Engineering and Applied Science Research
https://www.tci-thaijo.org/index.php/easr/index
Published by the Faculty of Engineering, Khon Kaen University, Thailand

An improved MOPSO technique based optimal location and size of DGs in distribution power grids considering true multi-objectives

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Received 17 February 2023
Revised 25 July 2023
Accepted 4 August 2023

Abstract

Distribution grids have received a lot of attention lately because of the increase in load demand. Promoting the widespread use of distributed generation (DG) is a strategy to meet the growing demand for energy. To achieve the best technical, economic, commercial, and regulatory objectives, DG planning must consider the optimal location and size of DGs. In this research, multi-objective particle swarm optimization (MOPSO) is improved and proposed to find the optimal location and size of DGs subject to equality and inequality constraints during power flow analysis using the Newton-Raphson method. It is a multi-objective optimization problem where properly installing DGs should simultaneously reduce total active power loss, total annual economic loss, and voltage profile improvement. The Pareto set represents the optimal solutions to multi-objective optimization problems. The clustering-based Pareto front reduction process is applied to reduce the size of the Pareto set by grouping similar solutions together, which can provide a diverse and compact subset of the Pareto set. Furthermore, fuzzy set theory is employed to select the best compromised solution from the Pareto optimal set based on decision preferences. The proposed algorithm is validated on IEEE 33 and IEEE 69 bus radial distribution systems to ensure its effectiveness and robustness by comparing its performance with other nature-inspired heuristic-based algorithms in terms of the aforementioned objectives. Detailed comparisons show that the proposed technique can determine the locations and sizes of DG units more effectively than other methods. The study is performed by MATLAB M-Files.

Keywords: Multi-objective optimization, MOPSO, Distributed generation, Active power loss, Annual economic loss, Voltage profile

1. Introduction

The electricity distribution companies have challenges because of the competitiveness of the electricity markets and the growth of electrical load demand. However, increasing the distribution system's capacity might not be a cost-effective solution. To overcome these challenges, distribution companies implement proper system planning and design. The feasible solution to the challenge of increasing power demand is distributed generation (DG), which is also an attractive choice for rural areas. DG can be off-grid connected locally to an isolated consumer or on-grid integrated into the main grid, benefiting both utilities and consumers. DGs are typically located close to the load they serve, such as residential, commercial, or industrial facilities, in contrast to centralized power plants that are located far away from the consumers. Additionally, DG investments may help create a competitive electricity market [1].

DGs are offering several advantages in terms of flexibility, efficiency, and reliability. The key features and benefits of DGs are: DGs allow for decentralized power generation, reducing the reliance on large, centralized power plants. This decentralization helps to improve the overall reliability and stability of the electrical grid by reducing transmission losses and enhancing voltage stability. DGs can improve power quality by reducing voltage sags, voltage flicker, and other power disturbances. They can quickly respond to changes in load demand and help maintain stable voltage levels within acceptable limits. DGs located near the load centers reduce transmission and distribution losses associated with long-distance power transmission from centralized power plants. This localized generation improves the overall energy efficiency of the electrical system. DGs often utilize renewable energy sources (RES) such as solar photovoltaic (PV) panels, wind turbines (WT), fuel cells, or small-scale hydroelectric generators. Integrating DGs with RES helps reduce greenhouse gas emissions and promote the use of clean and sustainable energy. DGs can serve as backup power sources during grid outages or emergencies, ensuring continuous power supply to critical facilities like hospitals, data centers, or telecommunications infrastructure. This backup capability enhances the resilience and reliability of the electrical grid. DGs can be integrated with demand response programs, allowing them to adjust their output based on grid conditions or price signals. This enables better demand management and load balancing, contributing to the stability of the electrical grid. Overall, DGs play a crucial role in creating a smart grid and improving the efficiency, reliability, and sustainability of electrical power systems by providing localized generation and integrating RES [2, 3]. The technology of DG introduces several services to electric distribution companies for environmental, economic, and technical reasons. DG power systems based on RES may handle environmental concerns, energy emergencies, and mitigate the shortcomings of a single RES by making the greatest use of each individual energy source. The primary drawbacks of RES, such as WT and PV, are their discontinuity in energy generation. The traditional distribution system only allowed electricity to

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doi: 10.14456/easr.2023.42

flow in one direction. However, when DG was introduced into the system in an uncontrolled manner, a reverse power flow was created, which negatively affected the quality of the electrical system by increasing the voltage rating of important buses, causing power losses, and even causing a blackout. Most current research has focused on these concerns, which need to be addressed [4].

Proper placement and size of DGs must be provided for the DG units to achieve the required performance in DG resources, reduce power losses, increase reliability, improve the voltage profile, and the improve power quality characteristics of the power grid [5]. Distributed generators can be categorized according to the type of power delivered to the power grid as DGs supplying only active power, such as PVDG systems; only reactive power, such as synchronous compensators and capacitors; reactive and active power, such as DGs based on synchronous machines; and active power that absorbs reactive power, like DG systems of wind turbines [6].

Planning and designing the DG injection into the distribution grid is not a simple plug-and-play step. However, a robust model is needed to support the power grid operator and decision-maker in determining the optimal location, type, and size of the DG units. Several studies have shown that one of two strategies can be used to allocate and size a DG in the main distribution grid. The first was a typical approach based mainly on optimal power flow, sensitivity index, and repetitive load flows. While the second solution used artificial intelligence (AI) methods to choose the best location and size for the DG, interest in using optimization techniques to balance competing goals by minimizing obstacles and maximizing benefits has grown [7].

An improved sunflower optimization algorithm was presented in [8] to create the optimal position and size of DG in the grid to minimize power losses. For optimal placement and sizing of different types of DG units, a genetic algorithm (GA) technique was proposed to reduce active power losses while improving voltage profiles [9]. Additionally, GA is proposed for the power management of a grid integrated hybrid DG system [10]. The authors [11] studied several optimization algorithms to determine the optimal size of DG units in a power distribution system. These algorithms have been tested on standard test systems. In a different study, GA was combined with an analytical approach to locate DGs for reducing losses in the grid [12]. To solve the problem of optimal placement of DG while dealing with a time-varying load, a novel approach based on dynamic programming was proposed. The clonal differential evolution algorithm was proposed for the best size and placement of DG, considering cost reduction elements and uncertainties [13]. The comprehensive teaching and learning-based optimization techniques were created to decrease annual energy waste and investment costs in the networks [14]. The best DG placements using various approaches were compared in the analysis [15]. The optimal distribution generation placement (ODGP) problem was addressed in [16] using the invasive weed optimization method. The issues of the best size, location, and type of DGs in power grids were addressed in [17] using a novel mixed-integer linear programming (MILP) approach. The authors employed the particle swarm optimization (PSO) approach to finding the best design for a PV system on the grid, considering reducing power losses and improving the voltage profile [18]. The binary PSO technique was utilized to find the best location and capacity for various DG types. This technique was primarily used to reconfigure the test networks in the best possible way, considering several objectives [19]. In [20], a method based on probabilistic load flow and GA was introduced to find the optimum DG location while considering photovoltaic output power, wind power production, fuel costs, and future load growth. The discrete PSO was proposed in [21] to determine the best capacity and position of DGs.

A hybrid technique based on a fuzzy and one-rank cuckoo search algorithm was introduced as a novel method to find the best placements and capacities of DG units in power systems to minimize total active power losses and improve voltage profiles [22]. The best trade-off solution among Pareto's set of outcomes of the Pareto optimality technique has been chosen in [23] to address the problem of DG unit allocation and sizing in the radial distribution systems. Hybrid techniques combining two evolutionary algorithms, such as GA with PSO [24], GA with graph theory [25], and GA with tabu search [26], have been proposed to determine the best placement of DGs. A hybrid optimization strategy based on the gray wolf optimizer (GWO) algorithm with a loss sensitivity factor was suggested, in order to increase voltage stability and reduce overall power loss in the IEEE 33-bus radial distribution system [27]. Elephant herding optimization (EHO) with PSO was utilized to address the multi-objective DG placement problems of three distribution networks. The formulation of a multi-objective DG allocation issue enhances the performance of distribution systems, the objective functions considered include minimization of power loss, decrease of voltage variation, and improvement of voltage stability [28].

