivity, as well as the reduction of operating and O&M costs, has been provided. For the DG placement and sizing with different power factors (PF), improved single- and multi-objective Harris Hawks optimization algorithms, called IHHO and MOIHHO can be used to minimize active power losses, reduce voltage deviation (VD) and increase the voltage stability index (VSI) [22].

In [23], an interactive fuzzy satisfying method based on the hybrid modified shuffled frog leaping algorithm is proposed to solve the problem of the multi-objective optimal placement and sizing of DGs in the distribution network. The objective functions in this problem are: minimizing total electrical energy losses, total electrical energy cost and total pollutant emissions produced. Researchers in [24, 25] present an overview of the most recent models and methods applied to the ODGP problem, analysis and methodology to calculate the optimal location and effective optimal size. The goal of optimal DG placement is to provide the best DG placements and sizes to optimize electrical distribution network operation and planning, considering DG capacity constraints.

This method considers the voltage dependency of static loads, and line charging capacitance. Compared to the improved version of the classical forward-backward ladder method, i.e., ratio-flow, the results show that the proposed power flow algorithm has strong convergence ability. The results of the previous research show that the placement and sizing of DGs is a single or multi-objective optimization problem, which if solved properly by any intelligent optimization algorithm, can contribute to improving network parameters. The method proposed in this article, in comparison to the mentioned existing works, substantially extends the solution space by the system designer's commitment to using two DGs in the multi-objective optimization problem-solving. Moreover, the simultaneous employment of three decision-making methods as the proposed method of this research creates higher performance and precision of the final optimal solution choice compared to the existing investigations.

Highlights

– Minimize the real power distribution and position parameters of the entire system.
– View very high accuracy in the placement and sizing of the proposed system compared to other paper.
– Evaluate and confirm multi-objective evolutionary algorithms based on decision making.
– View very high accuracy in improving total system losses and costs.
– View improvements and compare results with recent studies.

2. Methodology

Improving the voltage profile, reducing the total system losses, and reducing the cost of DGs have been considered in previous research in order to determine the optimal DG placement and sizing in the standard IEEE 33-bus network. In this paper, in the first stage, with the help of Matlab software, the backward-forward load distribution with the power summation method is done for the standard IEEE 33-bus radial distribution network to obtain the average value of network voltages, the total amount of network losses, and the amount of active bus power output of the slack bus. In the second stage, using the iterative search (IS) algorithm, all possible responses related to the placement and sizing of the two DGs are obtained, leading to the reduction of the total system losses, improving the voltage profile, reducing the cost, and satisfying the problem constraints. Of all the answers, three answers are extracted through three methods of fuzzy logic, weighted sum, and the shortest distance from the origin as the best answers. According to the three objective functions of the problem, each of these answers has its advantages and is considered to be an indicator. Then, in the third stage, the multi-objective non-dominated sorting genetic algorithm (NSGA-II) is used to reduce the computation time compared to the IS algorithm for the optimal placement and sizing of two DGs. In the NSGA-II algorithm, its effective parameters are set and executed for thirty six states. Each time the program is run, depending on the amount of change in the algorithm parameters, several answers are obtained. Among these answers, through the methods of fuzzy logic, weighted sum, and the shortest distance from the origin, three answers are extracted and compared with the answers of the iterative search algorithm. Each of the NSGA-II algorithm responses, which is less different from the IS algorithm responses, is selected as the answer.

3. Optimal placement and sizing problem formulation

3.1. Backward-forward load distribution functions by power summation method

According to Fig. 1, which is related to the standard IEEE 33-bus radial distribution network and the necessary information in [8] that is related to this network, the backward-forward load distribution is done by a power summation method on this network and by programming in

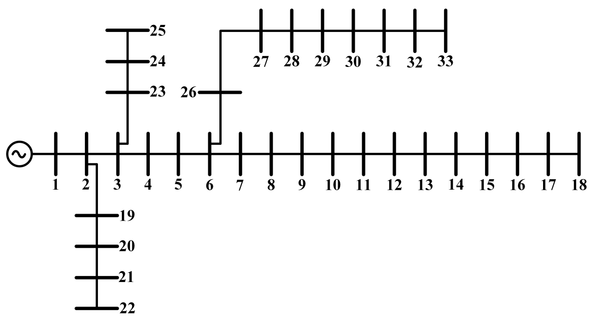


Fig. 1. Single-line diagram of standard 33-bus radial distribution network

MATLAB software. Then the amount of bus voltage, line losses, and the amount of active power generation of the slack bus are obtained. Backward-forward load distribution consists of two parts, backward sweep and forward sweep, which are explained in the following.

