

Multi-Objectives Techniques for Distributed Generation Installation under Multi-Load Model

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Abstract- Integration of renewable energy resources into distribution system is indeed crucial for several compelling reasons, encompassing technological advancement, economic advantages and environmental sustainability. In this study, a single and multi-objective Integrated Immune Moth Evolutionary Programming (IIMFEP and MO-IIMFEP) was proposed to optimally integrate Distributed Generation (DG) based on Photovoltaic (PV) solar panels on a Radial Distribution System (RDS). The proposed IIMFEP and MO-IIMFEP managed to alleviate the setback experienced in the traditional Evolutionary Programming (EP) and Moth Flame Optimization (MFO) which found to be stuck at local optimum. The IIMFEP and MO-IIMFEP are utilized to identify the optimal size and location of a DG within a multi-load model to minimize total active power losses, total voltage deviation and total operating cost. In this paper, a comparison is made between various voltage-dependent load models and the significance of considering multiple load models is highlighted. Consequently, there are four categories of voltage-dependent loads are used: constant power (CP), commercial, residential and industrial. In MO-IIMFEP, fuzzy logic determines the optimal compromise solution among non-dominated Pareto solutions. The IEEE 69-Bus Radial Distribution Systems (RDS) is used to validate the efficacy of IIMFEP and MO-IIMFEP and the outcomes are contrasted with EP, MFO, MO-EP and MO-MFO, respectively. The findings indicate that the proposed algorithms exhibited superior performance compared to the other two regarding the best solutions for single-objective and multi-objective problems.

Keywords Total active power loss, multi-objective optimization, total voltage deviation, DG, distribution system.

1. Introduction

Integration of Distribution Generators (DGs) has resulted in a significant development in the field of electrical power distribution, specifically the transformation of radial distribution systems (RDS). This transformation entails transitioning from a passive to an active structure, enabling

multidirectional power flows [1]. DG refers to deploying small-scale power-producing units near end-users, unlike the conventional model of big centralized power plants. DGs can be integrated into the distribution network or connected locally for an independent consumer. When linked to the distribution system, DGs have the capability to generate electricity close to the point of use and inject it into the grid,

thereby diminishing the dependence on centralized power plants. There are two main categories for DG units: conventional and renewable. Conventional DG units include generators powered by diesel and natural gas. Renewable DG units, meanwhile, consist of biomass generators, wind turbines (WT) and solar photovoltaic (PV) modules [2]. The incorporation of DG offers numerous advantages, such as enhanced grid resilience, enhanced control and management of power flows to optimize supply-demand balance, decreased transmission and distribution losses and improved voltage profile [1]. Furthermore, the utilization of DG sourced from renewable energy plays a significant part in reducing greenhouse gas emissions and the seamless integration of sustainable energy into the distribution grid. Although the integration of DG provides many advantages, it also poses difficulties in grid administration and control. DG integration enables a bidirectional power flow, accommodating diverse and demanding operating situations. These conditions include fault currents, the occurrence of reverse power flow, terminal voltage levels, stability concerns and harmonic distortion [1]. Improper installation of DG into the distribution system has the potential to compromise voltage stability, diminish power quality and escalate network losses. Hence, it is imperative to carefully ascertain the optimal site and sizing for deploying DG to achieve maximum efficiency and utilization.

Selecting an appropriate metaheuristic optimization technique for DG placement in a distribution system is crucial in design and planning decision-making. The optimal placements and dimensions of DGs in distribution systems have been identified through various optimization algorithms, either conventional or hybrid, in the published literature for single-objective and multi-objective problems. The primary emphasis of single-objective optimization issues lies in optimizing a solitary objective function. Therefore, the main objective in this case is to minimize power losses. On the contrary, multi-objective optimization entails the concurrent optimization of two or more contradictory objective functions.

In single objective optimization problems, various strategies, such as atom search optimization (ASO) [3], particle swarm optimization (PSO) [4] and salp swarm algorithm (SSA) [5], have been employed to address the issue of DG allocation problems to minimize power loss and improve the overall performance of the RDS. In [6], the PSO algorithm is utilized to determine the optimal configuration of PV arrays and wind turbines, along with the corresponding optimal energy storage capacity, with the aim of minimizing the overall cost. Meanwhile, study in [7] utilized the modified genetic algorithm (GA) for the allocation of optimal DG units for cost minimization. The GA [8], continuous-domain ant colony optimization (ACOR) [9] and the equilibrium optimization method [10] have been employed for the optimal allocation of distributed generators within RDS, considering variations in load circumstances. Under the examined load conditions, the studies additionally indicate that there is a reduction in real power losses and an improvement in the voltage profile.

The weighted sum and Pareto optimal front methodologies are the most common approaches for addressing multi-objective problems in a multi-objective

framework. The weighted sum method utilizes the linear combination of weighted objective functions to consolidate multiple competing objectives into a single objective. Concurrently, the Pareto optimal front endeavours to ascertain a non-dominated solutions based on the dominant concept. Subsequently, the decision-maker may select the optimal solution from the set of non-dominated solutions.

The researchers in the cited works [11]–[14] utilized the weighted sum method to tackle the challenges of multi-objective optimization related to DG allocation. The study presented in reference [11] utilized a water flow optimization (WFO)-based method to allocate DG units capable of injecting both active and reactive power, with the objective of simultaneously minimizing losses and annual economic costs. In order to concurrently lower reactive power loss and improve the voltage profile, the grey wolf optimization approach, bat algorithm (BA) and gravitational search algorithm (GSA) were employed in [12]. Based on the findings, it can be concluded that the GWO demonstrates superior performance compared to the BA and GSA. In the study conducted in [13], the researchers employed the artificial hummingbird algorithm (AHA) to assess the ratings and positions of PV and WT. The authors of [14] proposed an innovative multi-objective spider monkey optimization (SMO) algorithm to determine the optimal size and placement of DG units in RDS, aiming to minimize distribution losses and voltage deviation.

The Pareto approach was used in studies to estimate the ideal placement and capacity of DG. Multi-objective whale optimization technique has been used by Hari Prasad C. et al. [15] to find the best position and size for multi-DG Type 1 units to minimize real power loss, minimize yearly economic loss total and improve voltage profile to maximize annual savings. In [16], the authors employed a MO particle swarm optimization (MO-PSO) technique to effectively allocate various types of DG resources to enhance four distinct indicators of performance, including power losses, DG cost, voltage profile and pollutant emission. A MO grasshopper optimization Algorithm was utilized by Belboul Z. et al. to determine the optimal output of hybrid renewable energy sources (HRES) in an off-grid community in Djelfa, Algeria, taking into account environmental impact, reliability and cost [17]. The researchers in [18] utilized the manta ray foraging optimization (MRFO) algorithm to ascertain the optimal configuration and positioning of multi-type multi-DG systems to reduce active power losses, DG cost and voltage profile.