Numerous optimization techniques have been proposed in the literature to solve optimization problems with multiple objectives, such as the multi-objective wind driven optimization (MOWDO) algorithm [5], the improved decomposition based evolutionary algorithm (I-DBEA) [29], the multi-objective-opposition-based chaotic differential evolution (MOCDE) algorithm [30], the improved multi-objective harris hawks optimization (MOIHHO) algorithm [31], and the multi-objective artificial electric field algorithm (MOAEFA) [32] to find the optimal position and size of DGs with different objectives and constraints. The multi-objective Whale optimization (MOWOA) algorithm was proposed to determine the optimal placement and size of DGs to reduce active power loss as well as economic loss [33, 34]. In [35], the authors suggested multi-objective Ant-Lion optimization (MALO) to find the best location and capacity for Distributed Energy Resources (DERs). Ant lion optimization (ALO) and multiverse optimization (MVO) were introduced in [36] for implementing DG and resolving the distribution system planning problem to enhance techno-economic and environmental characteristics while meeting the limitations of the system. The improved coyote optimization algorithm (ECOA) was suggested in [37] to find the optimal position and capacity of DGs in radial distribution networks. It is a multi-objective optimization issue where correctly installed DGs should simultaneously decrease power loss and operational expenses as well as increase voltage stability. To solve the multi-objective DG allocation problem, a novel metaheuristic algorithm, namely, multi-objective chaotic symbiotic organism search (MOCSOS), was proposed in [38]. MOCSOS was used to decide the optimal locations and sizes of DGs in a radial distribution system. This task was associated with the minimization of total voltage deviation and power loss and the maximization of the voltage stability index of the radial distribution system (RDS). A multi-objective PV planning model based on the multi-attribution decision-making theory (MADMT) approach and game theory was developed. In the operation of a distribution network, active power losses, voltage deviation, voltage harmonic distortion, and the static voltage steady index were taken into consideration and analyzed [39]. Single- and multi-objective optimization for PVDG implementation in the probabilistic power flow (PPF) algorithm was proposed in [40].

Other soft computing methods, such as the stud krill herd algorithm [41], the artificial gorilla troops optimizer (GTO) [42], the teaching-learning based optimization (TLBO) [43], the salp swarm optimization algorithm (SSA) [44], the ant colony algorithm (ACA) [45], the modified elephant herding optimization (EHO) [28], and other methods, have been successfully used by researchers to specify the optimal location of DG units.

In the last decade, Researchers have applied different nature-inspired heuristic-based methods to optimally allocate DGs in RDS. In the literature, nearly all studies have considered power loss as an objective to minimize. Some other objective functions that have been introduced are cost minimization, voltage deviation minimization, elimination of greenhouse gas emissions, profit maximization, system reliability, etc. At the same time, these objective functions are contradictory. Consequently, the problem of DG allocation in RDS becomes a complex multi-objective optimization (MOO) problem since it is quite difficult to optimize several contradictory objectives simultaneously. Thus, most studies typically transform the weighted sum of the objectives in the MOO formulation to a single objective; the challenge is to determine a precise weight for each objective function. Finding this weight might be difficult, particularly if you don't know much about the subject. However, there is another method for resolving MOO problems that optimizes all of the objective functions at once. This method produces a Pareto set of the non-dominated solutions. The Pareto approach is better suited for the DG allocation problem under consideration than the traditional weighted sum approach because, with the Pareto approach, the trade-off non-dominated solutions can be found in a single run rather than multiple runs by varying the weights (typically in steps) [38].

It may be observed from the literature survey that only some works are available that have utilized the Pareto-based multi-objective optimization methods as compared with the conventional weighted sum method. Furthermore, the best compromised solution of the Pareto set has been selected in a few of these studies.

This study proposes an enhanced MOPSO algorithm with a Pareto set and clustering technique-based framework to identify the best locations and capacities of PVDG units in terms of reducing total active power loss, total annual economic loss, and improving the voltage profile simultaneously. Additionally, fuzzy set theory is used to select the best compromised solution of the Pareto optimal set. In the proposed technique, the local and global best particles are considered sets rather than individuals, as in standard MOPSO. The size of these two sets plays a critical role in the effectiveness of the approach. The optimum size of these sets can be identified by trial and error. The proposed technique is validated on standard IEEE 33 bus and IEEE 69 bus radial distribution systems. The key contributions of this research are as follows:

1. Formulate a true multi-objective DG allocation problem that can maintain conflicting objectives simultaneously,
2. Enhance MOPSO algorithm to solve the formulated MOO problem simultaneously and effectively,
3. Show the efficacy of the proposed MOPSO over other MOO techniques in solving the problems considered in several scenarios.
4. Indicate the importance of integrating DGs in the power distribution networks: The obtained results of this study show that properly installing the DGs can mitigate power losses, economic losses, and improve the voltage profile while satisfying all considered constraints of the network's structure as well as DGs.

The remaining sections of the paper present the following: the formulation of the problem and the statement of the objective functions of this work are presented in Section 2. The proposed computation procedure using the enhanced MOPSO technique to determine the optimum capacities and locations of DG units in several distribution power systems is introduced in Section 3. Whereas, after analysis and discussion, the simulation results for all the considered systems are reported in Section 4. Finally, Section 5 includes the concluding remarks for the study.

2. Problem statement

The primary goal of optimal multi-objective DG unit locations and capacities is to maximize annual profit while minimizing active power losses and improving the voltage profile, thereby improving system performance and reliability. The cost of the DG units after penetration and losses in the network are the two most important determinants of the total system cost. The annual economic loss without DG represents the energy lost during power distribution, while the annual economic loss with DG represents the annual economic loss due to losses during power distribution during DG's presence as well as the annual additional load from DG integration. The difference between the annual economic loss with and without DG provides an indication of the total annual cost savings achieved through the appropriate penetration of DG. Another important objective, voltage deviation (VD), is intended to provide information about bus voltage requirements when DG is present. The following subsections provide descriptions of each of these objectives:

2.1 Problem objectives

2.1.1 Active power loss

Power losses result from inefficient power delivery and are a waste of resources. These power losses are mainly caused by the radial structure of the distribution networks and the considerable value of the resistance of the conductors. Appropriate location of DG in the grid reduces these power losses, but non-optimum locations can increase power losses in the grid.

Corresponding to the line connecting the two buses i and j in Figure 1, the following equations can be used to calculate the total active power losses in the distribution systems:

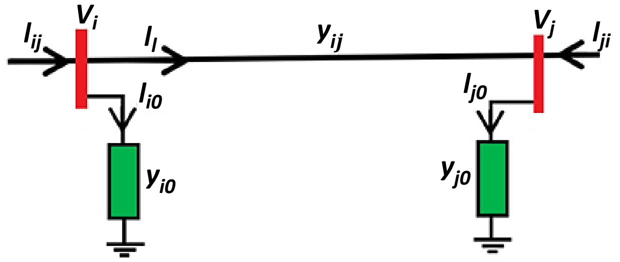

Figure 1 Line model for calculating line flows.

The power loss in line ij can be calculated using the following equations:

$$S_{Loss,ij} = V_i I_{ij}^* + V_j I_{ji}^* \quad (1)$$

$$S_{Loss,ij} = P_{Loss,ij} + jQ_{Loss,ij} \quad (2)$$

where V_i and V_j represent the voltage at buses i and j, respectively. I_{ij} and I_{ji} represent the measured currents at buses i and j, respectively. $P_{Loss,ij}$ represents the active power losses, and $Q_{Loss,ij}$ represents the reactive power losses in line ij.

One of the objective functions is the minimization of the total active power losses (TAPL) of the system, which can be calculated by summing the active power losses of all the branches in the grid, it is expressed as given in the following equation:

$$TAPL = \sum_{k=1}^{N} P_{Loss,ij_k} \quad (3)$$

where N represents the line number in the grid.

