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Original Article

Optimal Planning of DGs in Radial Distribution System Using Many-Objective Arithmetic Optimization Algorithm and Multi-Criterion Decision-Making TOPSIS Approaches

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Abstract - *This paper presents an optimal DG planning method using a Pareto-based Many-Objective Arithmetic Optimization Algorithm (MOAOA) to improve four technical metrics of the distribution system: mitigation of Electrical Energy Not Served (EENS), total voltage deviation minimization, enhancement of voltage stability index, and energy loss curtailment. The method is tested on a standard IEEE-33 bus distribution system and compared with other methods like MOPSO, MOGWO, and NSGA-II. The study aims to address the challenges of improper DG integration in distribution networks.*

Keywords - *Distributed Generation (DG), Arithmetic Optimization Algorithm (AOA), Multiobjective Particle Swam Optimization (MOPSO), Multi Objective Gray Wolf Optimization (MOGWO), Non Dominated Sorting Genetic Algorithm (NSGA-II) Distribution system, Optimal siting and sizing.*

1. Introduction

The persistent surge in demand for electrical power coupled with the extensive evolution of distribution networks has rendered the effective management of the distribution system a matter of paramount significance in contemporary research and discourse. Further, in recent years, worldwide attention has been focused on the problems that accompany traditional fossil fuel power plants. This has prompted power utilities across the globe to explore the option of Distributed Generators (DGs) integration in distribution systems. These DGs have unique characteristics such as environmental pollution mitigation, power distribution network loss minimization, system reliability enhancement, voltage profile improvement and deferment of new construction requirements for the energy facilities [1].

Nevertheless, the efficacy of DG interconnection within distribution systems is predominantly contingent upon the specificities of the DG location and size. Improper planning (location and size) of DG may culminate in counterproductive results [2]. The non-optimal planning of DGs is linked to the proliferation of power losses, stability issues, and reverse power flow within the distribution network. Thus, it is imperative to optimize the planning of DGs within the distribution network strategically.

The planning problem associated with DGs typically entails the optimization of multiple objectives aimed at boosting the overall performance of the distribution system. Given the complex, many-objective, mixed-integer, non-linear, and non-concave nature of the DG planning problem, numerous researchers employ nature-inspired metaheuristic optimization algorithms to tackle this challenge effectively.

Authors in [3] applied a Genetic Algorithm (GA) to locate and size DGs considering multiple objectives. Multiple DGs are planned in the distribution network [4] using a particle swarm optimization algorithm. The investigation also addressed the DG planning problem while considering various load models.

2. Literature Review

The authors employed the cuckoo search optimization algorithm to address the many-objective DG planning problem. In a study outlined in [5], an artificial bee colony algorithm is utilized to minimize real power loss while optimally siting and sizing DG installations. The utilization of a whale optimization technique, as detailed in [6], has been employed for the optimization of DG site selections and sizes, with a primary focus on real power loss reduction. This study places particular emphasis on incorporating diverse load models into the optimization framework. A many-objective problem was delineated in [7] wherein the objectives encompass the minimization of power loss and the enhancement of voltage profile. In reference [8], a weighted multiobjective multiverse optimization methodology has been proposed to address the DG planning problem. It is noteworthy that this investigation specifically considered the optimization of the Electrical Energy Not Supplied (EENS) objective in conjunction with several other technical objectives (real power loss, total voltage deviation, voltage stability index).

Authors in [9, 10] explored the application of the butterfly optimization algorithm for planning DGs in the distribution network with the objective of minimising system real power loss and loadability. An approach to many-objective DG planning is introduced in [11], accounting for cost, emission, voltage deviation, and voltage stability as distinct objectives. The resolution of this multifaceted problem is achieved through the implementation of the artificial gorilla troops optimizer algorithm. The artificial humming bird algorithm [12] is applied to find the best location and size of DGs with an objective to minimize losses and total voltage deviation.

The above-cited literature [7-12], while addressing multiple objectives, does not maintain the many-objective nature during the optimization process. The prevailing approach in the majority of these studies involves the utilization of a weighted-sum methodology to transmute the many-objective DG planning problem into a single-objective counterpart. Following the transformation, the problem is tackled using a single-objective optimization algorithm. The effectiveness of this approach relies on the predetermined bias weights assigned to each objective.

