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Advanced Pareto Front Non-Dominated Sorting Multi-Objective Particle Swarm Optimization for Optimal Placement and Sizing of Distributed Generation

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Abstract: This paper proposes an advanced Pareto-front non-dominated sorting multi-objective particle swarm optimization (Advanced-PFNDMOPSO) method for optimal configuration (placement and sizing) of distributed generation (DG) in the radial distribution system. The distributed generation consists of single and multiple numbers of active power DG, reactive power DG and simultaneous placement of active-reactive power DG. The optimization problem considers two multi-objective functions, i.e., power loss reduction and voltage stability improvements with voltage profile and power balance as constraints. First, the numerical output results of objective functions are obtained in the Pareto-optimal set. Later, fuzzy decision model is engendered for final selection of the compromised solution. The proposed method is employed and tested on standard IEEE 33 bus systems. Moreover, the results of proposed method are validated with other optimization algorithms as reported by others in the literature. The overall outcome shows that the proposed method for optimal placement and sizing gives higher capability and effectiveness to the final solution. The study also reveals that simultaneous placement of active-reactive power DG reduces more power losses, increases voltage stability and voltage profile of the system.

Keywords: distributed generation; placement and sizing; distribution system; power loss reduction; voltage stability; multi-objective particle swarm optimization (PSO); non-dominated sorting

1. Introduction

The distribution system is mostly configured radially with high resistance to reactance ratio, hence it contributes a major share of power losses in the electric network [1]. Besides this, the load demand is also increasing exponentially which eventually increases more power losses, decrease voltage profile and imbalance reactive power needs. Therefore, the installation of distributed generation witnesses many technical and economic benefits in the distribution system. Few of major benefits are; it reduces system power losses, improves voltage profile, strengthens voltage stability, increases overall network security, lessens the investment cost and elevates reliability of the system [2,3].

Despite many positive benefits from distributed generation (DG), it is a fact that after installation of DG in the distribution system, the operational and control behaviour will change. The non-optimal placement and sizing of distributed generation will increase more system losses, raises more fluctuations in the voltage profile and deteriorates voltage stability and power quality of the system as compared to existing one. Hence, in order to get maximum compensation from DG, it should be connected optimally in the network along with appropriate DG placement and sizing [4].

The DG placement (siting) and sizing (capacity) are mostly attained using optimization algorithms. Many power system researchers and planners have used diverse types of algorithms for optimal integration of DG placement and sizing in the distribution system. Most of the algorithms used are an analytical method, classical optimization technique, artificial intelligence (meta-heuristic) techniques and other miscellaneous techniques [5]. The authors [6–9] used the analytical method for optimal DG placement and sizing problem of different objective functions. The drawback of this algorithm is that it only handles the single-objective optimization problem. Optimal placement and sizing method using classical optimization algorithm have been used by [10–13]. Some authors had also used meta-heuristic based optimization algorithm. These algorithms include single-objective or multi-objective optimization techniques. The algorithms are mainly named as genetic algorithm (GA) [14], bat algorithm (BA) [15], artificial bee colony (ABC) [16], bacterial forging optimization algorithm (BFOA) [17,18], back-tracking and fuzzy expert [19], big-bang big crunch method (BB-BC) [20], imperialist competitive algorithm (ICA) [21], and PSO [2,22–24] are used for stressed problem. It is concluded that most of the research works are focused on the single objective. However, a few of the authors had worked on the multi-objective optimization with weighted techniques [16,25].

The integration of DG in the distribution system is a complex combinatorial multi-objective optimization problem, which needs to be solved with many practical objective functions and constraints. Practically, many objective functions have incommensurability and conflicts between them. It is not obligatory that all objective functions give a unique solution. Hence, the authors [26–28] worked for optimal sitting and sizing of multi-objective DG problem with respect to cost as objective functions. The authors [29–31] used the non-dominated sorting based multi-objective optimization algorithms, which basically maintains the diversity in the population and gives the final Pareto-solution.