It is important to note that in this work, the DG is simply described as a constant active power supply, making it a negative power load model. The load on the bus m should therefore be changed as follows when the DG unit is used:

$$P_m = P_{Load,m} - P_{DG,m} \quad (4)$$

2.1.2 Voltage profile improvement

The voltage quality in the distribution system is now more variable due to the installation of several DG types. The system voltages swell and sag as a result of improper sizing and positioning of the DG units. Therefore, the nominal range of voltage at each bus in the system must be carefully investigated and maintained as per IEEE 1547.

For the performance and reliability of the system, VD is another significant objective. Therefore, even under high-loading conditions, the system with the least VD is the one that performs better. The total VD can be calculated using the following equation:

$$TVD = \sum_{i=1}^{n} |1 - V_i| \quad (5)$$

Where n represents the number of buses in the grid and V_i is the voltage magnitude of the i^{th} bus. The system is operating at its best conditions when the TVD is at its smallest value.

2.1.3 Cost associated with investment

When one or more DG units are installed in the power grid, the TAPL is lower than in a network without DGs. Consequently, the annual economic loss (AEL) is provided without DG can be calculated using the following formula:

$$AEL_{woDG} = P_L^{woDG} * C_e * 8760 \quad (6)$$

Where C_e presents the energy loss cost per kWh in \$, P_L^{woDG} is an utter loss of active power without DG. The AEL with DG (AEL_{wDG}) cost will be

$$AEL_{wDG} = P_L^{wDG} * C_e * 8760 + \frac{C_{DG} \sum_{i=i}^{N_{DG}} P_{DGi}}{L_{DG}} \quad (7)$$

Where N_{DG} is the number of DG units inserted into the systems, P_L^{wDG} presents total active power loss when DG is installed, whereas C_{DG} represents the DG cost per kW generated, including capital expenditures for DG and deployment, operating costs, and costs of maintenance, and L_{DG} is years of the life span of DG, so

$$\text{Annual savings} = AEL_{woDG} - AEL_{wDG} \quad (8)$$

Efficient DG integration can reduce upgrade, operational, and management costs. Thus, the objective function is to minimize the costs associated with investments in the optimal locations and sizes of DG units.

2.2 System constraints

For the suggested problem, the constraints can be summarized as follows.

2.2.1 Power balance

The concept of power balance can be expressed mathematically as:

$$P_{ss} + \sum P_{DG} = \sum P_{loss} + \sum P_{load} \quad (9)$$

$$Q_{ss} + \sum Q_{DG} = \sum Q_{loss} + \sum Q_{load} \quad (10)$$

where P_{ss} and Q_{ss} are the active and reactive power injected into the system. $\sum P_{DG}$ and $\sum Q_{DG}$ are the total active and reactive power of DG units injected into the system. $\sum P_{loss}$ and $\sum Q_{loss}$ are the total active and reactive power losses in the system. $\sum P_{load}$ and $\sum Q_{load}$ are the total active and reactive power of the system load.

2.2.2 Location of DG units

Since bus 1 is a slack bus, the DG location should not be used there.

$$2 \leq DG_{location} \leq n_{buses} \tag{11}$$

2.2.3 Voltage profile

The bus voltage magnitude must meet the following constraints to maintain power quality:

$$V_{min} \leq V_i \leq V_{max} \tag{12}$$

2.2.4 Distributed generation boundary condition

The active power of DG units is restricted, thus satisfying the following constraint:

$$P_{DG}^{min} \leq P_{DG} \leq P_{DG}^{max} \tag{13}$$

2.2.5 Line capacity limit

The loading on each conductor must not be greater than the designated rating.

$$S_{line} \leq S_{rated} \tag{14}$$

2.3 Formulation of multi-objective optimization problem

The multi-objective optimization problem can be formulated mathematically as a non-linear limited problem as follows:

$$\textit{Minimize}\ [TAPL,\ TVD,\ AEL_{wDG}] \tag{15}$$

$$\textit{Subject to}\ g(x,u) = 0\ \ \textit{and}\ h(x,u) \leq 0 \tag{16}$$

where:

- *x*: represents the dependent variables vector, including real power generated on the slack bus, load bus voltages (V_L), generator reactive power outputs (Q_G), and loading on transmission line S_l. thus, *x* can be expressed as a $x^T = [P_{G_1}, V_{L_1} \dots V_{L_{NL}}, Q_{G_1} \dots Q_{G_{NG}}, S_{l_1} \dots S_{l_{Nb}}]$
- *u*: represents the control variables vector, including locations (L_{DG}) and sizes (S_{DG}) of installed DGs in the system. So, *u* can be expressed as $u^T = [L_{DG} \dots L_{DG}, S_{DG} \dots S_{DG}]$
- *g:* represents the equality constraints.
- *h*: represents the inequality constraint.

In a minimization problem, such as the problem under discussion, a solution x^1 dominates a solution x^2 if and only if:

$$1. \forall i \in \{1, 2, \dots, N_{obj}\}: f_i(x^1) \leq f_i(x^2) \tag{17}$$

$$2. \exists j \in \{1, 2, \dots, N_{obj}\}: f_j(x^1) < f_j(x^2) \tag{18}$$

The non-dominated solution is the one that satisfies the above criteria. Furthermore, the Pareto optimum set, or front, or simply Pareto set, is the collection of all non-dominated solutions.

3. The upgraded approach

3.1 Overview

The MOPSO technique is enhanced and used to identify the optimum sizes and locations of DG units, treating the total active power losses, total voltage deviation, and annual economic loss as objective functions. The MOPSO algorithm is applied to construct a Pareto set. In some cases, the size of Pareto sets can be so large that managing the set is extremely difficult. Therefore, a clustering technique is used to control the size of the optimal Pareto set [46]. On the other hand, the minimal objective values for all objective functions cannot be chosen simultaneously for a given solution in multi-objective optimization problems. Therefore, the best solution is the compromised solution. Fuzzy set theory is used to find the best compromised solution since one is only interested in one solution for decision making and practical reasons [47, 48].

3.2 MOPSO technique

PSO is a subset of artificial intelligence. This algorithm's idea is based on observations of fish, ants, bees, and birds in their natural habitats. It's a population-based algorithm that takes inspiration from the way birds fly and flocks of fish. The algorithm was developed by Kennedy et al. 1995 [49].

The following steps summarize the operating principle of the MOPSO algorithm, whereas the detailed steps were described in [50-52]:

Step 1: Set the time counter *t*=0 and randomly generate *n* particles,

Step 2: Update the time counter to $t = t+1$.

Step 3: Update the inertia weight, $w(t) = \alpha\, w(t-1)$. Where α is a decrement constant less than but close to 1.

Step 4: Using the global best ($x_{j,k}^{**}$) and individual best ($x_{j,k}^{*}$) of each particle, the j^{th} particle velocity in the k^{th} dimension is updated according to

$$v_{j,k}(t) = w(t)v_{j,k}(t-1) + c_1 r_1\left(x_{j,k}^{*}(t-1) - x_{j,k}(t-1)\right) + c_2 r_2\left(x_{j,k}^{**}(t-1) - x_{j,k}(t-1)\right) \tag{19}$$

Step 5: Based on the updated velocities, each particle changes its position according to

$$x_{j,k}(t) = v_{j,k}(t) + x_{j,k}(t-1) \tag{20}$$

If a particle violates its position limits in any dimension, set its position to the correct limit.

Step 6: The updated position of the j^{th} particle is added to the nondominated local set $Sj^*(t)$. The dominated solutions in $Sj^*(t)$ are truncated, and the set is updated accordingly. When the size of $Sj^*(t)$ exceeds a given value, the clustering algorithm is invoked to reduce the size to its maximum limit.

Step 7: The union of all nondominated local sets is formed, and the nondominated solutions extracted from this union are members of the nondominated global set $S^{**}(t)$. The size of this set is reduced by the clustering algorithm if it exceeds a given value.