3.1.1. Backward sweep: calculation of branches complex power

First, the branches are numbered according to Fig. 2, and then the network is divided into several parts. Next, starting from the last bus and moving towards the slack bus, the powers of branches are obtained. The powers of branches 1, 2, and 5 are obtained from the sum of branches' powers in Fig. 3.

$$S_n = S_i + \sum_{m \in M} S_m + \mathrm{Loss}_n\,, \tag{1}$$

where: S_n is the complex power of the branch n (KVA), S_i is the complex power of the load connected to the bus (node) i (KVA), M is the total of complex powers of branches which at the node i are connected to the branch n (KVA), S_m is the complex power of the branch m (KVA), Loss_n represent the losses of the branch n considered zero in the first iteration (KVA).

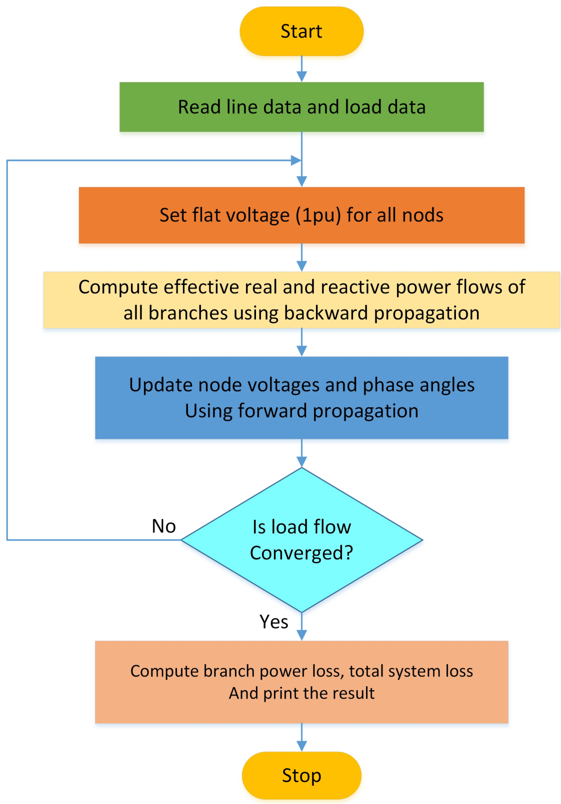


Fig. 2. Suggested flowchart for backward-forward sweep method

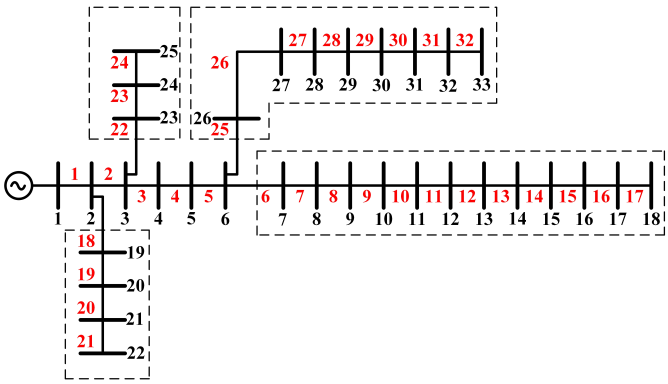


Fig. 3. Branch numbering and network segmentation to calculate branch power

3.1.2. Forward sweep and calculation of branches' currents

In the forward sweep, branches' currents, buses' voltages, branches' losses, and voltages' mismatch are calculated. For the forward sweep, we divide the network according to the figure. Then, starting from the first branch connected to the slack bus and moved to the end branches, at first, the branches' currents, then the voltages in the receiver bus of the branches, and next the branches' losses and the voltage mismatch are calculated. Then currents and losses of branches 18, 22, and 25 in Fig. 4, as well as voltages of buses 19, 23, and 26 that are not in the areas, are calculated directly.

$$J_n = \left(\frac{S_n}{V_j}\right)^* . \tag{2}$$

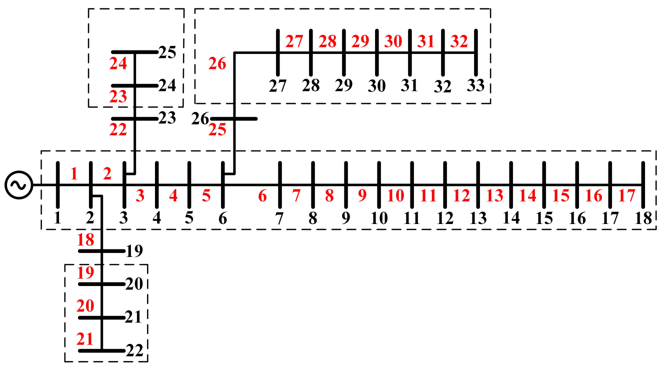


Fig. 4. Network segmentation to calculate branches' currents, buses' voltages, and lines' losses

3.1.3. Calculation of mismatch (convergence)

$$\Delta V^{i(k)} = \max\left(\left|V^{i(k)}\right| - \left|V^{i(k-1)}\right|\right), \tag{3}$$

where: $\Delta V^{i(k)}$ is the voltage difference in each bus, k is the number of repetitions, $V^{i(k)}$ is the voltage of the bus i in the k-th repeat (present step), $V^{i(k-1)}$ is the voltage of the bus i in the $k-1$-th repeat (previous step).