However, this paper proposes an advanced-PFNDMOPSO algorithm for identifying the optimal placement and sizing of DG in the distribution system. An optimal power flow model is presented for both single-objective as well as for multi-objective optimization. Two objective functions are considered for this research (I) minimization of total power loss and (II) maximization of voltage stability index, while maintaining the technical constraints. For the single objective optimization, the priority is given to 1st and 2nd objective function respectively, aiming to see the compatibility of proposed method. Whereas, for multi-objective optimization, both objective functions are optimized simultaneously. In addition to this, the performance of proposed algorithm is also modified in convergence speed using mutation operator. The fast convergence is preferable in any algorithm but it is feared that it may result in false Pareto-solution in the context of multi-objective optimization. Therefore, this operator helps in maintaining the particles within the search space. Basically, the mutation operator increases the explorative behaviour for all particles at the start of the algorithm and later its effect ceases gradually. The results showed that the proposed advanced PFNDMOPSO method gives higher capability and performance than other single and multi-objective optimization methods for optimal placement and sizing of DG problem.

Meanwhile, the rest of the paper contents such as Section 2 shows the DG modeling. Section 3 presents the problem formulation for load flow technique and objective functions including constraints. In Section 4, detailed explanation of multi-objective PSO optimization method is presented while, Section 5 provides fuzzy decision model. Section 6 presents the case studies of the problem and results respectively. Lastly, Section 7 presents the conclusion.

2. Distributed Generation (DG) Modeling

In most of the literature, the DG is modeled as an active power DG, which transfers only real power in the distribution system. Though, nowadays, various kinds of distributed generators are being integrated into the distribution system as they are identified with different types [2,32]. Such as Type-1 (Distributed Generator that injects only active power P, i.e., it could be photovoltaic, fuel cells, and micro-turbines with power factor 1), Type-2 (Distributed Generator that injects only reactive power Q, i.e., synchronous condenser/shunt capacitors or distributed static compensator (DSTATCOM), Type-3

(Distributed Generator that injects both active and reactive power PQ, i.e., synchronous generator, combine heat transfer (CHP), gas turbine or cogeneration) and Type-4 (Distributed Generator that injects active power but at the same time absorbs reactive power, i.e., induction generator). This paper utilizes the first three types of DGs, which are represented as negative P, Q and PQ loads respectively. The boundary condition of the real and reactive power DGs are also restricted, which is given as in Equations (1) and (2).

$$P_{DG}^{\min} \leq P_{DG} \leq P_{DG}^{\max} \tag{1}$$

$$Q_{DG}^{\min} \leq Q_{DG} \leq Q_{DG}^{\max} \tag{2}$$

3. Problem Formulation

3.1. Load Flow Technique

The traditional load flow techniques, which are modeled for power transmission system are not appropriate for distribution system due to its high resistance to reactance ratio [24]. Hence this paper utilizes a specially designed Backward/Forward Sweep Load Flow algorithm [33]. This load flow technique works on two sweeps, the backward sweep (updating current or power flow from the last junction to source junction) and forward sweep (updating voltage from the first junction to the last junction). Figure 1 represents the one-line diagram of two buses $m1$ and $m2$, connected through branch i. The power flow for referred distribution system at branch i can be computed by the following set of recursive Equations (3)–(5).

$$P_i = P_{m2} + P_{i\ loss} \tag{3}$$

$$Q_i = Q_{m2} + Q_{i\ loss} \tag{4}$$

$$V_{m2} = V_{m1} - I_i\left(R_i + jX_i\right) \tag{5}$$

where P_i and Q_i, are the real and reactive powers of the branch i interconnecting bus $m1$ with bus $m2$. P_{m2} and Q_{m2} are the real and reactive loads at bus $m2$. V_{m1} and V_{m2} are the voltage profiles of the buses $m1$ and $m2$ respectively. R_i, and X_i are the resistance and reactance of the branch i. I_i is the current flowing from $m1$ to $m2$. The power losses across each branch and of the whole system can be computed using Equations (6)–(8):

$$P_{i\ loss} = R_i \times \frac{(P_{m2}^2 + Q_{m2}^2)}{|V_{m2}^2|} \tag{6}$$

$$Q_{i\ loss} = X_i \times \frac{(P_{m2}^2 + Q_{m2}^2)}{|V_{m2}^2|} \tag{7}$$

$$T_{loss} = \sum_{i=1}^{i=nb-1} P_{i\ loss} + j \sum_{i=1}^{i=nb-1} Q_{i\ loss} \tag{8}$$

where $P_{i\ loss}$ and $Q_{i\ loss}$ are the real and reactive power losses for the branch i respectively, while T_{loss} is the total network loss.

