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Application of Many-Objective Arithmetic Optimization Algorithm and TOPSIS for Optimal Planning of DGS in Distribution Systems

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ABSTRACT- The traditional planning of distribution networks is changing because of the accelerated expansion of distributed generation (DG) technologies in various capacities and forms. However, the improper integration of DGs in current distribution networks can give rise to several technical difficulties despite the advantages provided by distributed generation technologies. This paper presents the optimal DG planning in the distribution system using a Pareto-based many-objective arithmetic optimization algorithm (MOAOA) for optimal DG planning problems in the distribution system. This work focuses on improving four technical metrics related to distribution systems: mitigation of electrical energy not served (EENS), total voltage deviation (TVD) minimization, voltage stability index (VSI) maximization, and energy loss mitigation. Two scenarios are considered: the first scenario primarily focuses on optimal planning of DGs supporting active power only (e.g. Micro-Turbines DGs), and the second scenario focuses on optimal planning of DGs supporting both active and reactive power support (e.g. BIOMASS DGs). The optimal Pareto fronts between the competing objectives are generated using the Pareto-based MOAOA algorithm. The TOPSIS (a technique for order performance by similarity to ideal solution) multi-criteria decision-making technique is utilized for selecting the best trade-off solution from the optimal Pareto front. The posited method is examined on two standard IEEE-69 bus distribution systems. The efficacy of the MOAOA is compared with the outcomes of MOPSO, MOGWO and NSGA-II.

Keywords: Distributed generation (DG), Arithmetic optimization algorithm (AOA), Multi objective Particle swam optimization (MOPSO), Multi Objective Gray Wolf Optimization (MOGWO), Non dominated sorting Genetic Algorithm (NSGA-II), Distribution system, Optimal siting and sizing, stability index (SI).

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1. INTRODUCTION

The significance of efficient distribution system management has grown as a result of the rising demand for electricity and the development of distribution networks. Distributed generators have been integrated as a result, providing reduced network losses, improved voltage profile, reduced environmental pollutants, and increased system reliability. [1]. However, the effectiveness of DG connectivity in distribution networks is primarily dependent on the location and size specifics of the DGs. An improperly planned DG (site and size) could have unfavourable effects. Reverse power flow, instability problems, and an increase in power losses in the distribution network are all associated with DGs that are not planned optimally [2]. As a result, strategically optimizing DG planning within the distribution network is crucial.

Planning for distribution networks (DGs) usually involves optimizing several goals to improve the distribution network's overall performance. Many researchers use nature-inspired metaheuristic optimization algorithms to successfully address the DG planning problem because it is a difficult, many-objective, mixed-integer, non-linear, and non-concave problem. [3]. Multiple DGs are planned in the distribution network [4] considering multiple technical objectives using particle swarm optimization algorithm. The cuckoo search optimization algorithm to address the many-objective DG planning problem was delineated in [5] wherein the objectives encompass the minimization of power loss and the enhancement of voltage profile.

2. LITERATURE REVIEW

In a study outlined in [6], an artificial bee colony algorithm is utilized to minimize real power loss while optimally siting and sizing DG installations. In reference [7], a 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.

Authors in [8], examined how to plan DGs in the distribution network using the butterfly optimization algorithm. An approach to many-objective DG planning is introduced in [9], 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 [10] is applied to find the best location and size of DGs with an objective to minimize losses and total voltage deviation. This study places particular emphasis on incorporating diverse load models into the optimization framework.

Moreover, the literature elucidates that a substantial portion of DG planning investigations overlooks the EENS objective. Despite being documented in select studies [7], 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 [11], [12] similarly omitted consideration for the EENS objective. Recognizing this research gap, our 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. We simultaneously optimize all the four considered objectives using a recently developed Pareto optimality-based many-objective arithmetic optimization algorithm (MOAOA) [13].The best trade-off solution from the Pareto front generated by MOAOA is chosen through technique for order performance by similarity to the ideal solution (TOPSIS) [11].

The contributions of this paper are as follows:

1) In this investigation, addressed four key objectives, incorporating the minimization of EENS through the application of a Pareto-optimality-based approach for DG planning.

2) The planning problem encompasses two distinct types of DGs: Type-1 DGs, exclusively proficient in injecting real power, and Type-2 DGs, endowed with the capacity to provide both active and reactive power.