If each of $\Delta V^{i(k)}$ exceeds the convergence criterion, the above steps are repeated until the convergence is achieved. In this paper, the convergence criterion has been considered 0.0001. That is to say, if the voltage mismatch is less than 0.0001, convergence is achieved and the load distribution ends. The results obtained after loading are as follows:

The total load of the whole system (total of loads connected to the bases) equals
3.715 + 2.3 Mvar.

The total active power loss of the entire system is 210.9983 ≅ 211 kW.

The slack bus value equals 3.926 MW.

The average bus voltage is 11.9677 kV, which equals 0.94532 P.

The average bus voltage differs from the main voltage by 0.6923. The purpose of the DG network is to reduce the voltage difference and losses of the entire system at the lowest cost.

3.2. Iterative search (IS) algorithm

This algorithm is a classical algorithm and is based on numerical calculations. In this algorithm, at first, we calculate the maximum values of the active power of each DG unit. Then, we calculate the minimum values of the active power of each DG unit which here is equal to 0.01 of the maximum active power of the slack bus. Then for each DG unit, from the minimum amount of active power of each DG unit with the step of the minimum active power of each DG unit to the maximum active power of each DG unit, we obtain all the active power outputs of each DG unit. In fact, each DG unit has 100 active power outputs.

In each of the three methods of obtaining the optimal answer, the optimal answer is a point in three-dimensional space that has three objective functions. The optimal response of each method is different from the other two methods. The choice of a method for obtaining the optimal answer depends on the researcher's priority of the objective function. Also, Table 1 shows the parameters required for obtaining the cost function.

Table 1. Parameters required for obtaining the cost function

DG size (MW)	Cost (USD)
7 860.1	44.9271
9 200.1	10.9948
4 700.2	60.12666
9 880.2	60.15353
9 900.2	90.15361
0000.3	20.15396

In fact, using the IS algorithm, Fig. 5, we obtain the original Pareto front. The answers extracted from this front are our main answers compared to the answers of the NSGA-II algorithm because the NSGA-II algorithm gives us approximately the main answers of Pareto front.

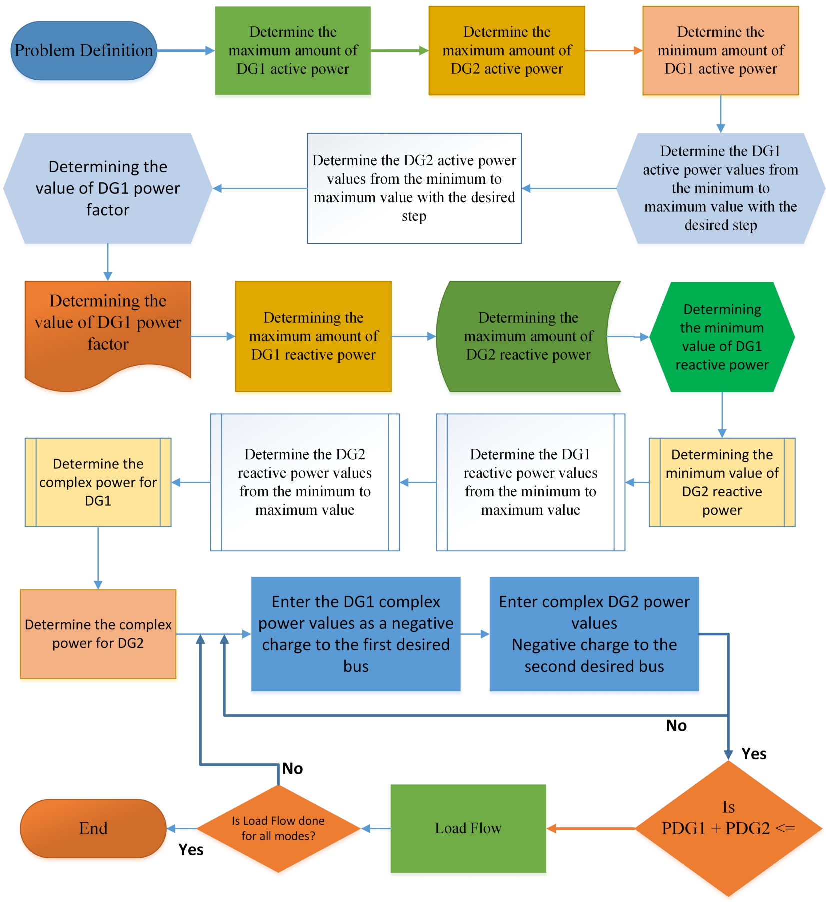


Fig. 5. Designed flowchart for Iterative search algorithm

3.2.1. Maximum and minimum amount of DGs' active power

$$\begin{cases} P\max \mathrm{DG1} = \dfrac{P\mathrm{stack}}{3} \\ P\max \mathrm{DG2} = \dfrac{P\mathrm{stack}}{3} \end{cases}, \tag{4}$$

$$\begin{cases} P\min \mathrm{DG1} = \dfrac{1}{100} \times P\max \mathrm{DG1} \\ P\max \mathrm{DG2} = \dfrac{1}{100} \times P\max \mathrm{DG1} \end{cases}. \tag{5}$$