Step 8: The external Pareto-optimal set is updated as follows.
Copy the members of $S^{**}(t)$ into the external Pareto set.
1. Search the external Pareto set for nondominated individuals and remove all dominated solutions from the set.
2. If the number of individuals stored externally in the Pareto set exceeds the maximum size, reduce the set by clustering.

Step 9: The individual distances between members in $S_j^*(t)$, and members in $S^{**}(t)$ are measured in objective space. If $X_j^*(t)$ and $X_j^{**}(t)$ are the members of $S_j^*(t)$ and $S^{**}(t)$ that give the minimum distance, they are considered to be the locally best and the globally best of the j^{th} particle selected.

Step 10: If the number of iterations exceeds the maximum preset limit, then stop; Otherwise, go to step 2.

3.3 Reduction of Pareto set by the clustering algorithm

The Pareto set size can grow significantly for some types of problems. By grouping neighboring points or penalizing the most congested points, The Pareto optimal front can be sized down to an acceptable size. The process of removing the busiest places is iterative. Therefore, the Pareto optimal collection is managed using the hierarchical clustering algorithm [53].

3.4 The best compromised solution selection

In this study, the best compromised solution is chosen using fuzzy set theory. This idea states that each Pareto front of the set is first assessed using a linear membership function in the range [0, 1]. The following definition describes the linear membership function for the n^{th} objective of the i^{th} Pareto front [54].

$$\mu_i = \begin{cases} 1 & F_i \le F_i^{\min} \\ \dfrac{F_i^{\max} - F_i}{F_i^{\max} - F_i^{\min}} & F_i^{\min} < F_i < F_i^{\max} \\ 0 & F_i \ge F_i^{\max} \end{cases} \tag{21}$$

The normalized membership function (μ^k) is calculated as

$$\mu^k = \frac{\sum_{i=1}^{N_{obj}} \mu_i^k}{\sum_{k=1}^{M}\sum_{i=1}^{N_{obj}} \mu_i^k} \tag{22}$$

Where M is the Pareto set size. The best compromised solution is the k^{th} member of the Pareto front that gets the highest value of μ^k.

The detailed process of optimizing the size and position of DG units using the proposed MOPSO algorithm in combination with the clustering technique and fuzzy set theory is shown in the flow chart in Figure 2.

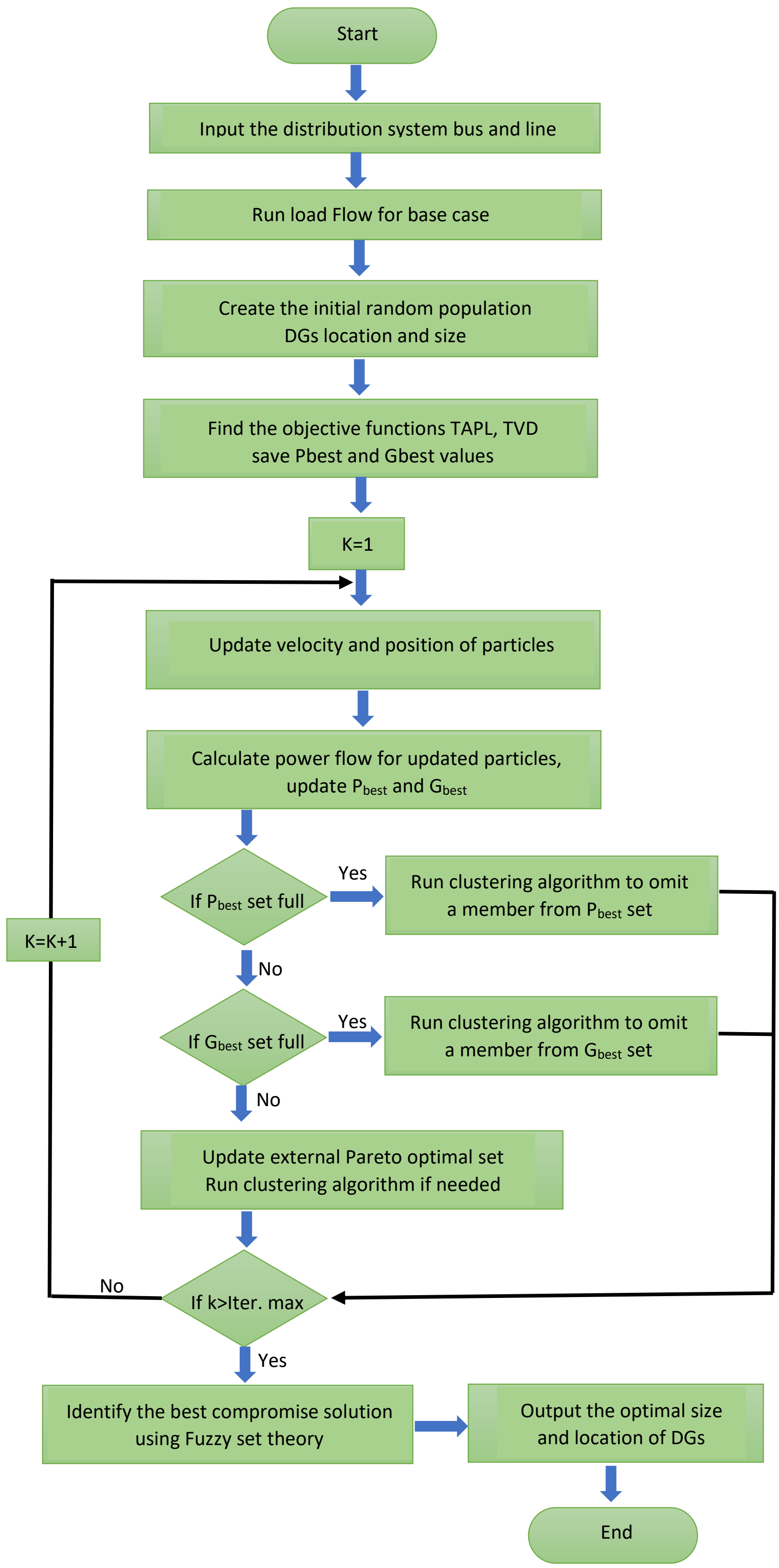

Figure 2 Flowchart of the proposed MOPSO technique.

4. Simulation results and discussions

The standard IEEE 33 and IEEE 69 bus systems are used to test the effectiveness of the proposed technique. In order to achieve greater economic and technical benefits, both test systems have been expanded to include one, two, or three DG units. The lowest and highest DG ratings are assumed to be 10% and 80% of the system load, respectively. A 12.66 kV and 100 MVA are taken as the base values for the calculations. The minimum and maximum values of bus voltage are considered to be 0.95 pu and 1.05 pu, respectively [55].

To illustrate the long-term effects of optimum size and placement of DG units, the planning time for this integrated system is also considered to be 10 years since the overall DG life is expected to be 10 years. DG's fed-in power cost is estimated at $30 per kW as a lump sum, and the cost of energy loss is estimated at $0.05 per kWh [55].

The complexity is increased by simultaneously evaluating two of the TAPL, AEL_{wDG}, and TVD objectives. As a result, this case is broken into two scenarios to explore the effects of altering the relative importance of the two objectives, AEL_{wDG}, and TVD. While the number of DGs is considered to be 3 for comparison with other methods. The clustering theory approach is employed to select only subsets from the Pareto optimal set with less crowded and optimal trade-off solutions. Additionally, the use of the proposed technique should make it possible to compare the results of the ongoing study with other results already published in the relevant literature. To do that, the best compromise solution among the Pareto sets is selected using fuzzy set theory.

4.1 Study system-1: IEEE 33-bus

In this section, the standard IEEE 33 bus distribution system in Figure 3 is considered [18]. The total demand for active and reactive power is 3.72MW and 2.31 Mvar, respectively. Prior to the DG installation, the total active and reactive power of the substation is 3.92 MW and 2.44 Mvar, respectively. The bus number 18 has a minimum voltage of 0.913 pu. While the TAPL is 202.5 kW, and the AELwoDG equivalent is $88,772.6.