However, it is noteworthy that, for a specific solution, these bias weights are predefined, potentially rendering the solution impractical for distribution utilities with divergent biases towards the objectives. Furthermore, imperfect solutions may be produced as a result of choosing the wrong bias weights [8]. Some researchers have used Pareto optimality based many-objective algorithms to address these concerns effectively.

Pareto optimality-based many-objective algorithms are capable of optimizing multiple objectives simultaneously, thereby avoiding the need for converting the many-objective problem into a single-objective one. A game theory-based Pareto optimality approach is implemented in [13] for optimal DG planning in the distribution network. In [14], the authors developed a many-objective framework by using a Multiobjective Grey Wolf Optimization Algorithm (MOGWO) to solve the DG planning problem. The following gaps were identified from the above discussions. The literature elucidates that a substantial portion of DG planning investigations overlooks the EENS objective. Despite being documented in select studies [8], it is noteworthy that these investigations, as previously highlighted, amalgamate the EENS objective with other parameters utilizing a weighted-sum methodology. Studies utilizing the Pareto optimality-based approach [13, 14] similarly omitted consideration for the EENS objective. Recognizing this research gap, this study proposes a many-objective DG optimal planning problem that takes into account energy loss, total voltage deviation, voltage stability index, and EENS as primary objectives. This study presents simultaneous optimization of all four considered objectives using a Pareto optimality-based Many-Objective Arithmetic Optimization Algorithm (MOAOA) [15].

The best-compromised solution from the Optimal Pareto front generated by MOAOA is chosen through the Technique for Order Performance by Similarity to the Ideal Solution (TOPSIS). TOPSIS, [14] a widely utilized multi-attribute decision-making tool, plays a central role in aiding decision-makers to identify an optimal solution from a given set of alternatives. Within the framework of the proposed many-objective problem, TOPSIS effectively achieves a harmonious balance among energy loss, total voltage deviation, voltage stability index, and EENS. The contributions of this paper are as follows:

1. Four main goals were covered in this investigation, including the reduction of EENS by using a Pareto-optimality-based strategy for DG planning.
2. There are two different kinds of DGs in the planning problem: Type-1 DGs, which are only capable of introducing actual power, and Type-2 DGs, which are able to supply both reactive and active power.
3. Utilize TOPSIS's expertise during the decision-making phase after the optimization process. The planning results for each weight combination are methodically presented, and several combinations of weights are methodically selected.
4. The innovative application of MOAOA to tackle the intricacies present in the DG planning problem with four competing objectives is a significant feature of this study.

The subsequent sections of the paper are delineated as follows: Section 2 introduces the formulation of the objective function. Section 3 provides a detailed exposition of the MOAOA and TOPSIS. Section 4 expounds upon the results and ensuing discussions. The concluding remarks are presented in section 5.

3. Problem Formulation

The proposed multiobjective methodology encompasses four vital technical objectives of the distribution network that aim to enhance the overall performance of the distribution network. It is noteworthy that all four objectives are minimized simultaneously using the proposed methodology.

3.1. Objective Functions

3.1.1. Energy Loss

The parameter of significant importance in gauging the efficacy of the distribution is the energy loss (E_{loss}) of the network. Efforts should be directed towards minimizing the E_{loss} Within the network to the greatest extent possible. Hence, the E_{loss} This is taken as one of the minimization objectives of this study. It can be computed by using the below expression.

$$E_1 = E_{loss} = \lambda \times \sum_{p=1}^{nbus-1} I_p^2 R_p \quad (1)$$

Where λ, I_p, n bus and R_p respectively denote the conversion factor, current served by branch p and resistance of branch p.

3.1.2. Electrical Energy Not Supplied

The unmet energy demand, referred to as Electrical Energy Not Supplied (EENS), serves as a pivotal metric for assessing the reliability of services provided to consumers. $EENS$ empowers network utilities to identify vulnerable buses and formulate corresponding operational procedures. The $EENS$ of the distribution system, framed as a minimization objective, can be calculated using the equation outlined below:

$$E_2 = EENS = \sum_{m=1}^{nbus} P_{D,m} U_m \quad (2)$$

Where $P_{D,m}$ and U_m For a given bus m respectively denote the power demand and the annual failure rate. It is customary to estimate the reliability of the system based on the average rate of failure (τ_s), annual time of outage (U_s) and average outage time (r_s). These parameters are computed as shown below [16]:

$$\tau_s = \sum_m \tau_m, U_s = \sum_m \tau_m r_m \; ; r_s = \frac{U_s}{\tau_s} = \frac{\sum_m \tau_m r_m}{\sum_m \tau_m} \quad (3)$$

Where τ_m, U_m and r_m Respectively denote the average rate of failure, annual time of outage and average outage time for the component m of the system. Enhancing the reliability of the distribution network is achievable through the reduction of line failure rates. The failure rate of a given line is typically influenced by the magnitude of the current it carries.