3.2.2. Adverb problem

$$P_{\mathrm{DG1}i} + P_{\mathrm{DG2}j} \le \frac{P_{\mathrm{slack}}}{3} \quad i : 1 : 100 \quad j : 1 : 100. \tag{6}$$

3.3. Multi-objective non-dominated sorting genetic algorithm (NSGA-II)

3.3.1. Functions of the NSGA-II algorithm

The main advantage of this algorithm is its computing speed. The calculations speed of this algorithm is in the order O (MN2), (M is the number of target functions and N is the population size).While the calculations speed of the algorithm NSGA-I is a subset of O (MN3), the calculations speed of the algorithm (NSGA-II) in Fig. 6 is much faster than the algorithm (NSGA-I).

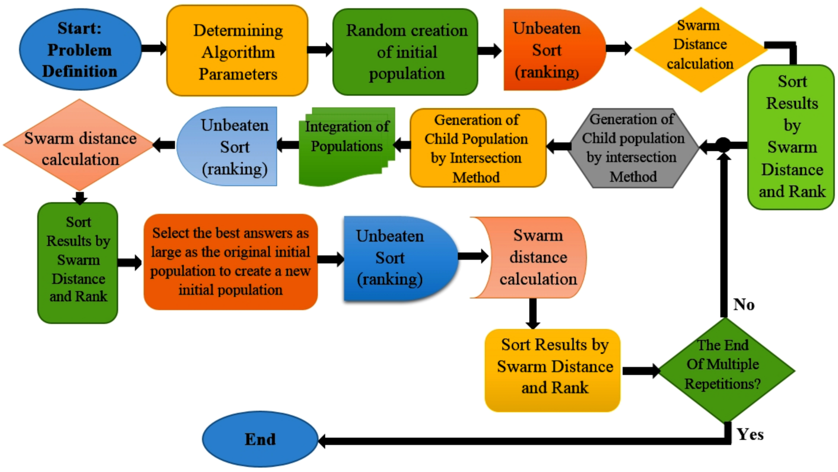


Fig. 6. Designed flowchart with NSGA-II algorithm

3.3.2. Dominating

It is said that x dominates y and is represented by $x \leq y$, if and only if:
For all objectives, x is better than y.

$$\forall_i\colon X_i \leq y_i\,. \tag{7}$$

The solution x dominates the solution y, if the solution x is no worse than y in all objectives and the solution x is strictly better than y in at least one objective.

$$\exists_{i0}\colon X_{i0} \prec y_{i0}\,. \tag{8}$$

3.3.3. Crowding distance

$$d_i^j : \frac{\left|f_j^{\text{previous}} - f_j^{\text{subseqent}}\right|}{f_j^{\max} - f_j^{\min}}, \tag{9}$$

$$di = d_i^1 + \ldots + d_i^m = \sum_{j=1}^{m} d_i^j \quad i : 1, \ldots, n. \tag{10}$$

The greater crowding distance, the more variation in the algorithm's answers.

3.3.4. Uniform crossover and mutation

$$\text{First parent position:}\quad X_1:\ X_{11}, X_{12}, \ldots, X_{1n}\,, \tag{11}$$

$$\text{Second parent position:}\quad X_2:\ X_{21}, X_{22}, \ldots, X_{2n}\,, \tag{12}$$

$$\alpha:\ \ (\alpha_1, \alpha_2, \ldots, \alpha_n) \qquad \alpha_i \in (0,1), \tag{13}$$

$$\text{First child:}\ \ Y_1:\ (y_{11}, y_{12}, \ldots, y_{1n}), \rightarrow y_{1i}:\ \alpha_i X_{1i} + (1-\alpha_i)X_{2i} \quad i:\ 1, \ldots, n, \tag{14}$$

$$\text{Second child:}\ \ Y_2:\ (y_{21}, y_{22}, \ldots, y_{2n}), \rightarrow y_{2i}:\ \alpha_i X_{2i} + (1-\alpha_i)X_{1i} \quad i:\ 1, \ldots, n, \tag{15}$$

$$\text{if:}\ \ \alpha_i = 1\ \Rightarrow \begin{cases} y_{1i} = X_{1i} \\ y_{2i} = X_{2i} \end{cases}, \tag{16}$$

$$\text{if:}\ \ \alpha_i = 0\ \Rightarrow \begin{cases} y_{1i} = X_{2i} \\ y_{2i} = X_{1i} \end{cases}, \tag{17}$$

$$\begin{cases} X = (X_{11}, X_{12}, \ldots, X_{1n}) \\ X\text{new} = \text{binari}\,(x) \\ n\_mn = [\pi_m \times n\_\text{var}] \end{cases}, \tag{18}$$

where: X is the position of the population member selected randomly, Xnew is the binarized selected member, n_mn is the number of components affected by mutation. π_m is the mutation impact rate $0 \leq \pi_m \leq 1$, n_var is the number of components of Xnew.