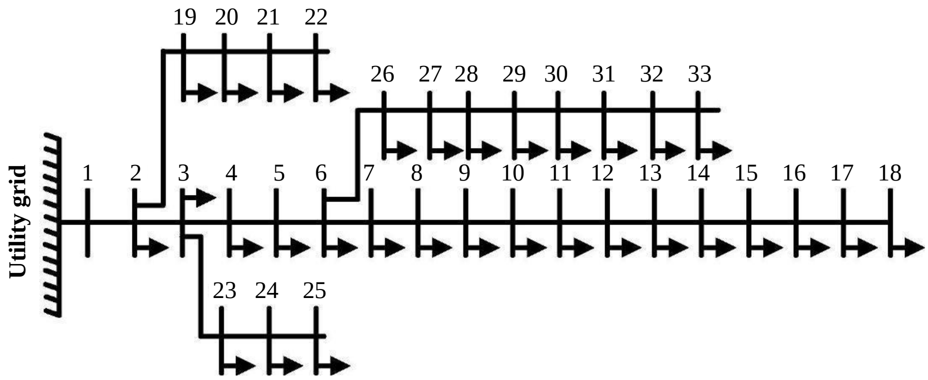

Figure 3 IEEE 33-bus system, source [18].

4.1.1 Minimization of TAPL and TVD simultaneously (Case-I)

In this case, the TAPL and TVD are considered to determine the optimal size and location of 3DG units simultaneously. The obtained simulation results of the proposed method are compared to the existing optimal solutions in the literature and then presented in Table 1. The Table 1 shows the best sites and sizes of DGs, minimum bus voltage magnitude, bus number that has the minimum voltage value, total active power loss, annual economic loss, and total annual savings. The results of the proposed method provide most compromising solution for multi-objective DG integration problem of distribution systems than existing literature methods such as MOCDE, MOWOA, and MALO methods. According to these results, three DGs of 653 kW, 800 kW, and 800 kW can be placed in buses 13, 25, and 30 respectively. The total annual savings for this scenario is $55863, and the lowest bus voltage value is 0.9816 pu on bus 25. However, the proposed method significantly improved the performance of active distribution systems with respect to power loss reduction, annual economic reduction, and bus voltage deviation reduction.

Figure 4 shows the best compromised solution as determined by fuzzy set theory, and also shows the Pareto optimum fronts for the proposed MOPSO approach for specifying the optimal placement and capacity of DGs to decrease power losses and voltage deviations of the 33-bus radial system.

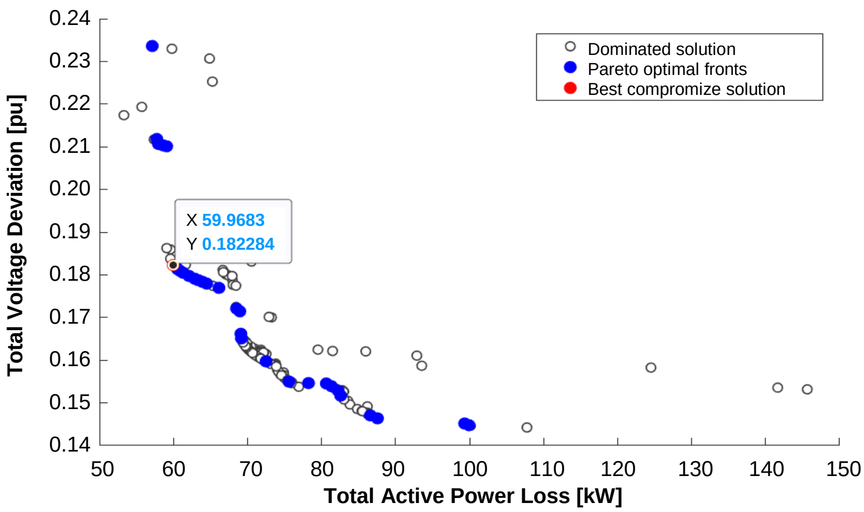

Figure 4 Pareto optimal fronts for case-I

4.1.2 Minimization of TAPL and AEL_{wDG} simultaneously (Case-II)

In this case, TAPL and AEL_{wDG} are considered objectives that must be minimized simultaneously, and three DGs are adopted to be installed on three different nodes in the 33-bus system. The simulation results obtained by the proposed approach and different optimization methods available in the literature such as MOCDE, MOWOA and MALO are shown in Table 1. The results show that the optimal size of three DGs are 685.6 kW, 586 kW, and 621.4 kW, and their positions are bus 16, 29, and 30. The worst bus voltage value for this scenario is 0.98 pu at bus 25, which is now slightly decreased as compared to 0.9816 pu in the previous scenario. While TAPL has decreased from 59.96 kW to 43.19 kW, and the total annual savings have increased from $55863 to $64174.

The best compromised solution of the proposed method, which is chosen by applying fuzzy set theory, along with the selected non-dominated solutions that provide the Pareto optimal fronts, are shown in Figure 5.

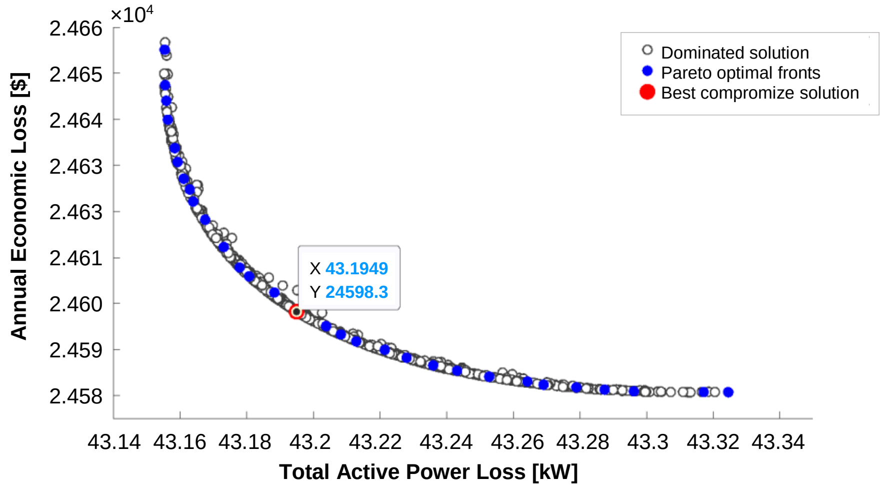

Figure 5 Pareto optimal fronts for case-II

Table 1 Results of 33 bus for multi-objectives

Case	Methods	DG size/location [kW/Bus No.]	Min bus voltage [pu/Weakest bus]	TAPL [kW]	AEL [$]	Total Annual Savings [$]
Base case	-	-	0.913/18	202.5	88,772.6	-
Case-I	Proposed MOPSO	653.9/13 800/25 800/30	0.9816/25	59.96	32,909	55,863
	MOCDE [30]	1074.7/13 1024.4/24 1177.7/33	0.9813/29	79.61	44,700	47,288
	MOWOA [34]	856.7/13 772.5/25 1072.8/30	0.9688/NR	73.75	38,312	50,460
	MALO [35]	992.2/7 983.3/16 1110.3/31	0.9720/11	94.25	50,538	38,233
Case-II	Proposed MOPSO	685.6/16 586/29 621.4/30	0.9800/25	43.19	24,598	64,174
	MOCDE [30]	758.4/14 986.5/24 1032.3/30	0.9671/33	73.08	40,339	51,649
	MOWOA [33]	707.6/25 748.9/14 1015.9/30	0.9653/30	74.45	40,029	52,389
	MALO [36]	864/14 1183/24 1217/30	0.9783/11	70.64	40,732	48,040

The effect of the integration of DG on the bus voltages for the 33-bus system in various scenarios is presented in Figure 6. The figure shows that the optimal deployment of DGs has improved the system node voltage profile significantly as compared to the base case condition. Furthermore, the investigated cases have confirmed that the increasing number of DGs reduces DG penetration in the system.