Hybrid methods have been developed to address the drawbacks of traditional approaches to DG allocation solving problems. The efficiency and convergence accuracy of these hybrid methods are improved over those of the traditional algorithm [19]. The authors in reference [20] incorporate ten distinct chaotic maps (CM) into the standard stochastic fractal search (SFS) algorithm. This integration results in ten different variations of the CMSFS algorithm, which are employed to address the problem of determining the optimal location and size of the unity and non-unity power factor of DG in RDS. The findings reveal that the CMSFS method yields a more effective solution compared to the conventional SFS approach. The authors of [21] put forth a proposal to

improve the SSA and GWO algorithms by combining these two algorithms, resulting in a new algorithm termed Hybrid SSA-GWO. The primary objective of SSA-GWO is to address the DG allocation in RDS to minimize real power loss and improve the voltage profile. The authors of [22] proposed an enhanced harris hawks optimization algorithm (HHO) in which hawks boundary verification is modified. The authors proposed that whenever the hawk exceeds the boundary limit, it should revert to the best solution rather than the minimum or maximum position of the hawk. In [23], the oppositional hybrid sine cosine muted differential evolution algorithm (O-SCMDEA) was developed by hybridizing the sine cosine operator (CSA) with the differential evolution algorithm (DEA). The proposed approaches in [22], [23] have been evaluated to investigate the effects of distributed generation (DG) with different power factors on both single and multi-objective functions. The Improved Salp Swarm Algorithm (ISSA) is used to solve the optimal utilization of renewable energy sources (PV and WT) with the reconfiguration of RDS to reduce costs associated with power loss and network load reliability. This hybrid approach is developed by incorporating the DEA operators into conventional SSA. The outcomes demonstrated the superior performance of the ISSA over the traditional SSA [24].

This study introduces a novel optimization approach called Integrated Immune Moth Flame Evolutionary Programming (IIMFEP) to address the optimization of Distributed Generation based on Photovoltaic (DGPV) in the IEEE 69-Bus RDS with constant power load and practical voltage-dependent load models. The IIMFEP method primarily focuses on minimizing total real power loss as a single objective function for DGPV allocation. Additionally, a multi-objective IIMFEP Algorithm using the Pareto approach (MO-IIMFEP) is employed to optimize three objectives: total power loss, voltage deviation and operational cost. Comparative analysis shows that the proposed approaches outperform the original evolutionary programming (EP) and Moth Flame Optimization (MFO) methods across various load configurations, regardless of whether the objective function is single or multi-objective.

2. Problem Formulations

2.1. Objective Functions

This research aims to identify the optimal placement and capacity of DGPV in RDS to reduce total active power loss in single-objective problems while minimizing total active power loss, total voltage deviation and total operating costs in multi-objective problems. In single-objective optimization, determining the superiority of a solution is predicated on the value of the objective function. This investigation aims to minimize the value of the objective function; thus, the solution exhibiting a lower objective function value is deemed more favorable. The solution is improved when the value of the objective function is decreased. In subsections, the primary objectives and associated mathematical calculations are presented.

2.1.1 Total Active Power Loss

Total active power losses (P_{LOSS}) in a distribution system are determined by accumulating active power losses across all line sections in the system, which can be calculated using the following equation [24]:

$$P_{LOSS} = \sum_{x=1}^{N_{br}} I_x^2 \times R_x \quad (1)$$

Where I_x is the current that flows through branch x , x is a branch number, R_x is the resistance at branch x and N_{br} is the maximum number of branches.

Distribution systems exhibit high line losses as a result of their radial topological configuration [25]. The first objective function (OF) is shown as:

$$OF1 = \min(P_{LOSS}) \quad (2)$$

2.1.2 Total Voltage Deviation

It is desirable to reduce the variance of the bus voltage as an OF to acquire the optimal voltage for the consumer utilizing voltage-sensitive equipment. A total voltage deviation (TVD) can be determined by [26]:

$$TVD = \begin{cases} 0, & \text{if } 0.95 \leq V_t \leq 1.05 \\ \sum_{t=1}^{N_b} |V_{ref} - V_t|, & \text{else} \end{cases} \quad (3)$$

where t is the bus number, N_b is the total number of buses in the system, V_t is the voltage magnitudes at bus t and V_{ref} is the reference voltage that is set at 1.00 p.u.. The second OF (OF2) is therefore expressed as follows:

$$OF2 = \min(TVD) \quad (4)$$

2.1.3 Total Operating Cost

The minimization of total operating costs (TOC), which represents the third objective function in this study, is given by Eq. (5). The TOC encompasses costs related to the optimal capacity of DG installation and the overall power losses of the system.

$$OF3 = \min(TOC) \quad (5)$$

The following equation represents the pricing formula for total operating costs [27].

$$TOC = k_1 * P_{LOSS} + k_2 * \sum_{i=1}^{N_{DG}} P_{DG}(i) \quad (6)$$

P_{DG} is the real power supplied by DG, N_{DG} is the number of DG, k_1 denotes the cost coefficient of the real power supplied by the grid and k_2 denotes the cost coefficient of real power generated by the DG. The cost coefficient k_2 is set at 5 \$/kW, which is considered marginally higher than k_1 at 4

\$/kW, by accounting for DG installation and maintenance costs [28].

2.1.4 Multi-Objective Function

Multi-objective optimization is utilized in this study; consequently, all three objective functions are combined to minimize P_{LOSS} , TVD and TOC simultaneously. The mathematical expression for the fitness of the multi-objective problem is expressed as:

$$OF_{multi_obj} = \min(P_{LOSS}; TVD; TOC) \quad (7)$$

Various techniques are employed in multi-objective optimization, including approaches like combining all functions into a single objective function, namely the weighted method and the ϵ -constraint method. These techniques simultaneously represent multiple objectives, such as the Pareto Optimal Front. Within the Pareto framework, a set of non-dominated solutions is generated, defining the optimal trade-off among the competing objectives. In this research, we employ the widely recognized and effective Pareto method. The Pareto technique consists of three stages: non-dominated sorting, crowding distance sorting and the selection of non-dominated solutions. Non-dominated sorting relies on the concept of dominance, where x_1 dominates x_2 if the fitness of x_1 is no worse than that of x_2 in all objectives or strictly better than x_2 in at least one objective [29].

The crowding distance indicators are utilized to determine the density of population solutions in the immediate surroundings of each individual. Initially, the individuals in the population are arranged in ascending order based on their front. Subsequently, each individual inside the front set is sorted according to each objective function, starting from the lowest value and progressing to the highest. For the individuals at the boundary of the front with the lowest and highest objective values, set their crowding distance to infinity. This is done to ensure that individuals on the boundary of the Pareto front are always selected. The crowding distance is calculated for the remaining individuals in the front set.

First, the computation involves determining the normalized difference between the objective values of neighboring individuals. In the objective space for objective m , the normalized difference for individual A between its neighboring individual B and C is provided by [30]:

$$d_{m(A)} = \frac{Fit_{m(B)} - Fit_{m(C)}}{\max(Fit_m) - \min(Fit_m)} \quad (8)$$

The symbol $Fit_{m(B)}$ and $Fit_{m(C)}$ denote the objective value of individual B and individual C , respectively, for objective m . The crowding distance for individual A , represented as Cd_A is determined by summing up the normalized differences for all objectives as follows [30]:

$$Cd_A = \sum_{m=1}^M d_{m(A)} \quad (9)$$

Here, M represents the maximum number of objective functions. After determining the crowding distance for each individual in the Pareto front, the subsequent step involves implementing the selection procedure. Larger crowding distance individuals are favored in the selection process because they represent less crowded areas of the Pareto optimum front, preserving population diversity.

By incorporating non-dominated sorting, crowding distance calculation and selection, the Pareto method helps explore and maintain a balanced set of solutions along the Pareto front. This enables decision-makers to identify the most appropriate solution among conflicting objectives in accordance with their preferences and priorities.