3.3.5. Objective functions: cost function and total losses

$$\begin{aligned} \cos_i\,(\text{USD}):\ \ &(37.25 \times (PDG1i + PDG2j)2) + (5243 \times (PDG1i + PDG2j)) + 3.635, \\ & i:\ 1:1, \quad j:\ 1:1, \end{aligned} \tag{19}$$

$$\text{Total(Loss)}i = \sum_{m}^{32} \text{Loss}_n, \quad i:\ 1:k, \tag{20}$$

where: Total(Loss) is total active losses of the whole system (kW), Loss_n represents the active losses of the line n (kW).

3.3.6. Average voltages function and the per-unitization of the objective functions of the problem

$$\text{Mean\_Voltage\_}i = \frac{\sum\limits_{n=1}^{33} \text{Voltage\_Bus}_n}{33} \quad i:1:1, \tag{21}$$

$$\text{Voltage\_Bus\_}n(\text{pu}) = \frac{|\text{Voltage\_Bus}_n\ (\text{kV})|}{12.66\ (\text{kV})}, \quad i:1:33, \tag{22}$$

$$\text{Voltage\_}i(\text{pu}) = 1 - \left(\frac{\sum\limits_{n=1}^{33} \text{Voltage\_Bus}_n(\text{pu})}{33} \right) \quad i:1:k, \tag{23}$$

$$\cos_{\max} = \left(-37.25 \times \left(\frac{P_{\text{slack}}}{3}\right)^2\right) + \left(5243 \times \left(\frac{P_{\text{slack}}}{3}\right)\right) + 3.635, \tag{24}$$

$$\cos_i(\text{pu}) = \frac{(-37.25 \times (P\text{DG1i} + \text{PDG2j})^2) + (5243 \times (\text{PDG1i} + \text{PDG2j})) + 3.635}{\cos_{\max}}, \tag{25}$$

$$\text{Total(Loss)}i(\text{pu}) = \frac{\sum\limits_{m}^{32} \text{Loss}_n\ (\text{kW})}{211\ (\text{kW})}, \quad i:1:k. \tag{26}$$

3.3.7. Optimal answer extraction techniques

– Fuzzy logic

$$\mu_K = \begin{cases} 1 \\ \dfrac{j_{k\max} - j_k}{j_{k\max} - j_{k\min}}, & j_k \le j_{k,\min} j_{k,\min} \le j_k \le j_{k\max} j_k \ge j_{k,\max}, \\ 0 \end{cases} \tag{27}$$

$j_{k\max}$ and $j_{k,\min}$ are the maximum and minimum values of the k-th objective function. For each solution i, the membership function is calculated as follows:

$$\mu^i = \frac{\sum\limits_{k-1}^{n} \mu_k^i}{\sum\limits_{i=1}^{m} \sum\limits_{k=1}^{n} \mu_k^i}, \tag{28}$$

where n is the number of objective functions, and m is the number of solutions. The solution with the maximum value of μ^i is the best solution for compromise.

– Weighted sum and minimum distance from the origin

$$\min: \ h_i = (w_1 f_{1i} + w_2 f_{2i} + w_3 f_{3i})/3, \tag{29}$$

$$\min: \ \|d_i\| = \sqrt{(f_{1i})^2 + (f_{2i})^2 + (f_{3i})^2} \quad i:1:1:n, \tag{30}$$

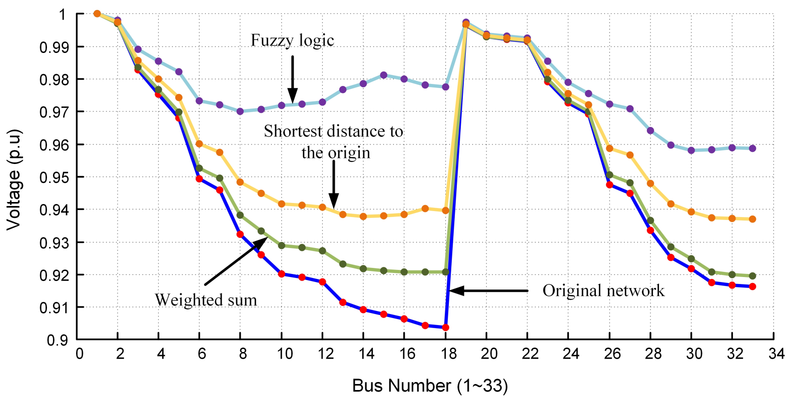
where i is the number of responses and w_1, w_2 and w_3 are objective functions coefficients, and since all three objective functions have the same value for us, we consider all these coefficients equal to $\frac{1}{3}$. Here, f_1, f_2 and f_3 are the objective functions of the problem.