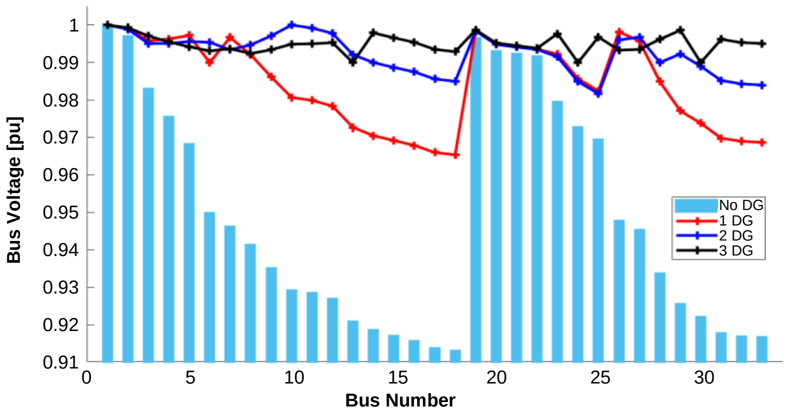

Figure 6 Bus voltage profile with and without DGs for the IEEE 33-bus system.

4.2 Study system-2: IEEE 69-bus

The IEEE-69 bus radial distribution system is considered in this case study, as shown in Figure 7 [18]. For the initial case, the total real and reactive load demands in the system are 3.8 MW and 2.7 Mvar, respectively. Whereas, the TAPL is 225 kW, the AEL_{woDG} is \$98,550, and the minimum bus voltage value is 0.909 pu on bus number 65.

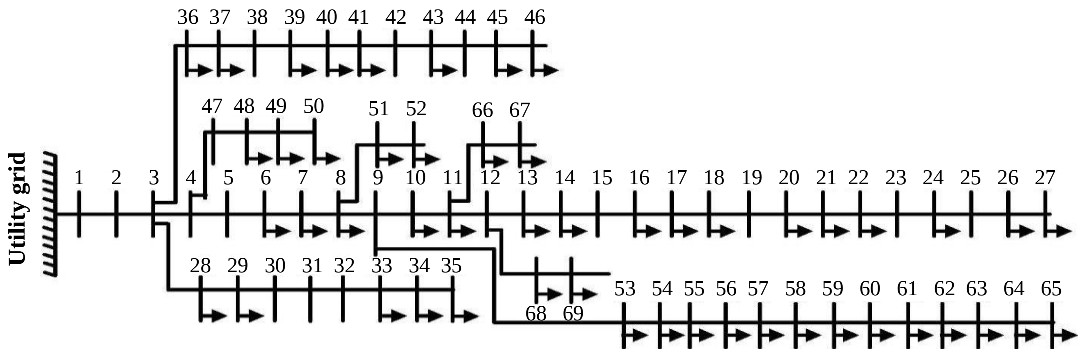

Figure 7 IEEE 69-bus system, source [18].

4.2.1 Minimization of TAPL and TVD simultaneously (Case-I)

In this case, the IEEE 69 bus system is considered to demonstrate the effectiveness of the designated method and compare it with other well-established optimization algorithms in the literature. To minimize TAPL and TVD simultaneously, three DGs have been considered to be installed in the system. Table 2 shows the best site and size of DGs, the minimum bus voltage magnitude, the bus number that has the minimum voltage value, the total active power loss, the annual economic loss, and the total annual savings. From Table 2, it can be seen that the proposed method provides the most cooperative results for the optimal size and location of multiple objectives for the DG allocation problem to the possible injection of DG in contrast to the existing methods in the literature like the MOCDE, MOWOA, and MALO. The proposed method offers higher line loss reduction and voltage deviation than these methods. The results of the best compromise solution to this scenario demonstrate that three DGs of sizes 848.9 kW, 1550.2 kW, and 298 kW, respectively, may be inserted at bus 10, 21, and 61 to simultaneously achieve minimal TAPL and TVD. For this case, the worst bus voltage value in the system is 0.9943 pu at bus number 50, and the overall annual savings come to \$84904. Figure 8 shows the Pareto optimal fronts and the best compromised solution of the proposed approach.

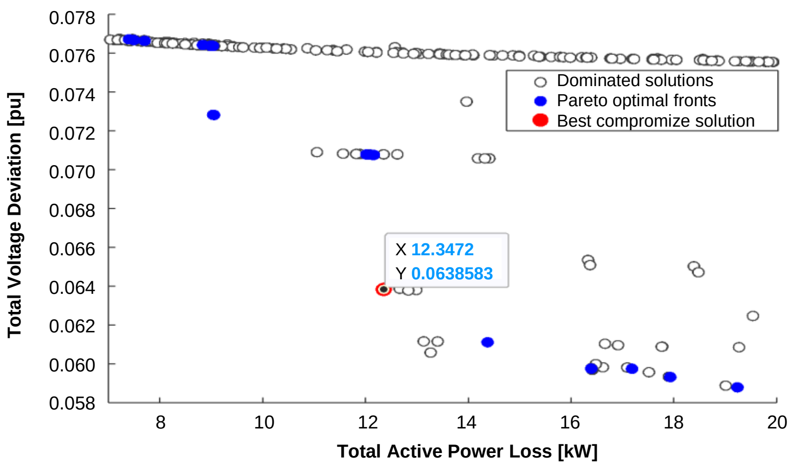

Figure 8 Pareto optimal fronts for minimization of TAPL and TVD

4.2.2 Minimization of TAPL and AEL_{wDG} simultaneously (Case-II)

In the present case, the proposed approach is applied to obtain the best location and capacity of three DGs handling TAPL and AEL_{wDG} as objectives to be minimized simultaneously Table 2 summarizes the simulation results of the proposed MOPSO for the 69-bus standard test system, in which 3 DGs operate simultaneously at different buses associated with present methods in the literature such as the MOCDE, MOWOA, and MALO. The results show that three DGs with capacities of 264.5 kW, 829.7 kW, and 1647.5 kW may be deployed at buses 50, 53, and 61, respectively. When comparing the results of the case-II to those of the case-I, it can be seen that the worst bus voltage value of the case-II is 0.9782 pu at bus 27, which is now slightly lower than 0.9943 pu in the previous case; the TAPL is increased from 12.35 kW to 15.2 kW; and the overall annual saving is reduced from $84904 to $83519.

Figure 9 shows Pareto optimal fronts for minimization of TAPL and AEL_{wDG} and the best compromised solution, which is chosen by applying fuzzy set theory to the Pareto optimal fronts.

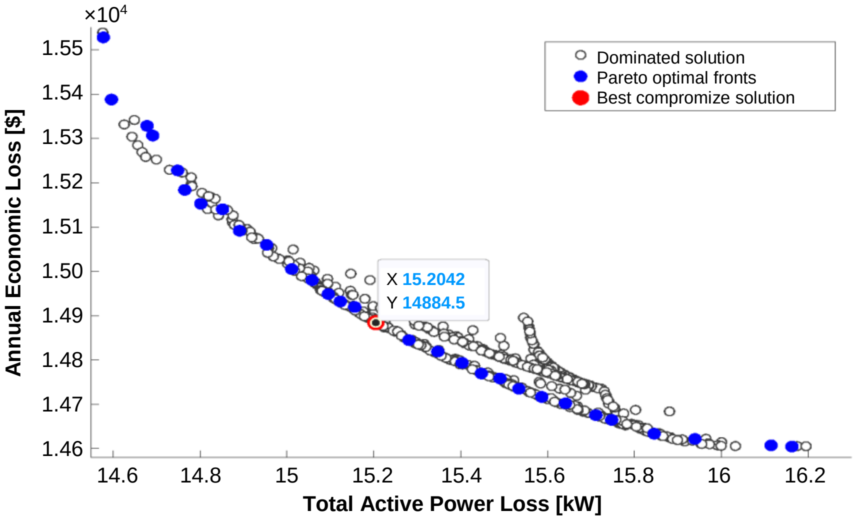

Figure 9 Pareto optimal fronts for minimization of TAPL and AEL_{wDG}

Table 2 Results of IEEE 69-bus system for multi-objectives

Case	Method	DG size/location [kW/Bus No.]	Min bus voltage [pu/Weakest bus]	TAPL [kW]	AEL [$]	Total Annual Saving [$]
Base Case	-	-	0.909/65	225	98,550	-
Case-I	Proposed MOPSO	848.9/10 298/21 1550.2/61	0.9943/50	12.4	13,500	84,904
	MOCDE [30]	661.8/11 439.8/19 2038.9/61	0.9910/65	74.3	41,968	56,551
	MOWOA [34]	489/11 476.5/18 1680.3/61	0.9780/NR*	96.72	50,796	47,754
Case-II	Proposed MOPSO	264.5/50 829.7/53 1647.5/61	0.9782/27	15.2	14,885	83,519
	MOCDE [30]	406.5/12 314.7/21 1707.3/61	0.9775/65	69.8	37,847	60,672
	MOWOA [33]	399.6/18 1726.4/61 462.4/66	0.9790/65	70.5	37,891	60,721
	MOALO [36]	525/11 427/17 1925/61	0.9781/27	68.7	38,721	50,051