3) Following the optimization phase, during the decision-making stage, we capitalize on the capabilities of TOPSIS. Multiple combinations of weights are systematically chosen, and the planning outcomes for each weight combination are systematically presented.

4) A noteworthy aspect of this research lies in the pioneering utilization of MOAOA to address the complexities inherent in the DG planning problem with four conflicting objectives.

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 encapsulated in *section 5*.

3. PROBLEM FORMULATION

The proposed multi-objective 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} is taken as one of the minimization objectives of this study. It can be computed by using the below expression:

$$F_1 = E_{loss} = \zeta \times \sum_{j=1}^{nbus-1} I_j^2 R_j \tag{1}$$

Where ζ, I_j, $nbus$ and R_j respectively denote the conversion factor, current served by branch j and resistance of branch j.

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:

$$F_2 = EENS = \sum_{m=1}^{nbus} P_{D,m} U_m \tag{2}$$

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 [14]:

$$\tau_s = \sum_m \tau_m;\ U_s = \sum_m \tau_m r_m; r_s = \frac{U_s}{\tau_s} = \frac{\sum_m \tau_m r_m}{\sum_m \tau_m} \tag{3}$$

where τ_m, U_m and r_m respectively denote 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:

$$F_3 = TVD = \sum_{m=1}^{nbus}(|1 - V_m|)^2 \quad (5)$$

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 loading limit. In order to prevent such undesirable phenomena, utilities strive to maximize the voltage stability index (VSI) of the network. The VSI which is taken as a maximization objective, is shown in below equation [15]:

$$F_4 = VSI = \min\,(SI_n);\, n = 2, 3, \ldots\ldots, nbus \quad (6)$$

(Stability index) $SI_n = |V_m|^4 - 4[P_m X_{mn} - Q_m R_{mn}]^2 - 4[P_m R_{mn} + Q_m X_{mn}]|V_m|^2$ (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 branch 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 lower and upper 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 arithmetic optimization algorithm (AOA) [13] represents a recent advancement in the domain of metaheuristic optimization algorithm. 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 position update of the solutions.

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

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

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. This phase is guided by the division and multiplication operators. The exploration phase of the AOA is mathematically modelled as:

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

$$Y = (UL - LL) \times \mu + LL \quad (14)$$

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.

The exploitation stage of the AOA aims at refining the obtained solutions by performing deep search. This phase is guided by subtraction and addition operations. The exploitation phase of the AOA is mathematically modelled as:

$$x(t+1) = \begin{cases} BEST(x) - MOP(t) + Y, & if\ r_3 < 0.5 \\ BEST(x) + MOP(t) + Y, & otherwise \end{cases} \quad (15)$$

where r_3 denotes 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 trade-offs between the conflicting objectives. Mathematically, Pareto optimality is formulated as follows:

$$minimize\ \{y_1(p), y_2(p), \ldots.\, y_L(p)\} \quad (16)$$

such that $p \in P$, where P denotes the array of all feasible solutions and $L \geq 2$. One solution say p_1 dominates other solution p_2, provided the following two conditions are met [11]:

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 in one objective $j \in \{1,2,\dots,L\}$ (17)

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 effectively trace this front. In the proposed methodology, Many Objective arithmetic optimization algorithm (MOAOA) is applied to generate the Pareto front, and TOPSIS is applied to identify the best trade-off solution from the Pareto front.

4.3 Technique for order preference by similarity to ideal solution

The best trade-off solution from the Pareto front generated by the MOAOA is selected using TOPSIS method. The various stages involved in this method are in [11]:

Stage I: In this stage, the decision matrix $X = (x_{ai})$ of the order $n_1 \times n_2$ is framed where $a = 1,2,\dots,n_1$ denotes the alternatives and $i = 1,2,\dots,n_2$ denotes the objectives.