4. Simulation and results

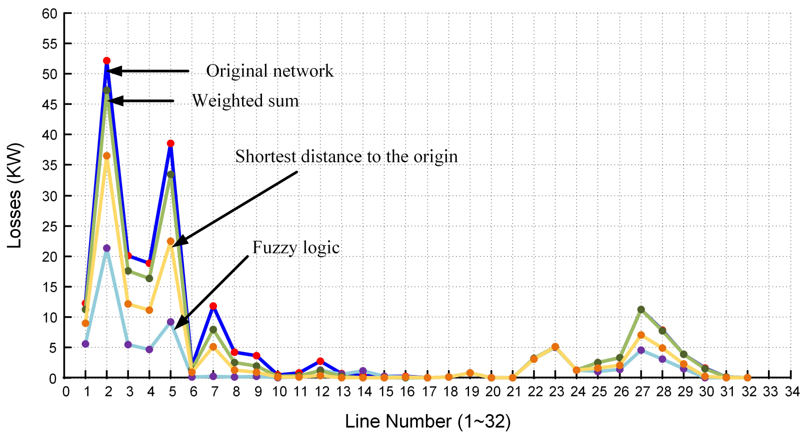
The modeling results are performed for 3 different steps. In the first step, the load distribution results on the standard IEEE 33-bus radial distribution system are shown to determine the system parameters without the presence of DGs. In the second step, after placing two DGs in the mentioned system, the IS algorithm is used to determine all possible answers to the problem and then with three different methods, the best optimal answers from all possible answers are obtained as references for comparison with the best answers of the NSGA-II algorithm. In the third step, the simulation results are performed for 36 states. The answers obtained by the NSGA-II algorithm are shown in each case of setting the parameters of this algorithm.

4.1. Step 2: results of IS algorithm with two DGs

In this section, the total answers, the best answer, the voltage profile, and the losses profile of the IS algorithm are shown in Fig. 7.



(a)



(b)

Fig. 7. (a) voltage profile for IS algorithm; (b) losses profile for IS algorithm

In Fig. 7(a), it can be clearly seen that the fuzzy logic algorithm has shown the best result for the voltage profile. It is also confirmed in Fig. 7(b) that the fuzzy logic has found the best responses to reduce losses.

4.2. Modeling result

In the previous part, different steps were performed in modeling and the optimal answers were obtained by algorithms and compared with other results. Those optimal and accurate results are presented here through the final decision.

In Fig. 8 the mismatch index of the two algorithms for decision-making by the fuzzy logic method is equal to 0.00087. The mismatch index of the two algorithms for decision-making by the weighted sum is equal to 0.00039. The mismatch index of the two algorithms for decision-making with the shortest distance from the original method is equal to 0.00268.

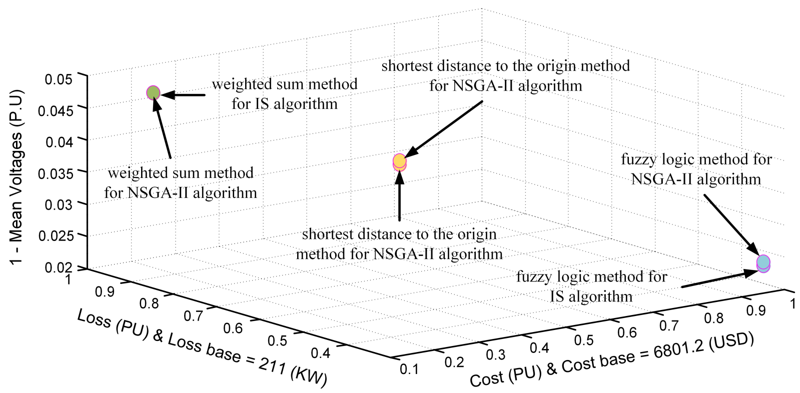


Fig. 8. Comparing the best answers of the IS algorithm with NSGA-II algorithm considering three different decision making methods

4.3. The best-case scenario of NSGA-II algorithm for decision making by the fuzzy logic method

4.3.1. Thirtieth case:

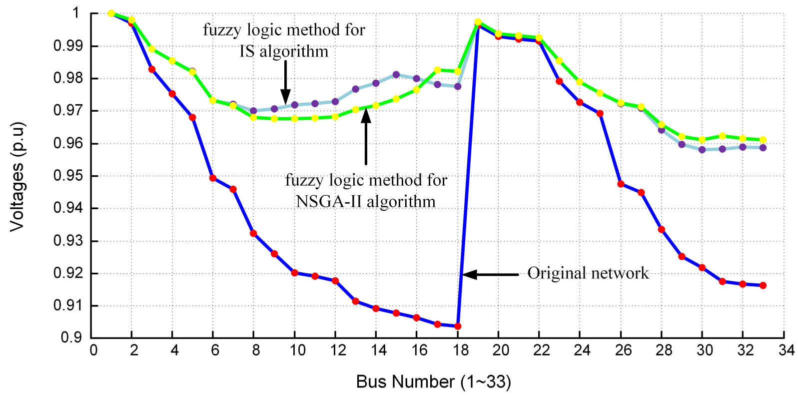
In this case, the comparison of the profile voltage, and the comparison of the profile losses are shown in Fig. 9.