*NR: not reported

In Figure 10, the impact of PVDG integration on the voltage profile for several scenarios of the IEEE 69-bus system is shown for comparison. This figure demonstrates that the voltage profile has improved since DGs were installed. While bus number 65 had the lowest voltage level in the initial scenario without DG inserted, the location of bus number 65 is distant from the substation.

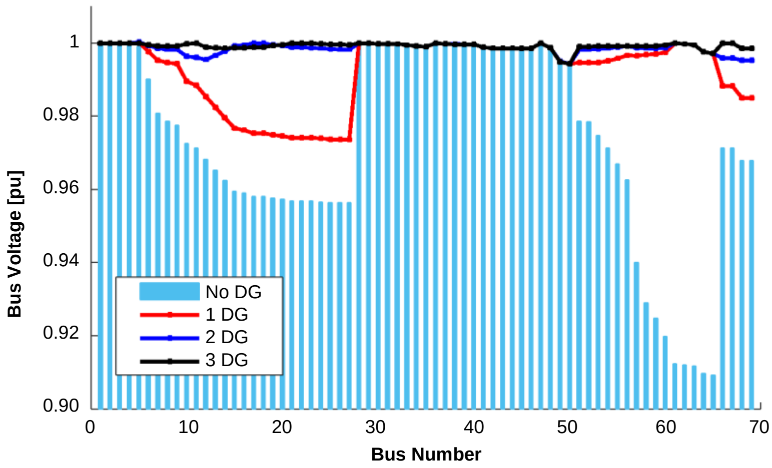

Figure 10 Effect of DGs on bus voltage profile for the IEEE 69-bus system.

5. Conclusions

This study has presented an enhanced MOPSO technique for the optimal location and size of DG units in radial distribution systems, considering real multi-objectives with different conflicting objectives, including the minimization of total active power loss, total annual economic loss, and total voltage deviation. The clustering algorithm is applied to reduce the size of the Pareto set by clustering similar solutions together and then identifying representative solutions from each cluster, which can provide a diverse and compact subset of the Pareto set. Fuzzy set theory has indeed been employed to select the best-compromise solution of a Pareto optimal set, considering the decision preferences of the distribution system operator.

The effectiveness and robustness of the proposed algorithm were successfully validated on IEEE-33 bus and IEEE-69 bus radial distribution systems. By comparing its performance with other nature-inspired heuristic-based algorithms, the results showed that the proposed method provides improved performance with optimal results in all the considered cases and under the constraints imposed. Four specific simulation cases are investigated: case 1 without a DG, case 2 with only one DG, case 3 with two DGs, and case 4 with three DGs. In each case, DGs are integrated into the system simultaneously. The total active power loss and the total annual economic loss are shown to be greatly decreased with improvements in the voltage profile when DG units of optimal sizes are located in optimal positions. Therefore, the installation of PVDG systems can improve the reliability of the distribution network's operation.

In the future, the proposed method will be tried on larger and more complex networks with several types of DGs and many devices already connected to the grid, such as capacitor banks, voltage regulators, switches, and filters. Distributed generators can also be integrated into electronic power converters that control the flow of active and reactive power.

6. Acknowledgements

The author thankfully acknowledges the Palestine Polytechnic University for its valuable support.

7. References

[1] Shaheen AM, Elsayed AM, Ginidi AR, El-Sehiemy RA, Elattar EE. Improved heap-based optimizer for DG allocation in reconfigured radial feeder distribution systems. IEEE Syst J. 2022;16(4):6371-80.
[2] Çelik D, Meral ME. Current control-based power management strategy for distributed power generation system. Control Eng Pract. 2019;82:72-85.
[3] Meral ME, Çelik D. Comparison of SRF/PI- and STRF/PR-based power controllers for grid-tied distributed generation systems. Electr Eng. 2018;100:633-43.
[4] Çelik D, Meral ME. A novel control strategy for grid connected distributed generation system to maximize power delivery capability. Energy. 2019;186:115850.
[5] Alzahrani A, Hafeez G, Ali S, Murawwat S, Khan MI, Rehman K, et al. Multi-objective energy optimization with load and distributed energy source scheduling in the smart power grid. Sustainability. 2023;15(13):9970.
[6] Eltamaly AM, Mohamed YS, El-sayed AHM, Elghaffar ANA. Impact of distributed generation (DG) on the distribution system network. Ann Facul Eng Hunedoara - Int J Eng. 2019;17(1):165-70.
[7] Kumar M, Soomro AM, Uddin W, Kumar L. Optimal multi-objective placement and sizing of distributed generation in distribution system: a comprehensive review. Energies. 2022;15(21):7850.
[8] Nguyen TT. Enhanced sunflower optimization for placement distributed generation in distribution system. Int J Electrical Comput Eng. 2021;11(1):107-13.
[9] Eid A, Kamel S, Korashy A, Khurshaid T. An enhanced artificial ecosystem-based optimization for optimal allocation of multiple distributed generations. IEEE Access. 2020;8:178493-513.
[10] Praveen Kumar T, Subrahmanyam N, Maheswarapu S. Genetic algorithm based power control strategies of a grid integrated hybrid distributed generation system. Technol Econ Smart Grids Sustain Energy. 2021;6(1):1-14.
[11] M'hamdi B, Teguar M, Tahar B. Optimal DG unit placement and sizing in radial distribution network for power loss minimization and voltage stability enhancement. Period Polytech Elec Eng Comp Sci. 2020;64(2):157-69.
[12] Vatani M, Solati Alkaran D, Sanjari MJ, Gharehpetian GB. Multiple distributed generation units allocation in distribution network for loss reduction based on a combination of analytical and genetic algorithm methods. IET Gener Transm Distrib. 2016;10(1):66-72.