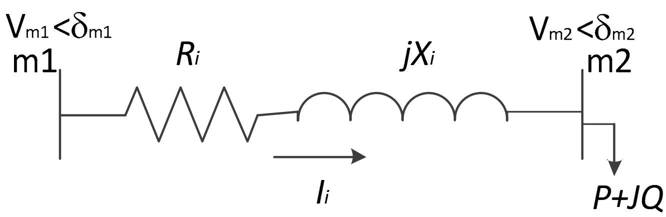

Figure 1. One-line diagram of two-bus radial distribution system.

3.2. Objective Functions

A constrained non-linear optimization problem is designed for multi-objective DG placement and sizing problem in the distribution system. The proposed optimal power flow model is designed in such a way that it works for single objective and multi-objective optimization. The objective functions of this paper are to reduce the active component of power losses and to improve the voltage stability of radial distribution system.

3.2.1. Power Loss Reduction

The fact that about thirteen percent of total power generation is wasted as $(I^2 \times R)$ losses in the distribution system [17,19]. Therefore, the first objective of this paper is to minimize the power losses in radial distribution system. The mathematical expression for power loss reduction can be described as in Equation (9):

$$f_1 = \min\left(\sum_{i=1}^{i=nb-1} P_{i\ loss}\right) \tag{9}$$

3.2.2. Voltage Stability Index

The voltage stability index (VSI) is an indicator, which shows the stability of distribution system [16,34,35]. This paper is intended to observe the voltage stability of the system with the installation of different types of DGs. The Equation (10) is used to represent the VSI index of proposed model. Equations (11) and (12) are representing the mathematical expression for voltage stability index as second objective function. In order to maintain the security and stability of distribution system, the VSI value should be greater than zero; otherwise distribution system is under critical condition of instability.

$$VSI_{m2} = |V_{m1}|^4 - 4.0\{P_{m2} \times X_i - Q_{m2} \times R_i\}^2 - 4.0\{P_{m2} \times R_i + Q_{m2} \times X_i\}\,|V_{m1}|^2 \tag{10}$$

$$f'_2 = \max\sum_{mi}^{Nb}(VSI_{mi}) \tag{11}$$

where VSI_{m2} is the VSI for bus $m2$ and VSI_{mi} is the VSI for whole system $(mi = 2, 3, 4 \ldots Nb)$; Nb is the total number of buses. In order to improve the voltage stability index, the second objective function can be presented as below:

$$f_2 = \left(\frac{1}{f'_2}\right) \tag{12}$$

3.3. Network Constraints

The Equations (13)–(16) represents the equality and non-equality constraints of the proposed model.

3.3.1. Power Balance

$$P_{substation} + \sum P_{DG} = \sum P_{loss} + \sum P_{load} \tag{13}$$

$$Q_{substation} + \sum Q_{DG} = \sum Q_{loss} + \sum Q_{load} \tag{14}$$

where $P_{substation}$ and $Q_{substation}$ are the total real and reactive power injection by substation in to the network. ΣP_{DG} and ΣQ_{DG} are the total real and reactive power, injected by DG. ΣP_{loss} and ΣQ_{loss} are the total real and reactive power loss in the network. ΣP_{load} and ΣQ_{load} are the total real and reactive power losses of the network respectively.

3.3.2. Position of DG

Bus 1 is the substation or slack bus, so position of the DG should not be used at bus 1.

$$2 \leq DG_{position} \leq n_{buses} \tag{15}$$

3.3.3. Voltage Profile

In order to maintain the quality of power supplies, the voltage profile of every bus in the network should satisfy the following constraint.

$$V^{\min} \leq V \leq V^{\max} \tag{16}$$

4. Multi-Objective Optimization (MOO), Dominate, Non-Dominated and Pareto Optimal Solution

In the real world, many problems have multiple objectives which need to be optimized simultaneously. Therefore, in a multi-objective optimization (MOO) problem, one needs to find the best compromise solution among the whole set of solution. Commonly, the non-dominated sorting approach is executed to find the best compromise Pareto-set.

i MOO: It can be expressed as follows:

$$\min F(u) = [f_1(u), f_2(u), \ldots, f_{M_{obj}}(u)],\ u \in U$$

$$\text{subject to}: \ g_i(u) \leq 0, i = 1, 2, \ldots, m$$

$$h_i(u) = 0, i = 1, 2, \ldots, l$$

where $F(u)$ is the function of u and M_{obj} is the total number of objective functions. The u and U are the decision variable and its space respectively. $g_i(u)$ and $h_i(u)$ are the constraint functions of the problem respectively.

ii Dominated: Let us say a decision vector u_1 is said to dominate u_2, if and only if, the following conditions are satisfied.