This study utilizes Fuzzy decision-making techniques to determine the optimal compromise option from a set of Pareto front/non-dominated solutions. For each objective m , the membership function is endowed with a value of zero and one to represent the individuals with the highest and lowest fitness values, respectively. For the remaining fitness (between the maximum and minimum fitness), the membership function for objective m , denoted by $\mu_{A,m}$ at a particular individual A , is computed as follows [31]:

$$\mu_{A,m} = \frac{Fit_{\max(m)} - Fit_{m(A)}}{Fit_{\max(m)} - Fit_{\min(m)}} \quad (10)$$

The normalized membership function for each individual A is mathematically represented as:

$$\mu^A = \frac{\sum_{m=1}^M \mu_{A,m}}{\sum_{A=1}^N \sum_{m=1}^M \mu_{A,m}} \quad (11)$$

Here, N represents the total number of individuals in the non-dominated solutions. Subsequently, the membership function that has been normalized is arranged in descending order. The best compromise solution is determined by choosing the individual with the highest value of the normalized membership function.

2.2 Load Models

The impact of a DG Type 1 installation on the system is investigated using a variety of voltage-dependent load models. While most evaluations have assumed a constant power load, in practice, loads change depending on voltage. Specifically, the magnitude of the voltage on a given bus influences the actual and reactive load demands. Residential, commercial and industrial are typical classifications for practical voltage-dependent load models. The mathematical expression of various load models is expressed as [28]:

$$P_{Lt_new} = P_{Lt} \times V_t^\alpha \quad (12)$$

$$Q_{Lt_new} = Q_{Lt} \times V_t^\beta \quad (13)$$

In this instance, P_{Lt} and P_{Lt_new} denote the initial and updated real power loads at node t . Similarly, Q_{Lt} and Q_{Lt_new} represent the initial and updated reactive power loads at node t . Table 1 displays the relationship values α and β , which associate various load categories [28].

In conventional power flow studies employing a constant power load model, $\alpha = 0$ and $\beta = 0$ are presumed. During investigations, particular attention is given to the comparative analysis between the assumption of a constant power load model and the practical load models. When delving into the influence of multi-load models, we assume that the 69-Bus RDS exclusively caters to residential customers when analyzing residential loads. Conversely, when examining commercial loads, one might infer that all loads within the 69-Bus system are expressly designated for commercial consumers. Similarly, when commercial loads are studied, it is assumed that all loads within the system are associated with commercial consumers.

Table 1. Relationship values of voltage-dependent load

Load Model	α	β
Constant	0	0
Industrial	0.18	6
Commercial	1.51	3.4
Residential	0.92	4.04

2.3 Problem Constraints

In a distribution system DG allocation optimization problem, equality and inequality constraints play a significant role in determining the optimal placement and size of DG.

2.3.1 Equality Constraint in Power Balance Equation

The power balance equation is a fundamental principle that ensures the conservation of power in a system. The total power supplied or generated by a system is equivalent to the total power output and total power loss in the system. In the distribution system, it is essential that the total incoming power, which comprises power from both the main grid and DG units, is equal to the total outgoing power, encompassing both loads and losses, for every individual node. This restriction can be expressed as follows [32]:

$$P_{substation} + \sum_t^{N_{DG}} P_{DG(t)} = \sum_t^{N_b} P_{load(t)} + \sum_{t,t+1}^{N_{br}} P_{LOSS(t,t+1)} \quad (14)$$

Where $P_{substation}$, $P_{DG(t)}$ and $P_{load(t)}$ represent the active power of the main substation, of the DG at bus t and of load at bus t , respectively.

2.3.2 Inequality Constraint

The optimization issue is constrained by inequality limits that impose limitations on both the voltage variable limit and the DG capacity limit.

Voltage Limits

Voltage limits are essential in maintaining system stability as they ensure that the voltage magnitude at each node does not exceed the acceptable thresholds. At all system buses,

the voltage, V_i must be remained between 0.95 p.u. and 1.05 p.u. [21].

$$0.95 \text{ p.u.} \leq V_i \leq 1.05 \text{ p.u.} \quad (15)$$

DG Capacity Limits

DG units are subject to both upper and lower constraints on their generation capacity, which must be adhered to. Therefore, the active power injected by a DG at the i -th bus, $P_{DG,i}$ is set as follows [33]. 10% of total real power demand $\leq P_{DG,i} \leq 80\%$ of total real power demand needs to be set as the inequality constraint. The total capacity of the DG sources should not exceed the total system demand based on Eq. (16).

$$P_{DG,T} = \sum_{i=1}^{N_{DG}} P_{DG(i)} \leq \sum_i^{N_b} P_{load(i)} \quad (16)$$

Where $P_{DG,T}$ is the total DG power. This restriction is necessary for the stability and dependability of the power system. If DG capacity significantly exceeds system demand, power flow reversals may occur, posing potential instability and operational difficulties [34].

3. Overview of The Proposed Optimization Method

Optimization refers to a mathematical process used to arrive at the optimal solution. Depending on whether the analysis focuses on a single objective or multiple objectives, the value may presume a maximum or a minimum. Multi-objective optimization is the optimization of a problem with multiple objectives. This study aims to evaluate the effectiveness of the IIMFEP and MO-IIMFEP techniques in resolving DG allocation problems. The proposed IIMFEP is constructed by incorporating moth characteristics as in MFO into the EP mechanics and considering the cloning process as in Artificial Immune System (AIS) into account to solve single objective problem optimization. By adopting the Pareto method in the proposed IIMFEP, multi-objective IIMFEP is constructed to tackle the multi-objective optimization problem.

3.1 The Proposed IIMFEP

The IIMFEP approach is an improved version of the EP methodology [35], integrating the moth feature from MFO [36] and the cloning process from AIS [37]. The main framework of the proposed method is derived from the EP technique, which itself is composed of multiple stages: initialization, parent population generation, offspring breeding using the Gaussian mutation technique, fitness assessment of the offspring population, merging parent and offspring populations, ranking and selection of the new population to be employed in the subsequent iteration. The iterative procedure continues until the optimization reaches convergence. The cloning procedure is employed in the proposed algorithm to increase the size of the parent population. In the process of breeding the offspring, the utilization of the Chaos Local Search mutation technique is preferred over the Gaussian mutation technique to facilitate a more extensive exploration of prospective candidates. The inclusion of the moth operator occurs after the first fitness evaluation to boost the potential

solution. Generally, the individuals in the proposed IIMFEP approach are updated twice throughout the optimization process. The complete flowchart of the IIMFEP algorithm is depicted in Fig. 1.