Stage II: Transform the decision matrix into a normalized form to ensure all criteria are on the same scale. Each element (n_{ai}) of the normalized matrix is obtained as follows:

$$n_{ai} = \frac{x_{ai}}{\sqrt{\sum_{a=1}^{n} x_{ai}^2}} \quad (18)$$

Stage III: Introduce weights for each criterion to reflect their relative importance. Multiply each normalized value by the corresponding weight (w_i).

$$u_{ai} = w_i \times n_{ai} \quad (19)$$

Stage IV: Determine the positive-ideal solution (PIS) and negative-ideal solutions (NIS) by selecting the maximum and minimum values for each criterion, respectively.

$$PIS = \begin{cases} max\ (w_{ai})\ \forall\ a, for\ the\ benfit\ criterion \\ min\ (u_{ai})\ \forall\ a, for\ the\ cost\ criterion \end{cases} \quad (20)$$

$$NIS = \begin{cases} min\ (w_{ai})\ \forall\ a, for\ the\ benfit\ criterion \\ max\ (w_{ai})\ \forall\ a, for\ the\ cost\ criterion \end{cases} \quad (21)$$

Stage V: Calculate the Euclidean distance $(Ed_a^+$ and $Ed_a^-)$ of each alternative from the ideal and negative-ideal solutions.

$$Ed_a^+ = \sqrt{\sum_{a=1}^{n_1}(w_{ai} - PIS)^2} \quad (22)$$

$$Ed_a^- = \sqrt{\sum_{a=1}^{n_1}(w_{ai} - NIS)^2} \quad (23)$$

Stage VI: Determine the relative closeness of each alternative to the ideal solution by the ratio of the negative-ideal distance to the sum of the ideal and negative-ideal distances.

$$CR = \frac{Ed_a^-}{Ed_a^+ + Ed_a^-} \quad (24)$$

The detailed flowchart of MOAOA-TOPSIS technique for optimal DG planning is depicted in *figure 1*.

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-69 bus distribution test systems are 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).

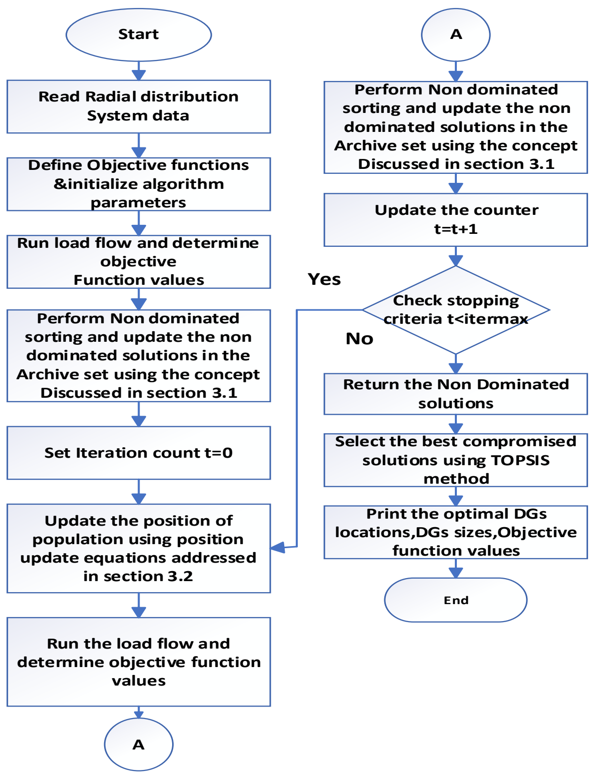

Figure 1. Flowchart of MOAOA-TOPSIS approach

In scenario-0, the load flow algorithm is executed on a distribution system that doesn't 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.

5.1 IEEE-69 bus system

Figure 2 depicts the single-line diagram of the 69-bus radial distribution system [8]. The system's real and reactive power demands are 3.801 MW and 2.693 MVAR. Base MVA and kV are 12.66 and 100, respectively.