[13] Rasid MM, Murata J, Takano H. Fossil fuel cost saving maximization: optimal allocation and sizing of renewable-energy distributed generation units considering uncertainty via clonal differential evolution. Appl Therm Eng. 2017;114:1424-32.
[14] Quadri IA, Bhowmick S, Joshi D. A comprehensive technique for optimal allocation of distributed energy resources in radial distribution systems. Appl Energy. 2018;211:1245-60.
[15] Tarraq A, Elmariami F, Belfqih A, Haidi T, Agouzoul N, Gadal R. Meta-heuristics applied to multiple dg allocation in radial distribution network: a comparative study. 2022 International Conference on Intelligent Systems and Computer Vision (ISCV); 2022 May 18-20; Fez, Morocco. USA: IEEE; 2022. p. 1-8.
[16] Rama Prabha D, Jayabarathi T. Optimal placement and sizing of multiple distributed generating units in distribution networks by invasive weed optimization algorithm. Ain Shams Eng J. 2016;7(2):683-94.
[17] Santos KVd, Higino Silva Santos L, Bañol Arias N, Camilo López J, Rider MJ, da Silva LCP. Optimal sizing and allocation of distributed energy resources in microgrids considering internal network reinforcements. J Control Autom Electr Syst. 2023;34:106-19.
[18] Al-Ammar EA, Farzana K, Waqar A, Aamir M, Saifullah, Haq AU, et al. ABC algorithm based optimal sizing and placement of DGs in distribution networks considering multiple objectives. Ain Shams Eng J. 2021;12(1):697-708.
[19] Essallah S, Khedher A. Optimization of distribution system operation by network reconfiguration and DG integration using MPSO algorithm. Renew Energy Focus. 2020;34:37-46.
[20] Ganguly S, Samajpati D. Distributed generation allocation on radial distribution networks under uncertainties of load and generation using genetic algorithm. IEEE Trans Sustain Energy. 2015;6(3):688-97.
[21] Musa I, Gadoue S, Zahawi B. Integration of distributed generation in power networks considering constraints on discrete size of distributed generation units. Electr Power Compon Syst. 2014;42(9):984-94.
[22] Suresh M, Edward B. Optimal placement of DG units for loss reduction in distribution systems using one rank cuckoo search algorithm. Int J Grid Distrib Comput. 2018;11(1):37-44.
[23] Hamida IB, Salah SB, Msahli F, Mimouni MF. Optimal network reconfiguration and renewable DG integration considering time sequence variation in load and DGs. Renew Energy. 2018;121:66-80.
[24] Mahmoud Pesaran HA, Nazari-Heris M, Mohammadi-Ivatloo B, Seyedi H. A hybrid genetic particle swarm optimization for distributed generation allocation in power distribution networks. Energy. 2020;209:683-94.
[25] Ouyang W, Cheng H, Zhang X, Yao L, Bazargan M. Distribution network planning considering distributed generation by genetic algorithm combined with graph theory. Electr Power Compon Syst. 2010;38(3):325-39.
[26] Gandomkar M, Vakilian M, Ehsan M. A genetic-based tabu search algorithm for optimal DG allocation in distribution networks. Electr Power Compon Syst. 2005;33(12):1351-62.
[27] Kamel S, Awad A, Abdel-Mawgoud H, Jurado F. Optimal DG allocation for enhancing voltage stability and minimizing power loss using hybrid gray wolf optimizer. Turk J Elec Eng Comp Sci. 2019,27(4):2947-61.
[28] Singh P, Meena NK, Bishnoi SK, Singh B, Bhadu M. Hybrid elephant herding and particle swarm optimizations for optimal DG integration in distribution networks. Electr Power Compon Syst. 2020;48(6-7):727-41.
[29] Ali A, Keerio MU, Laghari JA. Optimal site and size of distributed generation allocation in radial distribution network using multi-objective optimization. J Mod Power Syst Clean Energy. 2021;9(2):404-15.
[30] Kumar S, Mandal KK, Chakraborty N. Optimal DG placement by multi-objective opposition based chaotic differential evolution for techno-economic analysis. Appl Soft Comput. 2019;78:70-83.
[31] Selim A, Kamel S, Alghamdi AS, Jurado F. Optimal placement of DGs in distribution system using an improved Harris hawk's optimizer based on single- and multi-objective approaches. IEEE Access. 2020;8:52815-29.
[32] Naderipour A, Abdul-Malek Z, Mustafa MWB, Guerrero JM. A multi-objective artificial electric field optimization algorithm for allocation of wind turbines in distribution systems. Appl Soft Comput. 2021;105:107278.
[33] Hari Prasad C, Subbaramaiah K, Sujatha P. Optimal DG unit placement in distribution networks by multi-objective whale optimization algorithm & its techno-economic analysis. Electr Power Syst Res. 2023;214:1-11.
[34] Prakash DB, Lakshminarayana C. Multiple DG placements in radial distribution system for multi objectives using Whale Optimization Algorithm. Alex Eng J. 2018;57(4):2797-806.
[35] Soesanti I, Syahputra R. Multiobjective ant lion optimization for performance improvement of modern distribution network. IEEE Access. 2022;10:12753-73.
[36] Sultan MS, Kazmi SAA, Altamimi A, Khan ZA, Shin DR. Multi-Objective optimization-based approach for optimal allocation of distributed generation considering techno-economic and environmental indices. Sustainability. 2023;15(5):4306.
[37] Pham TD, Nguyen TT, Dinh BH. Find optimal capacity and location of distributed generation units in radial distribution networks by using enhanced coyote optimization algorithm. Neural Comput Applic. 2021;33:4343-71.
[38] Saha S, Mukherjee V. A novel multi-objective chaotic symbiotic organisms search algorithm to solve optimal DG allocation problem in radial distribution system. Int Trans Electr Energy Syst. 2019;29(5):e2839.
[39] Cai C, Chen J, Xi M, Tao Y, Deng Z. Multi-Objective planning of distributed photovoltaic power generation based on multi-attribute decision making theory. IEEE Access. 2020;8:223021-9.
[40] Kamel S, Selim A, Ahmed W, Jurado F. Single- and multi-objective optimization for photovoltaic distributed generators implementation in probabilistic power flow algorithm. Electr Eng. 2020;102:331-47.
[41] Chithra Devi SA, Yamuna K, Sornalatha M. Multi-objective optimization of optimal placement and sizing of multiple DG placements in radial distribution system using stud krill herd algorithm. Neural Comput Applic. 2021;33:13619-34.
[42] Ramadan A, Ebeed M, Kamel S, Agwa AM, Tostado-Véliz M. The probabilistic optimal integration of renewable distributed generators considering the time-varying load based on an artificial gorilla troops optimizer. Energies. 2022;15(4):1302.
[43] Hari Prasad C, Subbaramaiah K, Sujatha P. Techno-economic study by teaching learning-based optimization algorithm for optimal placement of DG units in distribution systems. J Sci Ind Res. 2023;82:278-86.
[44] Abid MS, Ahshan R, Al-Abri R, Al-Badi A, Albadi M. Multi-objective optimal planning of virtual synchronous generators in microgrids with integrated renewable energy sources. IEEE Access. 2023;11:65443-56.
[45] Ogunsina AA, Petinrin MO, Petinrin OO, Offornedo EN, Petinrin JO, Asaolu GO. Optimal distributed generation location and sizing for loss minimization and voltage profile optimization using ant colony algorithm. SN Appl Sci. 2021;3:248.
[46] Morse N. Reducing the size of nondominated set: pruning by clustering. Comput Oper Res. 1980;7(1-2):55-66.
[47] Dhillon JS, Parti SC, Kothari DP. Stochastic economic emission load dispatch. Electr Power Syst Res. 1993;26(3):179-86.

[48] Zaro FR, Abido MA. Multi-Objective particle swarm optimization for optimal power flow in a deregulated environment. 11th International Conference on Intelligent Systems Design and Applications; 2011 Nov 22-24; Cordoba, Spain. USA: IEEE; 2011. p. 1122-7.
[49] Kennedy J, Eberhart R. Particle swarm optimization. Proceedings of the ICNN'95—International Conference on Neural Networks; 1995 Nov 27 - Dec 1; Perth, Australia. USA: IEEE; 1995. p. 1942-8.
[50] Zaro F. True multi-objective optimal power flow in a deregulated environment using intelligent technique. J Eng Res Technol. 2017;4(3):110-8.
[51] Parvin M, Yousefi H, Noorollahi Y. Techno-economic optimization of a renewable micro grid using multi-objective particle swarm optimization algorithm. Energy Convers Manag. 2023;277:116639.
[52] Han H, Zhang L, Yinga A, Qiao J. Adaptive multiple selection strategy for multi-objective particle swarm optimization. Inf Sci. 2023;624:235-51.
[53] Zitzler E, Thiele L. Multiobjective evolutionary algorithms: a comparative case study and the strength Pareto approach. IEEE Trans Evol Comput. 1999;3(4):257-71.
[54] Modiri-Delshad M, Rahim AN. Multi-objective backtracking search algorithm for economic emission dispatch problem. Appl Soft Comput. 2016;40:479-94.
[55] Hanumantha Rao B, Sivanagaraju S. Optimum allocation and sizing of distributed generations based on clonal selection algorithm for loss reduction and technical benefit of energy savings. International Conference on Advances in Power Conversion and Energy Technologies (APCET); 2012 Aug 2-4; Mylavaram, India. USA: IEEE; 2012. p. 1-5.