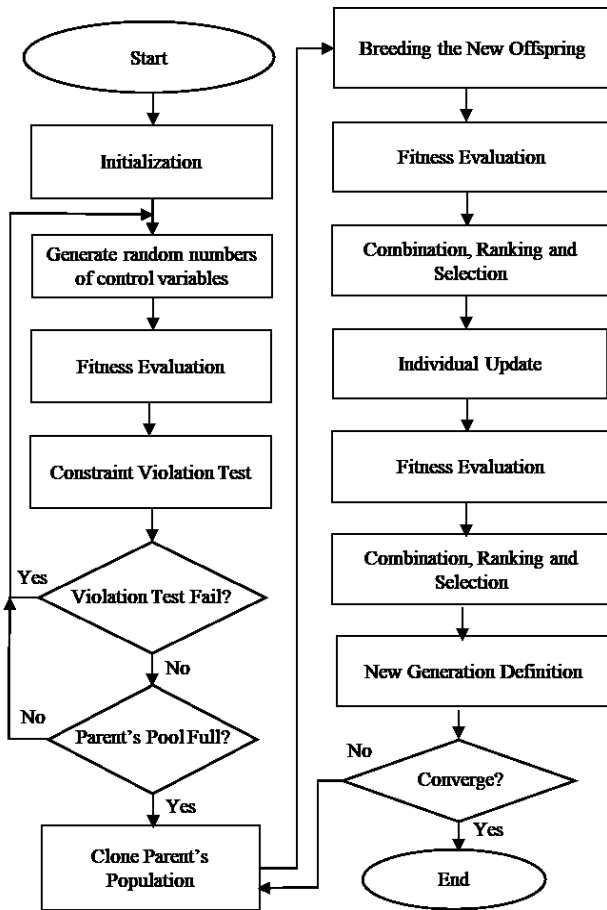


Fig. 1. Complete flow chart of the proposed IIMFEP.

A summary of the primary steps encompassing the IIMFEP algorithm is provided as follows:

Step 1: Algorithm Settings: Setting the algorithm's regulating parameter initialization.

Step 2: Selection of the Parent Population: The individuals in the parent population are generated randomly, denoted by the variable N . If the fitness of the generated individual satisfies the violation constraint, then the individuals are retained in the parent population. This process is repeated until the parent population consists of N individuals.

Step 3: Cloning Process: The cloning procedure cloned the parent population using an m factor. Consequently, the size of the clone parents increases by a factor of N multiplied by m .

Step 4: Breeding New Offspring: The IIMFEP algorithm utilizes the Chaotic Local Search with spiral mutation as its mutation strategy [20]. To begin, the chaos vector for the current iteration, denoted as $chaos_i$, is computed using the following formula:

$$chaos_i = \left\{ chaos_{i-1} + b - \left(\frac{a}{2\pi} \right) \sin(2\pi chaos_{i-1}) \right\} \text{mod}(1), \quad (17)$$

$$1 \leq i \leq max_{iter}$$

Where $chaos_{i-1}$ is the chaos vector from the previous iteration, i is the current iteration and $ch0$ is 0 to 1. Then map $chaos_i$ to a chaotic vector CH_i as follows:

$$CH_i = X_{min} + chaos_i \times (X_{max} - X_{min}) \quad (18)$$

Here, X_{min} and X_{max} are the minimum and maximum values of the variable X . Finally, the offspring, X_{mut} , is obtained by the following equation [38]:

$$X_{mut} = (1 - s) \times X + s \times CH_i \quad (19)$$

The shrinking factor s is expressed in Eq. (20):

$$s = (max_{iter} - iter + 1) / max_{iter} \quad (20)$$

The fitness of the offspring is then evaluated.

Step 5: Combination, Ranking and Selection I: The procedure of combining, ranking and selecting. The parent population and offspring population are initially combined. Following this, the process of ranking commenced. The fitness levels of the combined population are arranged in ascending order. During the process of selection, those who fall into the upper three-quarters of the population are included, while those in the lower quarter are eliminated. The individual who has been chosen will advance as the designated candidate in the following step.

Step 6: Individual Update: Update the individual by the moth operator. The moth is characterized based on its offspring population, while the flames are selected from the chosen individuals in Step 5. The individuals are updated utilizing the subsequent equation. The flame number is computed as follows after the moth and flame have been initialized [36]:

$$flame\ number = \text{round} \left(N_{flame} - iter \times \frac{N_{flame} - 1}{max_{iter}} \right) \quad (21)$$

Where N_{flame} represents the maximum number of flames. Then the distance between the j -th flame, F_j and the i -th moth, M_i is determined as:

$$D_i = |F_j - M_i| \quad (22)$$

The moth population is updated as follows:

$$\text{Moth}(M_i, F_j) = D_i \cdot e^{cd} \cdot \cos(2\pi t) + F_j \quad (23)$$

Where constant c is the constant that determines the shape of a logarithmic spiral, whereas d is the random number between r (decreases linearly from -1 to -2) to 1. Following this, the evaluation of the fitness values for the updated population of moths is carried out.

Step 7: Combination, Ranking and Selection II: The process of combining, ranking and selecting. Initially, the population of flames and the updated moth population are merged. The combined population is thereafter arranged in

ascending order based on their fitness function. During this step, an N number of moths/individuals are selected to proceed to the next iteration. The selected individuals are referred to as parents in the next iteration.

Step 8: Convergence Test: The aforementioned steps are iterated until the predetermined criteria for termination are met.

3.2 The Proposed MO-IIMFEP

The IIMFEP technique has been previously presented to address single-objective optimization problems. This section presents the proposed MO-IIMFEP technique as a solution for solving multi-objective optimization problems characterized by the need to optimize many competing objectives simultaneously. The Pareto approach is utilized inside the framework of the IIMFEP algorithm to create the Multi-Objective IIMFEP (MO-IIMFEP) algorithm, as shown in Fig. 2. The Pareto approach seeks to determine a set of solutions, referred to as the Pareto front, that illustrate the compromises between these objectives.

Modifications to Steps 5 and 7 of the IIMFEP algorithm include alterations to the combination, ranking and selection processes. The combination procedure is retained in MO-IIMFEP, while the Pareto technique was utilized for ranking and selection. The Pareto technique consists of a non-dominated sorting procedure, crowding distance ranking and non-dominated solutions selection. The parent and offspring

populations are merged in Step 5 of the combination procedure, while moths and flames are combined in Step 7. The combined population is then subjected to a procedure of non-dominant classification. Based on their dominance relationships, this procedure determines the front number of each individual in the combined population. A solution is considered non-dominant if no other solution in the population is superior in all objectives and at least as excellent in one objective. This procedure generates a set of Pareto fronts, with the first front containing solutions that are not dominated, the second front containing solutions that are dominated by the first front but not by each other and so on. Then, the solutions are ranked and grouped based on their respective front.

Subsequently, the computation of the crowding distance is performed for each solution within its corresponding front set. The calculation of the crowding distance involves determining the influence of adjacent solutions, specifically to a particular objective, denoted as objective j . After the computation of crowding distances for all solutions concerning each objective, the subsequent procedure involves aggregating the crowding distances for all objectives for each solution. Following the non-dominated sorting procedure and crowding distance computation, each individual possesses two distinct attributes: a non-dominated front number and a crowding distance value. These values will guide the selection of individuals in the selection process. Individuals with similar fronts are arranged in descending order based on their crowding distance values. In cases where two individuals have