The integration of DGs into the network serves as an effective strategy to diminish the current carried by the lines, thereby contributing to the reduction of line failure rates. This methodological approach aligns with the objective of improving the overall reliability of the distribution system. For any given line k, with the uncompensated failure rate τ_k^{uncomp} and fully compensated failure rate τ_k^{comp}, the failure rate post DG accommodation is given by:

$$\tau_k^{DG} = \frac{|I_k^{DG}|}{|I_k^{NODG}|}\left(\tau_k^{uncomp} - \tau_k^{comp}\right) + \tau_k^{comp} \quad (4)$$

Where I_k^{NODG} and I_k^{DG} For a given line k, respectively, indicate the current served by the line before and after DG integration.

3.1.3. Total Voltage Deviation

The magnitude of bus voltage serves as a crucial parameter indicative of the power quality supplied to consumers. Improving the network voltage profile involves mitigating deviations in bus voltage. To achieve this goal, a minimization objective is formulated, focusing on reducing the Total Voltage Deviation (TVD) across the network. The bus voltage being V_m, TVD is mathematically expressed as follows [13]:

$$E_3 = TVD = \sum_{m=1}^{nbus} (|1 - V_m|)^2 \quad (5)$$

3.1.4. Voltage Stability Index

The demand on the distribution network undergoes frequent changes; consequently, the bus voltage may collapse if the loading exceeds the critical l*oading limit. In order to prevent such undesirable phenomena, utilities strive to maximize the Voltage Stability Index (VSI), and Stability Index (SI) of the distribution system. The VSI, which is taken as a maximization objective, is shown below in Equation [13]:

$$E_4 = VSI = \min(SI_n) \quad n = 2, 3, \ldots\ldots, nbus \quad (6)$$

$$SI_n = |V_m|^4 - 4[P_m X_{mn} - Q_m R_{mn}]^2 - 4[P_m R_{mn} + Q_m X_{mn}]|V_m|^2 \quad (7)$$

Where P_m and Q_m Indicate the real and reactive power respectively injected at bus m. R_{mn} and X_{mn} Respectively denote the resistance and reactance of the line joining buses m and n.

3.2. Constraints

The four specified objectives, slated for simultaneous optimization, are delimited by the ensuing following set of constraints:

$$|V_{LL}| \leq |V_m| \leq |V_{UL}| \quad (8)$$

$$|V_{LL}| \leq |V_m| \leq |V_{UL}| \quad (9)$$

$$P_{DG,LL} \leq P_{DG} \leq P_{DG,UL} \quad (10)$$

Where V_{LL} and V_{UL} Denote the minimum and maximum limits of the bus voltage, respectively. P_{ss}, $P_{T,DG}$, $P_{T,D}$ and $P_{T,loss}$ Respectively indicate sub-station injected power, total power supplied by the DGs, total power demand on the distribution system and the total distribution system losses. $P_{DG,LL}$, P_{DG} and $P_{DG,UL}$ Respectively represent the lower limit of the DG rating, rated power of the DG and upper limit of the DG rating.

4. Many-Objective Optimization Methodology

4.1. Arithmetic Optimization Algorithm

The Many-Objective Arithmetic Optimization Algorithm (MOAOA) [15] represents a recent advancement in the domain of multiobjective optimization derived from the well-known AOA. AOA exhibits the capability to address optimization problems without necessitating the computation of their derivatives. In AOA, two variables, namely Math Optimizer Probability (MOP) and Math Optimizer Accelerated (MOA), are adjusted prior to the position update of the solutions.

$$MOA\ (t) = MIN + t\ \times \left(\frac{MAX-MIN}{t_{MAX}}\right) \tag{11}$$

$$MOP(t) = 1 - \left(\frac{t}{T}\right)^{\frac{1}{\alpha}} \tag{12}$$

Where t, t_{MAX}, MIN, MAX and α, respectively, denote the present iteration, maximum iteration number, minimum limitation value, maximum limitation value and the parameter of sensitivity.