In Fig. 9(a), it can be clearly seen that the fuzzy logic method for IS and NSGA-II has shown the equal results for the voltage profile. It is also confirmed in Fig. 9(b) that the fuzzy logic method for IS and NSGA-II has found the same responses to reduced losses.

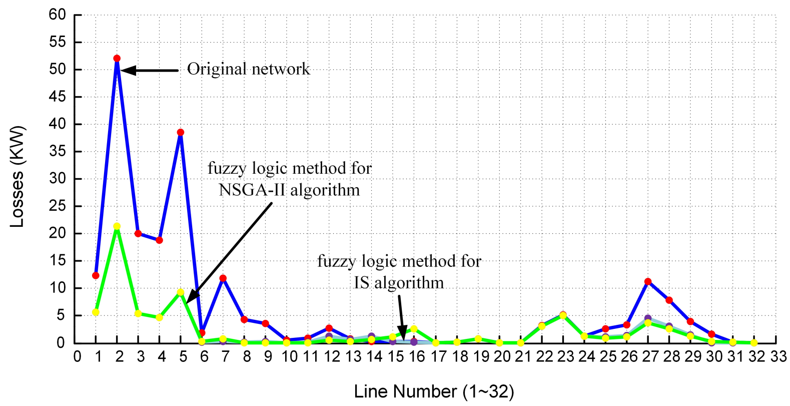
4.3.2. Eighteenth case

In this case, the comparison of the profile voltage, and the comparison of the profile losses are shown in 10.

In Figs. 10(a) and (b), it can be clearly seen that the fuzzy logic method for IS and NSGA-II are very close to each other, the shapes are on top of each other.

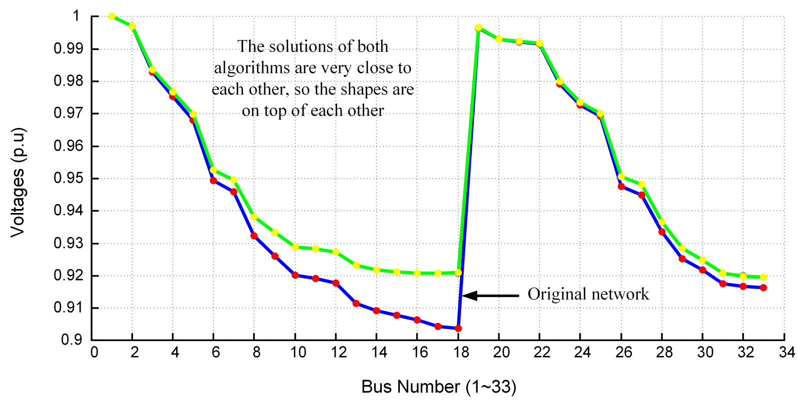


(a)

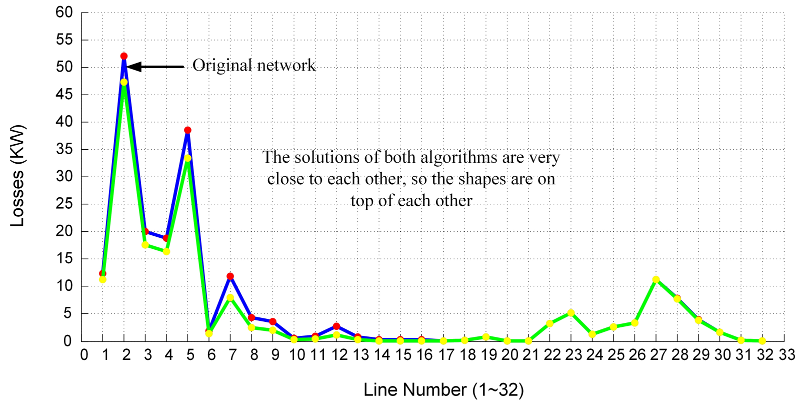


(b)

Fig. 9. (a) comparison of profile voltage; (b) comparison of profile losses of IS and NSGA-II algorithms for decision making by fuzzy logic method



(a) comparison of profile voltage



(b)

Fig. 10. (a) comparison of profile voltage; (b) comparison of profile losses of IS and NSGA-II algorithms for decision making by weighted sum method