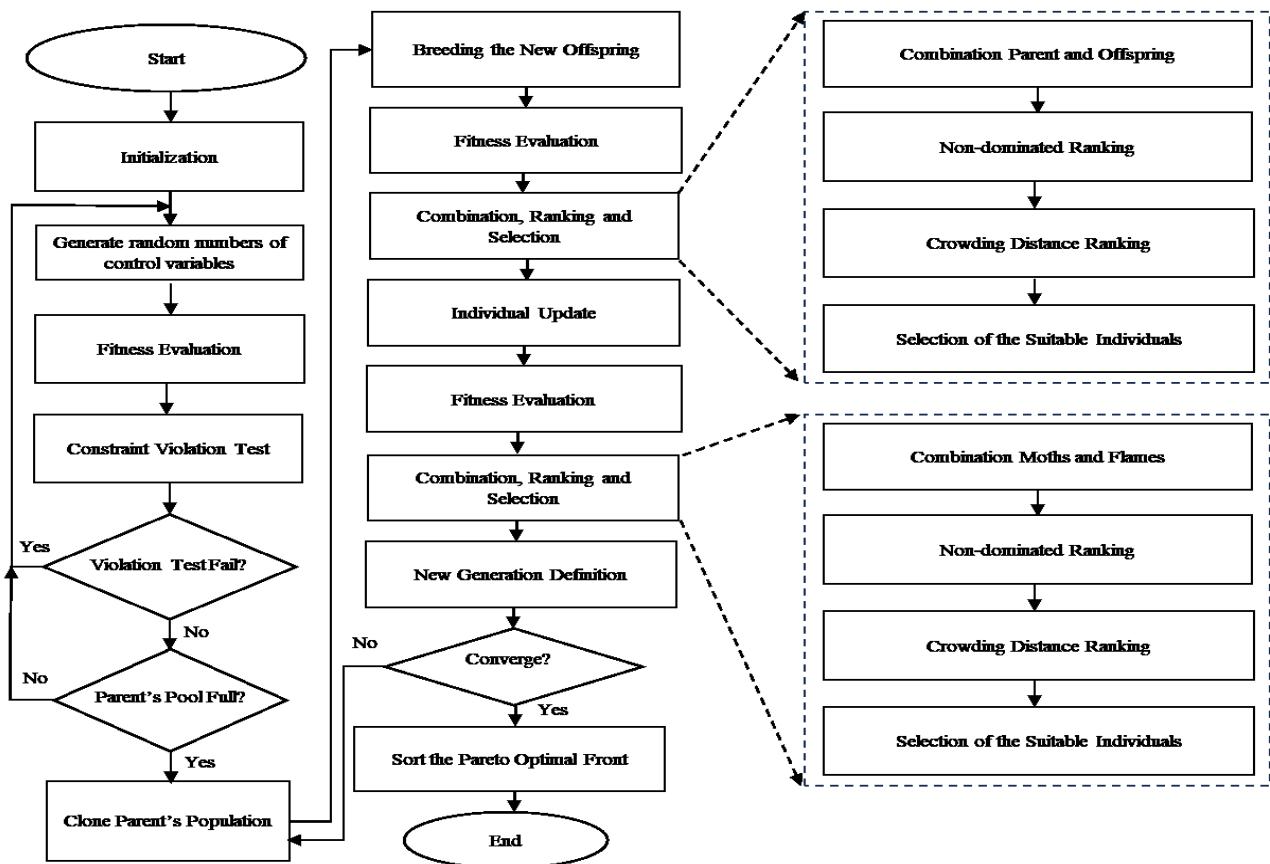


Fig. 2. Flow chart of the proposed MO-IIMFEP.

differing fronts, the higher-ranking front is given preference. It should be noted that Front 1 holds a higher ranking than Front 2, whereas Front 2 surpasses Front 3 and so on. In cases where two individuals possess similar fronts, priority is assigned to the individual with a higher crowding distance value. The selection process in Step 5 involves choosing individuals who rank within the top 75% of the combined population. Meanwhile, the selection process in Step 7 chooses only the top N individuals. The individuals that have been chosen are commonly known as non-dominated solutions. Convergence of the proposed MO-IIMFEP algorithm occurs when the maximum number of iterations is completed. Then, the optimal compromise solution is determined by employing Fuzzy-decision techniques on the non-dominated solutions.

4. Results and Discussion

This section evaluates the performance of the hybrid algorithms, namely IIMFEP and MO-IIMFEP, in addressing DGPV allocation problems on the IEEE 69-bus radial distribution system. The evaluation is conducted for a multi-load model that includes constant power load, industrial load, commercial load and residential load. Two scenarios are being examined. In scenario 1, the objective is to discover the optimal placement and sizing of three DGPV units to minimize the overall power loss in a system of single-objective optimization problems. In the meantime, scenario 2 determines the optimal location and capacity for three DGPV units to minimize power loss, lower TVD and minimize TOC, all of which are assessed for the multi-objective optimization problem.

In all scenarios, DG installation is constrained to three units. This limitation is based on the study conducted in [28], which found that installing DG that supplies active power at more than three locations does not substantially reduce power loss. The outcomes of multi-DGPV installations are compared to those without DGs in each scenario. The results are compared to those achieved using original EP and MFO algorithms. Every algorithm is limited to a maximum of 200 iterations and utilizes a population size of 20. The backwards-forward sweep approach is employed to do load flow analysis. The constant power load model and voltage-dependent load model are used to represent the loads in a power system network.

To evaluate the impact of the proposed method on the DGPV allocation problem for various load models, IEEE 69-Bus RDS is employed. The information regarding the per unit (p.u.) line resistance and reactance and load data has been obtained from [39]. Table 2 tabulates the specification for IEEE 69-Bus RDS; meanwhile, the total real and reactive power load demand for constant, industrial, commercial and residential loads are tabulated in Table 3.

Table 2. Specification for IEEE 69-Bus RDS

No. of branches	Rated Voltage	Substation Voltage
68	12.66 kV	12.66 kV

Table 3. Total power load demands for constant, industrial, commercial and residential load for 69-Bus RDS

Load Model	P_{total} (kW)	Q_{total} (kVar)
Constant	3801.49	2694.60
Industrial	3767.47	2047.66
Commercial	3530.54	2291.53
Residential	3632.58	2226.91

4.1 Scenario 1: Single-Objective Optimization (SOO)

To establish the effectiveness of the proposed IIMFEP approach, it undergoes rigorous testing on the IEEE-69 RDS, encompassing diverse load categories. Power loss minimization has been a widely studied optimization objective in the power system community. Therefore, the primary emphasis in scenario 1 is placed on the single objective function of minimizing the total power loss through the allocation of DGPV. This is done to enable meaningful comparisons between single-objective and multi-objective problems. This study assesses the effectiveness of the IIMFEP approach when compared to the MFO and EP approaches in the context of DGPV allocation within the system. Furthermore, the comparative analysis involves evaluating the performance of the system when DG installations are present, as opposed to when they are absent. The simulation results of the IIMFEP, MFO and EP algorithms, as applied to reduce the overall power loss in IEEE 69-Bus RDS with multi-load models, are presented in Table 4. The analysis of overall power losses demonstrates a notable reduction across all load models upon the integration of DGPVs into a system, regardless of the approach employed. The IIMFEP methodology demonstrates superior performance compared to the MFO and EP algorithms in terms of minimizing the overall power loss across all load settings.

In the constant load scenario, the overall power loss after installing three DGs using IIMFEP, MFO and EP optimization strategies is 69.42 kW, 69.69 kW and 76.21 kW, respectively, compared to the initial power loss of 224.98 kW before DG installation. The result achieved using IIMFEP is also superior compared to the work conducted in [15], which only achieved 69.69 kW solved using the whale optimization algorithm. A similar phenomenon can also be observed when this technique is compared with the optimization techniques reported in [5], [18], [22]. According to the IIMFEP methodology, the optimal bus numbers for the placement of DG units are 61, 11 and 18, corresponding to DG sizes of 1718.82 kW, 526.52 kW and 380.63 kW, respectively.