The exploration phase of the AOA aims at exploring the search space in quest of locating the optimal solution. The division and multiplication operators guide this phase. The exploration phase of the AOA is mathematically modelled as:

$$x(t+1) = \begin{cases} BEST(x) \div (MOP(t)+\beta)\ \times Y, & if\ r_2 < 0.5 \\ BEST(x) \times MOP(t)\ \times Y, & otherwise \end{cases} \tag{13}$$

$$Y = (UL - LL) \times \mu + LL \tag{14}$$

Where $x(t+1), BEST(x)$, β, UL, LL, μ and r_2 respectively represent the candidate position at iteration $t+1$, current best position, small integer value, upper limit of the search area, lower limit of the search area, parameter of control and a random number.

4.2. Concept of Pareto Optimality

Pareto optimality facilitates an invaluable framework for handling many conflicting objectives simultaneously. The majority of the many-objective swarm intelligence-based algorithms rely on this concept to generate a Pareto front representing the inherent tradeoffs between the conflicting objectives. Mathematically, Pareto optimality is formulated as follows [13]:

$$minimize\{y_1(p), y_2(p), \dots . y_L(p)\} \tag{15}$$

Such that $p \in P$, where P denotes the array of all feasible solutions and $L \geq 2$. One solution says p_1 dominates other solution p_2, provided the following two conditions are met:

1. $y_i(p_1) \leq y_i(p_2)$ for all objectives $i \in \{1,2,\dots,L\}$ and
2. $y_j(p_1) < y_i(p_2)$ for at least one objective $j \in \{1,2,\dots,L\}$

(16)

If any of the stated conditions are not met, solutions p_1 and p_2 do not share a dominant relationship; instead, they are incorporated into a non-dominant solution frontier commonly known as the Pareto front. The primary goal of any many-objective algorithm is to trace this front effectively. In the proposed methodology, MOAOA is applied to generate the Pareto front. The detailed flowchart of the MOAOA-TOPSIS technique for optimal DG planning is depicted in Figure 1.

4.3. Technique for Order Preference by Similarity to an Ideal Solution

The best tradeoff solution from the Pareto front generated by the MOAOA is selected using the TOPSIS method. The various stages involved in this method in reference [14]:

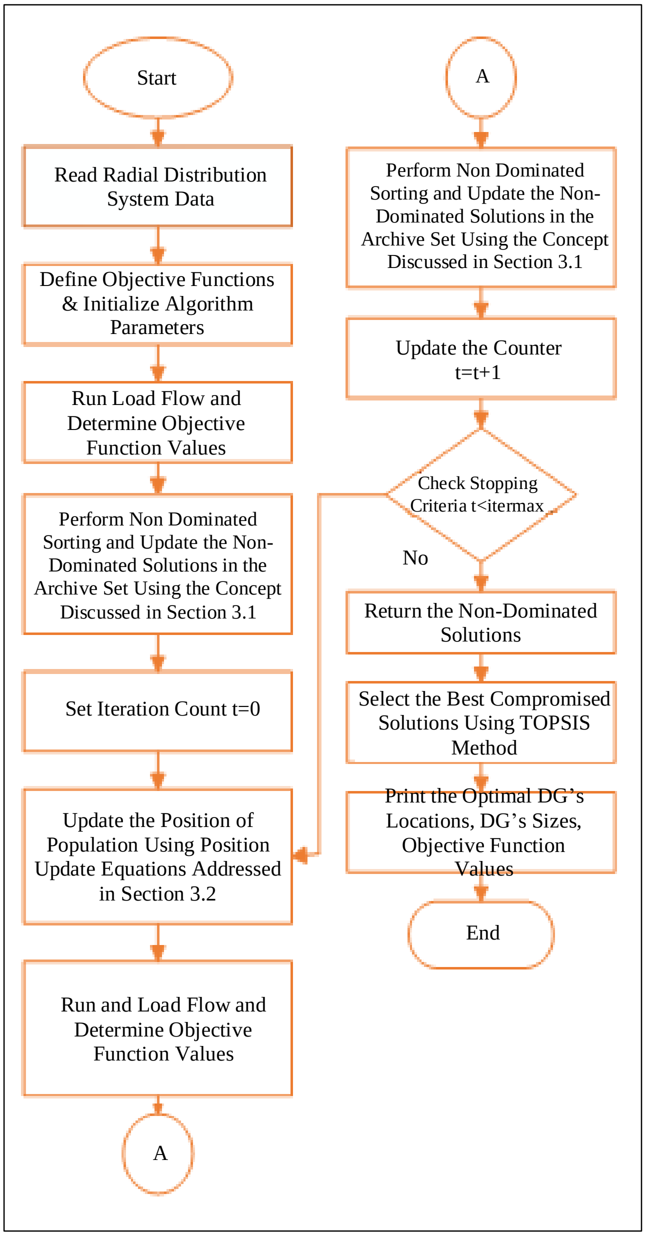

Fig. 1 Flowchart of MOAOA-TOPSIS approach

5. Results and Discussion

This section addresses the improvement of distribution system technical metrics, including energy loss mitigation, total voltage deviation mitigation, voltage stability index maximization, and mitigation of EENS by optimal DG planning utilizing Pareto-based MOAOA & TOPSIS approaches. The IEEE-33 distribution test system is considered in this work. The following scenarios are considered.

- Scenario-0: Without DGs.
- Scenario-1: Optimal Planning of DGs operating with unity power factor. (Type-1 DGs).
- Scenario-2: Optimal Planning of DGs operating with 0.9 power factor. (Type-3 DGs).

In scenario 0, the load flow algorithm is executed on a distribution system that does not have any DGs to get an initial glance at the system's technical metrics. A thorough analysis of the improvement of the above-cited technical metrics resulting from optimal planning (or) deployment of DGs operating at unity power factor in the system is covered in scenario 1.

In scenario 2, the improvement of the above-cited metrics resulting from optimal planning of DG units operating at 0.9 power factor is covered. The optimal Pareto front between the competing objectives is determined using the Pareto-based Many-Objective Arithmetic Optimization Method (MOAOA). TOPSIS method is executed for deciding on the best tradeoff solution from the optimal Pareto front. The outcomes of the TOPSIS-MOAOA algorithm are compared with MOGWO, MOPSO and NSGA-II algorithms.

The weights associated with the objectives $F_1\ (Energy\ loss), F_2\ (EENS), F_2(TVD), F_3(VSI)$ are coined as $w_{EL}, w_{EENS}, w_{vd}, w_{vs}$ in the third step of the TOPSIS method. All of the simulations were made in MATLAB and were run on a PC with 8 GB RAM with an Intel(R) Core (TM) i5-7200U CPU @ 2.50GHz processor. For all algorithms, a population size of 400, an archive size of 200, and a total number of 500 iterations have been taken into account. The remaining control parameters of all algorithms were initialized to the values quoted in [14].

5.1. IEEE-33 Bus System

Figure 2 depicts the single-line diagram of the IEEE 33-bus radial distribution system. The 33-bus system is described in depth in [17]. The system's real and reactive power demands are 3.715 MW & and 2.300 MVAR. Base MVA and kV are 12.66 & 100.

In scenario 0, load flow analysis is executed for the system's initial evaluation in the absence of DGs. The results of the load flow show an energy loss of 1848.2 MWh, a TVD of 0.1338 p.u., VSI of 0.6672 p.u and an EENS of 5.7727*104 kWh/year. The optimal Pareto fronts given by the MOAOA, MOPSO, MOGWO, and NSGA-II algorithms for scenarios 1-2 are portrayed in Figure 3. The results of the TOPSIS-MOAOA method (with equal weightage for scenarios 1-2, including DG locations, DG sizes and system technical metrics are presented in Table 1.