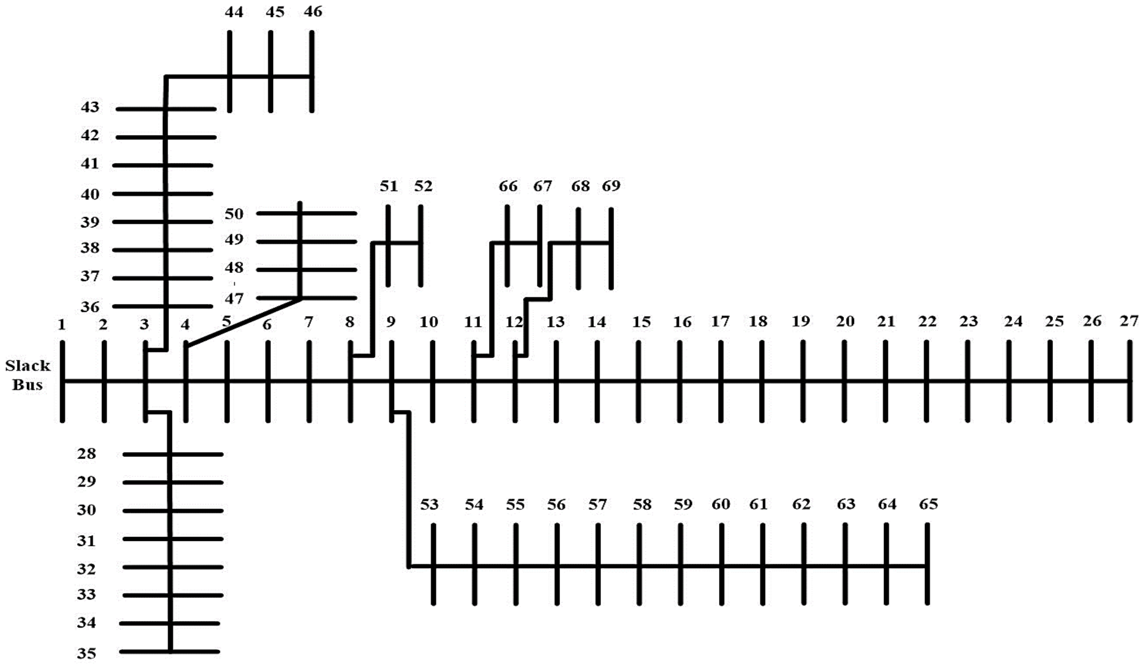

Figure 2. Single diagram of 69 bus system

In *scenario 1*, load flow analysis is carried out for the system's initial evaluation in the absence of DGs. The results of the load flow show an energy loss of 1970 MWh, a TVD of 0.0992 p.u., VSI of 0.6833 p.u. and an EENS of $8.4191*10^4$ kWh/year. The optimal Pareto fronts given by the MOAOA, MOPSO, MOGWO, and NSGA-II algorithms for scenarios 1-2 of the 69-bus system are portrayed in *figure 3*.

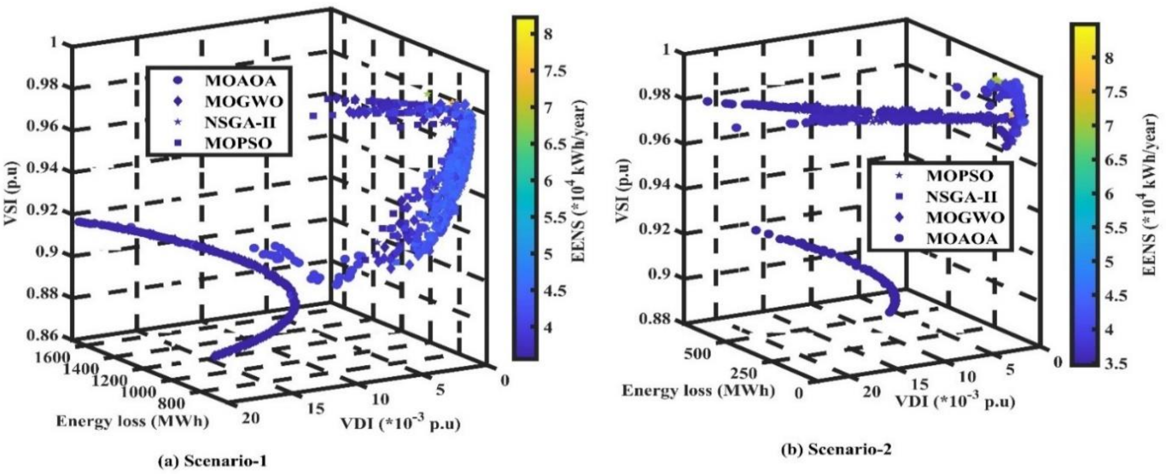

Figure 3. MOAOA, MOPSO, MOGWO, and NSGA-II algorithms' optimal Pareto fronts for scenarios 1-2 of the 69-bus system

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Table 1 presents the results of the TOPSIS-MOAOA method (with equal weightage ($w_{EL}, w_{EENS}, w_{vd}, w_{vs}$ =1/4)) for scenarios 1-2, including DG locations, DG sizes and system technical metrics. The following observations are drawn from the results listed in Table 1 for scenarios 1-2.