The practical voltage-dependent load model reveals that the industrial load exhibits the highest total power loss before DG compensation, amounting to 171.44 kW, followed by the residential load, which experiences a total active power loss of 164.94 kW and the commercial load, which encounters 157 kW of total active power loss. When DGs are installed into the system, the IIMFEP technique has effectively achieved the lowest total power loss when compared to the other two techniques, which are 28.69 kW, 41.19 kW and 37.61 kW in

Table 4. Performance analysis of the IEEE-69 bus system for Constant, Industrial, Commercial and Residential Load models using IIMFEP, MFO and EP Techniques for power loss minimization

Type of Load	Parameters	Without DG	With DG Installation			
			EP	MFO	IIMFEP	
Constant Power	P_{loss} (kW)	224.98	76.21	69.69	69.42	
	TVD (p.u.)	0.7313	0.0000	0.0000	0.0000	
	TOC (\$)	\$899.92	\$13,707.39	\$13,208.94	\$13,407.53	
	$Voltage_{min}$ (p.u.)	0.9092	0.9780	0.9790	0.9790	
	DG Size (kW)/Loc			390.66 (13)	459.63 (66)	1718.82 (61)
				1697.8 (63)	399.57 (18)	526.52 (11)
				592.05 (55)	1726.84 (61)	380.63 (18)
Total DG Size (kW)		2680.51	2586.04	2625.97		
Industrial Load	P_{loss} (kW)	171.44	30.49	28.82	28.69	
	TVD (p.u.)	0.6479	0	0.00	0.00	
	TOC (\$)	\$685.76	\$13,327.96	\$12,449.13	\$12,829.71	
	$Voltage_{min}$ (p.u.)	0.9196	0.9871	0.9863	0.9863	
	DG Size (kW)/Loc			562.91 (14)	376.75 (11)	1661.52 (61)
				406.73 (66)	413.28 (18)	504.57 (11)
				1671.55 (61)	1676.74 (61)	376.90 (18)
Total DG Size (kW)		2641.20	2466.77	2542.99		
Commercial Load	P_{loss} (kW)	157	42.81	41.82	41.19	
	TVD (p.u.)	0.6114	0	0.00	0.00	
	TOC (\$)	\$628.00	\$13,005.02	\$11,247.09	\$11,825.35	
	$Voltage_{min}$ (p.u.)	0.9242	0.9909	0.9838	0.9839	
	DG Size (kW)/Loc			332.45 (17)	355.55 (18)	1484.16 (61)
				1684.75 (61)	1507.35 (61)	491.52 (11)
				549.56 (10)	353.05 (69)	356.21 (18)
Total DG Size (kW)		2566.76	2215.96	2332.12		
Residential Load	P_{loss} (kW)	164.94	40.02	37.75	37.61	
	TVD (p.u.)	0.6312	0	0.00	0.00	
	TOC (\$)	\$659.76	\$13,384.99	\$11,873.44	\$12,275.79	
	$Voltage_{min}$ (p.u.)	0.9217	0.9889	0.9845	0.9845	
	DG Size (kW)/Loc			564.33 (14)	363.26 (11)	1561.93 (61)
				407.90 (66)	1577.41 (61)	497.36 (11)
				1672.76 (61)	403.82 (18)	365.78 (18)
Total DG Size (kW)		2644.98	2344.48	2425.07		

the industrial, commercial and residential load models, respectively. Across all voltage-dependent load models, it is noticeable that industrial load yields the lowest total power loss with DG compensation despite the highest total power loss before DG compensation. This is due to Industrial load generally having larger power demands than commercial and residential areas. Higher power demands result in more significant power losses in the distribution system. Meanwhile, the highest total power occurs in the commercial load model.

In addition, the table contains the observed TVD, TOC and minimal voltage magnitudes, denoted by the symbol $Voltage_{min}$. It has been observed that the installation of DG

increases the minimum voltage magnitude for all load classes. The analysis of TVD reveals that its magnitude is reduced across all load types when DG is present. The TVD maintains a zero value across all load models, indicating that all bus voltages in IEEE 69-Bus RDS are within the voltage constraint. This finding suggests that DG integration positively affects the voltage profile. Table 4 reveals that industrial loads have the highest TOC, while commercial loads have the lowest. The increase in TOC is due to the greater capacity of the installed DG required to mitigate the lowest power loss.

Figure 3 illustrates the comparative studies of total power loss with and without DG installation solved using the three techniques under different voltage dependent load models, validated on IEEE 69-Bus RDS. The graphical representation illustrates that implementing all three techniques effectively reducing the overall power loss of the system when three DG Type 1 units are installed into the system under constant power (CP), residential, commercial and industrial load models. Apparently, IIMFEP algorithm is more effective than EP and MFO in achieving the lowest overall power loss regardless of load model. This observation demonstrates the efficacy of the proposed method under consideration.

Figure 4 exhibits the voltage plots of IEEE 69-bus RDS for multi-load systems, including constant, residential, commercial and industrial load, both with and without DGs utilizing the proposed IIMFEP. The voltage plots for all load models exhibit enhancement resulting from the DG installation, as agreed in Fig. 4. This implies that IIMFEP managed to reduce the power loss and improve the voltage values in the system.

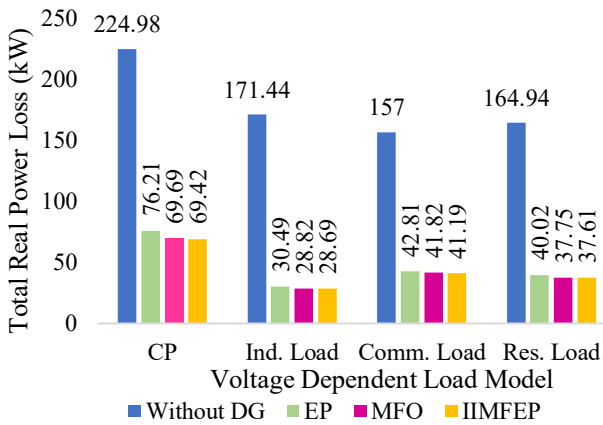


Fig. 3. The total power loss in the 69-Bus system utilizing IIMFEP, EP and MFO at various voltage-dependent load model.

4.2 Scenario 2: Multi-Objectives Optimization (MOO)

The effectiveness of the MO-IIMFEP technique is assessed through its implementation to address multi-objective optimization problems, which include both a

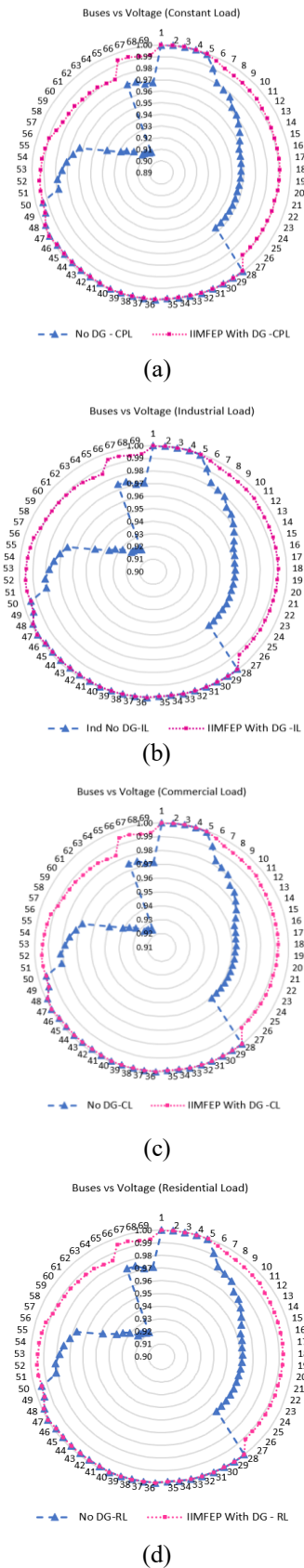


Fig. 4. Voltage values at all buses in the IEEE 69-Bus RDS without DG and with DGs utilizing the proposed IIMFEP for a) constant b) industrial c) commercial and d) residential load models.