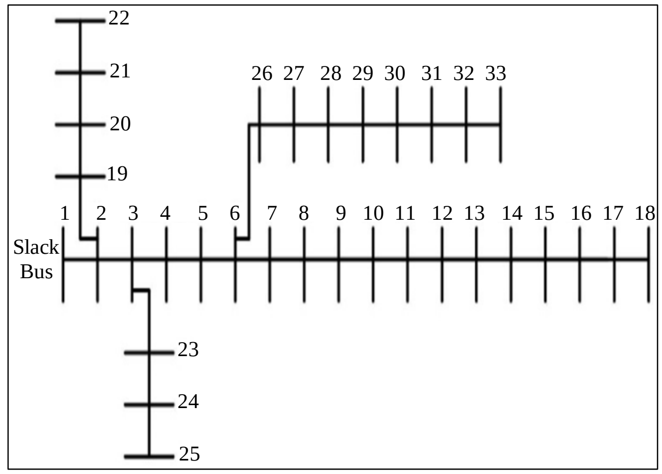

Fig. 2 Single diagram of 33 bus system

The following observations are drawn from the results listed in Table 1 for scenarios 1-2. In scenario-1, due to the connection of DGs operating up at optimal locations 14, 25, and 30 with optimal capacities of 1097 kVA, 820 kVA, and 1583 kVA respectively, network energy loss curtailed to 794.98 kW accounts for 57.03 % loss reduction, EENS is diminished to $4.376*10^4$ kWh/year, TVD is reduced to 0.0012 p.u and VSI is maximized to 0.9595 p.u.

In scenario 2, the optimal connection of DGs operating with 0.9 pf at optimal locations 14, 24, and 30 with optimal capacities of 887 kVA, 1354 kVA, and 1531 kVA in the system results in energy loss mitigated to 173.43 MWh, accounting for 90.64 % loss reduction, EENS mitigated to $4.251*10^4$ kWh/year, TVD mitigated to 0.00029 p.u. and VSI maximized to 0.9768 p.u.

In scenario 2, the system's technical metrics show a better enhancement as a result of the optimal deployment of Type-3 DGs working with 0.9 p.f. Figure 4 shows the voltage profile of the 33-bus system for the outcomes quoted in Table 1. From Figure 4, it has been perceived that the system voltage profile is improved in both scenarios. Better enhancement in the system voltage profile is attained due to optimal deployment of DGs working with 0.9 p.f.

5.2. Comparative Analysis

The comparison of the results produced by the MOAOA algorithm with those of the MOSPSO, MOGWO, and NSGA-II algorithms is shown in Table 2. It is seen that the MOAOA algorithm performs better in all scenarios based on the data given in Table 2.

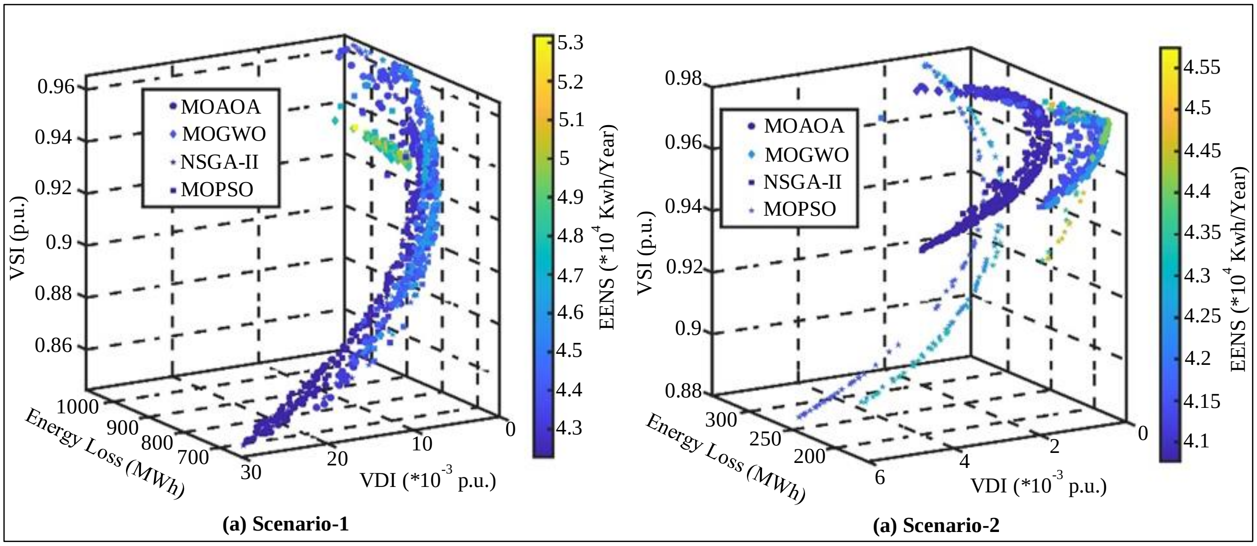

Fig. 3 MOAOA, MOPSO, MOGWO, and NSGA-II algorithms' optimal Pareto fronts for scenarios 1-2 of the 33-bus system