Table 1. Outcomes of 69 bus system for scenarios 0-2

Technical Metrics	Scenario-0	Scenario-1	Scenario-2
DG loc's/DG Sizes (kVA)	-----------	12/0418 21/0675 61/2164	16/0688 50/1041 61/2141
E_{loss} in MWh	1970	675.31	91.15
TVD in p.u	0.0992	0.000568	0.00022
VSI in p.u	0.6833	0.9763	0.9831
EENS in (*10^4 kWh/year)	8.4191	4.0492	3.9356
% E_{loss} reduction	-----------	65.74	95.38
Minimum Voltage in p.u	0.9092	0.994	0.9958

In scenario-1, due to the connection of DGs operating with upf at optimal locations 12, 21, 61 with optimal capacities of 481 kVA, 675 kVA, and 2164 kVA respectively, system energy loss curtailed to 675.31 MWh accounts for 65.74 % loss reduction, EENS is diminished to 4.0492*104 kWh/year, TVD is reduced to 0.0000568 p. u and VSI is maximized to 0.9763 p.u. In scenario 2, the optimal connection of DGs operating with 0.9 pf at optimal locations 16, 50, and 61 with optimal capacities of 688 kVA, 1041 kVA, and 2141 kVA in the system results in energy loss mitigated to 91.15 MWh, accounting for 90.64 % loss reduction, EENS mitigated to 3.93*104 kWh/year, TVD mitigated to 0.00022 p.u. and VSI maximized to 0.9831 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. *Fig 4* depicts the voltage profile of the 69-bus system for the outcomes quoted in *table 1*. From *figure 4,* it has been noted that the system voltage profile is improved in both scenarios, and better enhancement in the system voltage profile is attained due to optimal deployment of DGs working with 0.9 p.f.

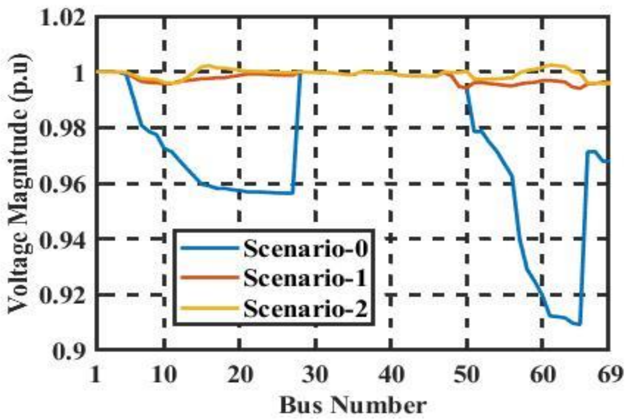

Figure 4. Voltage profile of IEEE-69 bus system for the outcomes of TOPSIS-MOAOA method (with equal weightage) for scenarios 0-2

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 for 69-bus system based on the data given in Table 1. Further evidence of the MOAOA algorithm's superiority over the MOSPO, MOGWO, and NSGA2 algorithms comes from the Pareto fronts shown in *figure 3*.

Table 2. Comparison results of MOAOA, MOPSO, MOGWO & NSGA2 for 69 bus system

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**	**12/418, 21/472 61/2164**	**675.310**	**4.04**	**0.00056**	**0.9763**
	MOPSO	18/627, 61/2079 64/200	705.240	4.10	0.00087	0.9638
	MOGWO	11/692, 21/446 61/2196	695.480	4.07	0.00063	0.9742
	NSGA2	18/700, 61/1678 64/484	685.031	4.12	0.00088	0.9727
2	**MOAOA**	**16/620, 50/937 61/1927**	**91.154**	**3.93**	**0.00022**	**0.9831**
	MOPSO	21/578, 50/890 61/1860	95.590	3.98	0.00043	0.9778
	MOGWO	21/578, 50/668 61/1863	95.616	4.06	0.00043	0.9780
	NSGA2	21/561, 50/803 61/1916	94.207	4.12	0.00036	0.9781

6. CONCLUSION

The study introduces a novel MOAOA algorithm for optimizing four technical parameters in a distribution system: energy loss reduction, total voltage deviation minimization, voltage stability index maximization, and EENS minimization. IEEE-69 bus radial distribution test systems were tested, with optimal planning for DGs with unity power factor and 0.9 pf. The optimal planning of DGs with unity pf results in (57-65) % loss reduction in both test systems, and optimal planning of DGs with 0.9 pf results in (90-95) % 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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