constant load model and practical voltage-dependent load models. The proposed MO-IIMFEP, MO-MFO and MO-EP techniques are employed to determine the optimal sizes and placements of multi-DGPVs on IEEE 69-Bus RDS. This analysis considers all the load models as those in the single objective problem. The primary goal is to reduce the total power loss, TVD and TOC. Table 5 tabulates the best compromise solutions derived from the non-dominated solutions identified using the MO-IIMFEP, MO-MFO and MO-EP algorithms for the installation of multi-DGPV in IEEE 69-Bus RDS for a multi-load model. It is worth mentioning that the findings indicate that all techniques can identify the optimal compromise solution for achieving the optimal sizing and placement of DG in the multi-load models. The MO-IIMFEP technique exhibits superior performance over MO-MFO and MO-EP algorithms. The aforementioned superiority is evident in its capacity to achieve the lowest total power loss, total voltage deviation and total operating cost across all the load settings regardless of load types. In the constant load scenario, the overall power loss after installing three DGs using MO-IIMFEP, MO-MFO and MO-EP optimization strategies is 75.00 kW, 75.33 kW and 84.68 kW, respectively, compared to the initial power loss of 224.98 kW before the DG installation. The total power loss obtained in MOO is marginally higher than that obtained in SOO using IIMFEP, which was 69.42 kW. In SOO, the total operational cost (TOC) is \$13,407.53 (Table 4) based on the cost of capacity of the DG and the cost of total active power losses for constant load using the proposed IIMFEP (refer to Table 4). In the meantime, the optimal TOC is slightly decreased using MOO. The MO-IIMFEP optimal TOC is \$9,836.73, less than the MO-MFO and MO-EP optimal TOCs, which are \$11,181.33 and \$12,084.64, respectively, as tabulated in Table 5. Apparently, the implementation of MOO managed to reduce the total operational cost as compared to those in SOO. All techniques effectively reduced the TVD to zero with DG installation, whereas the TVD was 0.7313 p.u. before DG compensation. All bus voltages are within the permitted range. In MOO, the power loss objective is sacrificed in an endeavour to reduce the total operating cost while all bus voltages are within their allowable limits specified by the standard. At this instance, the proposed MO-IIMFEP yields superior results for the two objective functions, namely total power loss and total operating cost and comparable performance for minimizing total voltage deviation compared to the other two optimization techniques. In order to attain the optimal outcome, MO-IIMFEP determines three optimal DG locations: 61, 17 and 64, each associated with DG sizes of 1123.29 kW, 403.91 kW and 380.15 kW, respectively tabulated in the table as 1123.29(61), 403.91(17) and 380.15 (64).

Furthermore, Table 5 tabulates the optimum sitting and sizing for multi-DG with practical voltage-dependent load models such as industrial, commercial and residential loads. The table indicates that the proposed MO-IIMFEP achieved the lowest total active power loss, lowest TOC value and managed to improve the voltage value while maintaining all bus voltages within the voltage constraint limit, compared to MO-MFO and MO-EP in all load settings. In the industrial load, a similar phenomenon is experienced where the MO-

IIMFEP method demonstrated the lowest overall power loss of 35.76 kW, notably lower than the power losses of 36.26 kW achieved by MO-MFO and 53.14 kW achieved by MO-EP. The overall running cost or TOC is determined by the combined expenses of the needed total DG size and the total power loss cost. Through MO-IIMFEP, 1780.50 kW of total DG size is needed; with MO-MFO, 2087.44 kW and MO-EP, 2426.36 kW. The overall running cost of \$9,045.57 optimized by MO-IIMFEP is more economical than the \$10,582.20 acquired by MO-MFO and \$12,344.36 optimized by MO-EP. MO-IIMFEP outperformed MO-EP and MO-MFO in achieving the lowest TOC. All techniques capable of attaining zero TVD ensure that the system operates within the allowable voltage limit. The same table can be used to refer to the results of other load models. The proposed MO-IIMFEP yields the lowest total power loss and the lowest TOC for voltage-dependent load models. In the meantime, all techniques capable of limiting all bus voltages within the 69-Bus RDS remain within the specified limit. The variation of load models has also witnessed non-uniform power loss reduction. For instance, in industrial load, MO-IIMFEP attains a total power loss of 35.76 kW, reduced substantially from 171.44 kW before DG compensation. The power loss is reduced to 47.39 kW from 157 kW in commercial load, while a reduction to 44.93 kW from the initial loss of 164.94 kW is experienced in residential load. The highest total optimal DG size is obtained for industrial load, amounting to 1780.50 kW, followed by residential load, worth 1641.12 kW and 1609.80 kW is the required DG capacity in commercial load. This impacts TOC listed in descending order: \$9,045.57 for industrial loads, \$8,385.34 for residential loads and \$8,238.54 for commercial loads. The TVD value of the uncompensated system worth 0.6479 p.u. for industrial load, 0.6312 p.u. for residential load and 0.6114 p.u. for commercial load, has been diminished to zero for all load models with DG compensation. This phenomenon implies that the incorporation of DG into the system results in an improvement of the voltage values across all load models. The Industrial load has the lowest total power loss across all voltage-dependent load models, followed by residential and commercial loads with the highest loss. To mitigate such remarkable losses in industrial load, it requires larger total DG Type 1 sizes. Consequently, the industrial load model requires the largest optimal total DG size, which in turn substantially contributes to the cost. Compared to commercial and residential load, industrial load has the highest TOC.

Figure 5 compares the results for Pareto fronts for the MO-IIMFEP algorithm, specifically for constant, industrial, commercial and residential load models. The Pareto front is a visual representation illustrating the trade-off between multiple objectives. The figures also illustrate the optimal compromise option, as shown by the arrow, achieved by implementing the fuzzy decision-making approach. When the DG size and location are optimized, the Pareto optimal front graph demonstrates that there exists a trade-off between the

Table 5. Performance analysis of the IEEE-69 bus system for constant, industrial, commercial and residential load models using MO-IIMFEP, MO-MFO and MO-EP techniques for multi-objective optimization