4.3.3. Eleventh case

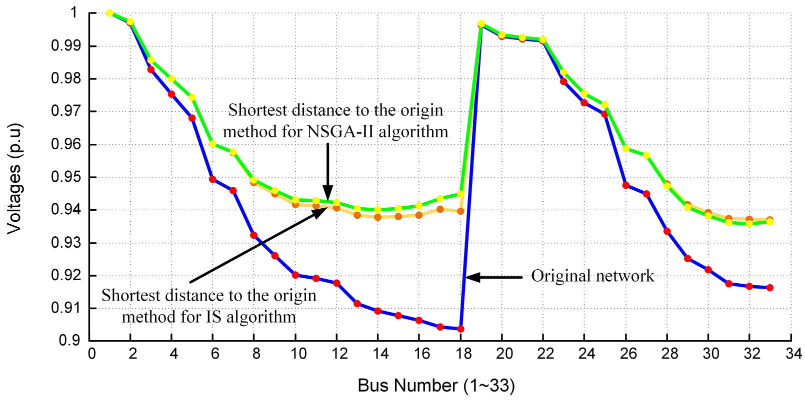
In this case, the comparison of the results, and the comparison of computation time of NSGA-II and IS algorithms for decision making by shortest distance from the origin method are demonstrated in Tables 2, 3. Also, the comparison of the profile voltage, and the comparison of the profile losses are shown in Fig. 11.

Table 2. Comparison of the results of NSGA-II and IS algorithms for decision making by shortest distance from the original method

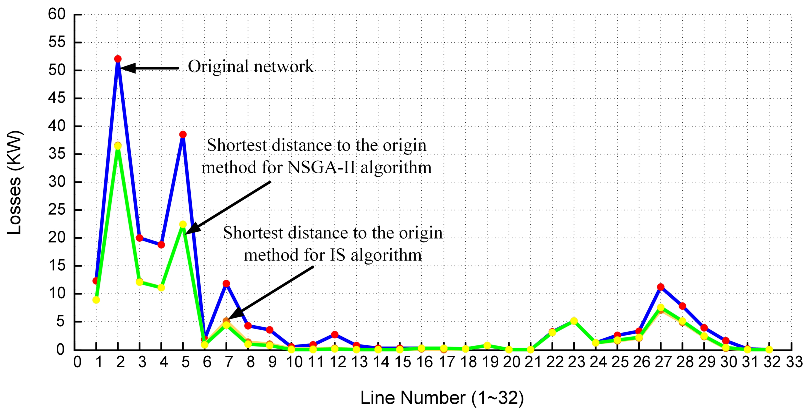
Method	First bus	Second bus	Value of DG1 for	Value of DG2 for	Cost	Total losses	Mean voltages
Network	–	–	–	–	–	210.998	0.94532
Shortest distance to IS	17	32	300.9932	261.7332	2942	129.905	0.95955
Shortest distance to NSGA-II	18	33	341.7650	223.7000	2956	130.2370	0.96013

Table 3. Comparison of computation time of IS and NSGA-II algorithms for decision making by shortest distance from the original method

Algorithm	Number of function evaluations (NFE)	Algorithm computation time (second)	Shortest distance to the origin computation time
Shortest distance to IS	2 455 200	23 424.95940	0.28543
Shortest distance to NSGA-II	4 451	28.44148	0.00017



(a)



(b)

Fig. 11. (a) comparison of profile voltage; (b) comparison of profile losses of IS and NSGA-II algorithms for decision making by shortest distance from the original method

In Fig. 11(a), it can be clearly seen that the shortest distance method for NSGA-II has shown the best results for the voltage profile. But it is confirmed in Fig. 11(b) that the shortest distance method for IS and NSGA-II has found the same responses to reduce losses.

5. Conclusion

In this paper, a new method of decision making for placement and sizing of two DGs in the power grid has been investigated. For this aim, power losses and voltage profiles, as well as cost have been separately considered as three objective functions. In this regard, IS and

NSGA-II algorithms have been employed to determine the possible solutions which are located in solution space. The comparison of IS and NSGA-II results verifies the correctness of the used evolutionary algorithm. It is worth noticing that to find answers close to the solutions for the IS algorithm and sometimes better than it, given to the existing knowledge of the problem, the parameters of the NSGA-II algorithm should be set and executed for at least a few cases. Hence, it still has less computational time than the IS algorithm. According to the simulation results it can be concluded that considering a cost-effective method and appropriate placement and sizing of DGs, the system parameters can be improved with NSGA-II algorithms. The results show that although the classical IS algorithm has a great variety of answers, it takes a lot of time to perform calculations. Compared to the IS algorithm, the NSGA-II intelligent algorithm has much fewer answers and is much faster. The selection of the final elite solution has been always a controversial issue among decision-makers. In this way, many classical and innovational decision making methods have been introduced and studied by researchers. The proposed method of research for decision making provides significant performance and efficiency by choosing the best optimal solution to perform in the smart grid.

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