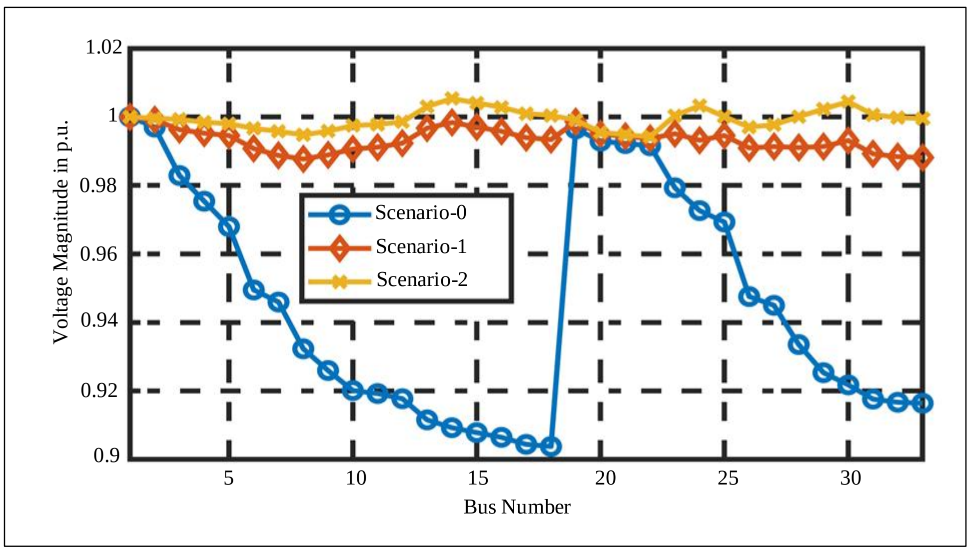

Fig. 4 Voltage profile of IEEE-33 bus system for the outcomes of TOPSIS-MOAOA method (with equal weightage) for scenarios 0-2

Table 1. Outcomes TOPSIS-MOAOA for scenarios 0-2

Technical Metrics	Scenario-0	Scenario-1	Scenario-2
DG loc's/DG Sizes (kVA)	-----------	14/1097, 25/0820 30/1583	14/0887 24/1354 30/1531
E_{loss} in MWh	1848.2	794.98	173.43
TVD in p.u	0.1338	0.00184	0.00029
VSI in p.u	0.6672	0.9517	0.9768
EENS in (*10^4 kWh/year)	5.7727	4.376	4.251
% E_{loss} Reduction	-----------	57.03	90.64
Minimum Voltage in p.u	0.9038	0.9877	0.9942

Table 2. Comparison results of MOAOA, MOPSO, MOGWO & NSGA2

Scenario No	Optimization Technique	DG loc's/DG Sizes (kW)	E_{loss} in MWh	EENS in (*10^4 kWh/year)	TVD in p.u	VSI in p.u
1	**MOAOA**	**14/1097, 25/819 30/1583**	**794.98**	**4.376**	**0.00184**	**0.9517**
	MOPSO	14/1073, 30/1516 25/889	802.74	4.482	0.00240	0.9452
	MOGWO	14/1135, 25/911 31/1432	816.17	4.451	0.00194	0.9484
	NSGA2	13/1177, 25/777 30/1530	796.94	4.549	0.00177	0.9506
2	**MOAOA**	**14/798, 24/1218 30/1377**	**173.43**	**4.2517**	**0.00029**	**0.9768**
	MOPSO	14/823, 24/1206 30/1358	175.82	4.2897	0.00032	0.9745
	MOGWO	13/831, 24/1011 30/1373	179.61	4.4068	0.00026	0.9542
	NSGA2	11/996, 25/924 30/1300	184.70	4.3862	0.00043	0.9664

6. Conclusion

This study uses a novel MOAOA algorithm for optimal distribution system planning of DG problems. It investigates four technical parameters: energy loss reduction, total voltage deviation minimization, enhancement of voltage stability index, and EENS minimization. IEEE-33 bus radial distribution test system is considered. The optimal pareto front is generated using MOAOA, and the best tradeoff solution is selected using the TOPSIS method. The optimal planning of DGs with unity pf results in a 57 % loss reduction in both test systems, and the optimal planning of DGs with 0.9 pf results in a 90 % loss reduction. The optimal planning of Type-3 DGs operating with 0.9 pf results in better enhancement in all the technical metrics. The MOAOA algorithm outperforms the MOPSO, MOGWO, and NSGA2 algorithms in terms of reaching the most effective solution.

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