Type of Load	Parameters	Without DG	With DG Installation		
			MO-EP	MO-MFO	MO-IIMFEP
Constant Load	Ploss (kW)	224.98	84.68	75.33	75.00
	TVD (p.u.)	0.7313	0.0000	0.0000	0.0000
	TOC (\$)	\$899.92	\$12,084.64	\$11,181.33	\$9,836.73
	DG Size (kW)/Loc		406.12 (60)	404.78 (11)	1123.29 (61)
			1307.94 (59)	392.09 (14)	403.91 (17)
			635.12 (19)	1379.14 (61)	380.15 (64)
Total DG Size (kW)		2349.18	2176.00	1907.34	
Industrial Load	Ploss (kW)	171.44	53.14	36.26	35.76
	TVD (p.u.)	0.6479	0.0000	0.0000	0.0000
	TOC (\$)	\$685.76	\$12,344.36	\$10,582.20	\$9,045.57
	DG Size (kW)/Loc		784.55 (11)	1208.23 (61)	952.30 (61)
			968.34 (61)	499.79 (10)	443.47 (64)
			673.47 (41)	379.42 (21)	384.74 (15)
Total DG Size (kW)		2426.36	2087.44	1780.50	
Commercial Load	Ploss (kW)	157	51.53	50.33	47.39
	TVD (p.u.)	0.6114	0.0000	0.0000	0.0000
	TOC (\$)	\$628.00	\$10,660.06	\$8,860.99	\$8,238.54
	DG Size (kW)/Loc		497.74 (20)	361.46 (10)	370.67 (16)
			620.88 (62)	353.05 (16)	851.95 (61)
			972.17 (57)	1017.42 (61)	387.18 (64)
Total DG Size (kW)		2090.79	1731.93	1609.80	
Residential Load	Ploss (kW)	164.94	46.98	46.28	44.93
	TVD (p.u.)	0.6312	0.0000	0.0000	0.0000
	TOC (\$)	\$659.76	\$10,563.56	\$8,893.85	\$8,385.34
	DG Size (kW)/Loc		838.46 (61)	847.18 (61)	377.85 (64)
			627.52 (57)	508.72 (13)	370.80 (18)
			609.15 (20)	385.85 (61)	892.47 (61)
Total DG Size (kW)		2075.13	1741.75	1641.12	

total power loss, TVD and TOC; specifically, the overall operating cost increases while the total power loss and TVD decrease.

The present study highlights the significance of the proposed MO-IIMFEP, which has demonstrated remarkable results specifically validated using IEEE 69-Bus RDS. Nevertheless, it is conceivable to conduct performance assessments on other test systems to investigate any limitations that may have gone unnoticed in prior

observations. Hence, it is not appropriate to claim that the proposed MO-IIMFEP can universally demonstrate effectiveness across many test systems and problem formulations.

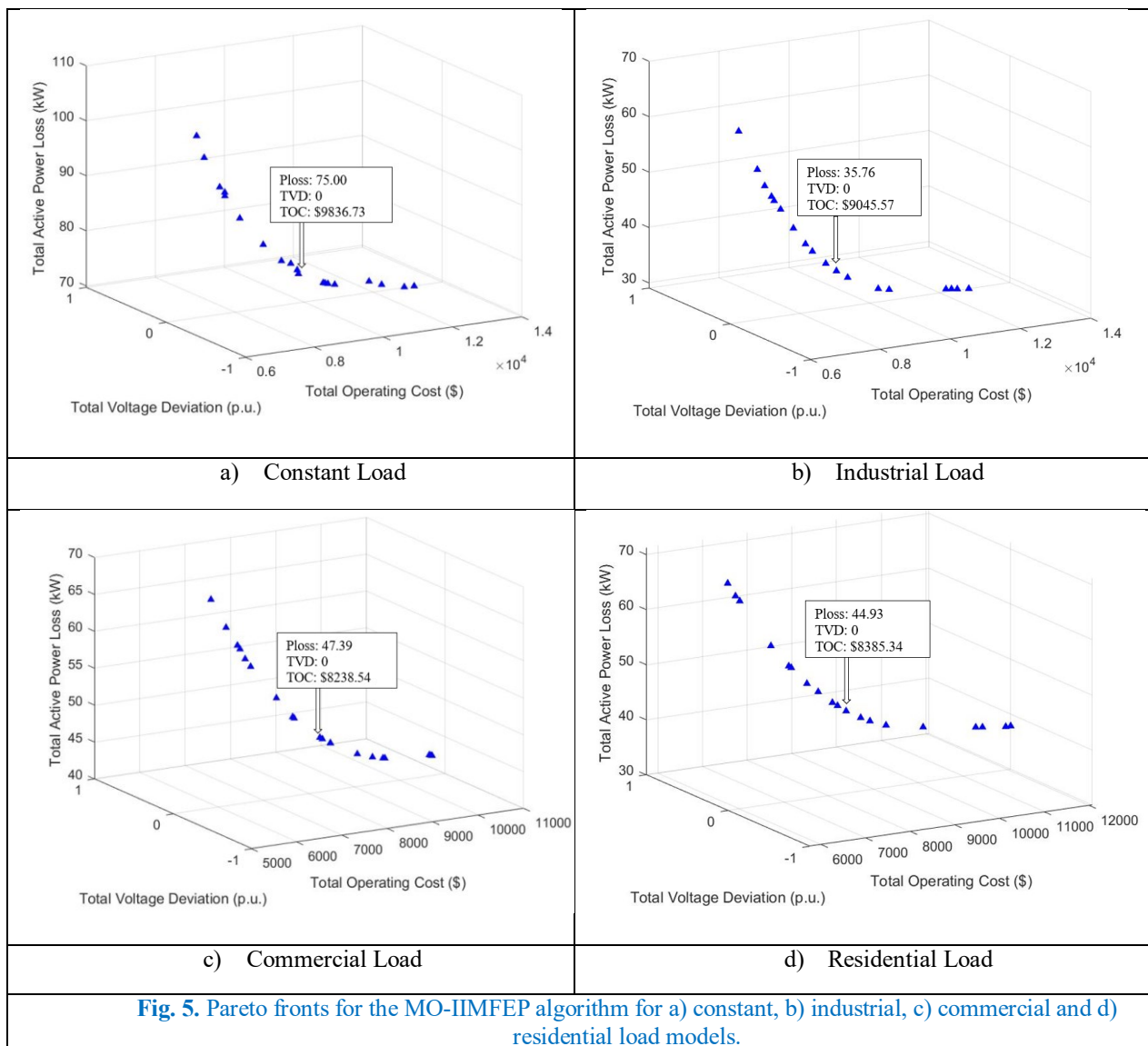


Fig. 5. Pareto fronts for the MO-IIMFEP algorithm for a) constant, b) industrial, c) commercial and d) residential load models.

5. Conclusion

This paper has presented an innovative IIMFEP algorithm, a robust amalgamation of EP, AIS, and MFO, tailored for addressing the complex challenges of DG sizing and location in multi-load models of IEEE 69-Bus RDS. The key strengths of our approach lie in its ability to outperform the traditional Evolutionary Programming (EP) and Moth Flame Optimization (MFO) methods by efficiently navigating away from local optima. The IIMFEP and MO-IIMFEP algorithms consistently demonstrated superior performance in both single-objective and multi-objective optimization techniques. Notably, the multi-objective framework of MO-IIMFEP, employing Pareto techniques, stands out as a formidable tool in concurrently minimizing total active power loss, total voltage deviation, and total operational cost. Noteworthy results have been achieved under industrial loads, where MO-IIMFEP minimized power loss to 35.76 kW with

zero voltage deviation and a TOC of \$9,045.57. Furthermore, the study showcases the adaptability of the proposed algorithms across different load configurations, including constant power and voltage-dependent load models. The clear trend of reduced power loss and improved voltage deviation across all load types underscores the efficacy of the IIMFEP and MO-IIMFEP algorithms in simultaneously addressing diverse optimization objectives. The findings underscore the feasibility and efficacy of the IIMFEP and MO-IIMFEP algorithms in optimizing the placement and sizing of DGs in distribution systems, making them promising tools for real-world applications.

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