- The solution in decision vector u_1 is no worse than decision vector u_2 in all objectives.
- The solution in decision vector u_1 is strictly better than u_2 in all objectives.

Mathematically, it can be expressed as:

$$\forall i \in \left\{1, 2, \ldots, M_{obj}\right\} : f_i(u_1) \leq f_i(u_2) \tag{17}$$

$$\exists j \in \left\{1, 2, \ldots, M_{obj}\right\} : f_j(u_1) \leq f_j(u_2) \tag{18}$$

iii Non-dominated:

A solution u is said to be non-dominated or Pareto solution of set $= [u_i]$; where $i = 1, \ldots, n$, if $u \in S$, and there is no solution $u' \in S$ for which u' dominates u.

iv Pareto-optimal solution:

Supposed that all the non-dominated solutions of set S are in set P, then Pareto front of set is S is given as in Equation (19) and can be seen in Figure 2.

$$P = \{\vec{f} = [f_1(u_1), f_2(u_2), \ldots, f_{M_{obj}}(u)]^T, u \in S\} \tag{19}$$

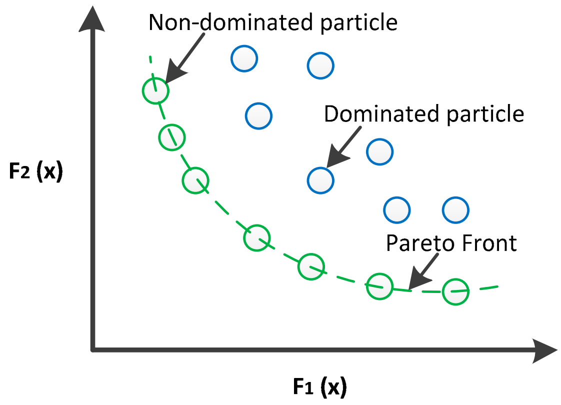

Figure 2. Dominated, non-dominated and Pareto-front solution set.

Multi-Objective Particle Swarm Optimization (PSO) Optimization Algorithm

Kennedy and Eberhart in 1995 introduced the PSO, inspired by the natural choreography of birds flocking or fish schooling [36]. Let v and S in search space are velocity and position of the particle. Therfore, the ith particle position can be written as $(S_i = S_{i,1}, S_{i,2} \ldots\ldots S_{i,d})$, where d is the dimensional space of the particle. The previous best ith particle position will be $(Pbest_i = Pbest_1, Pbest_2 \ldots\ldots Pbest_{i,d})$. The best particle among all, will be *gbest* and velocity of the particle i can be represented by $(V_i = V_{i,1}, V_{i,2} \ldots\ldots V_{i,d})$. Each particle's velocity closest to *pbest* and *gbest* is calculated by Equation (20). Moreover, each particle's current position is updated by Equation (21).

$$v_{id}^{k+1} = \omega \times v_{id}^{k} + c_1 \times rand() \times \left(pbest_{id} - v_{id}^{k}\right) + c_2 \times rand() \times \left(gbest_d - v_{id}^{k}\right) \tag{20}$$

$$S_{id}^{k+1} = S_{id}^{k} + v_{id}^{k+1}, i = 1, 2, \ldots, n,\ d = 1, 2, \ldots, m \tag{21}$$

where n is the number of particle, m is the dimensional numbers of member particles, k is kth iteration, ω is inertia weight factor, c_1 and c_2 are acceleration constants, $rand()$ is uniform random value in range (0, 1), whereas v_{id}^{k} and S_{id}^{k} are velocity and position of the particle i at kth iteration.

Multi-objective particle swarm optimization (MOPSO) is the extended version of PSO, which handles multiple objective functions simultaneously. The operational flow of this method was first presented by [37] in 2004. The author described that the first few initial solutions are randomly generated in the search space. Later, these solutions are used for updating the velocities and positions and finally improved solution sets will be obtained. Usually, it is known that PSO algorithm has a general drawback, that it converges at a very high speed. Fast convergence is preferred in any algorithm but it is feared that it may results in false Pareto-solution in the context of multi-objective optimization. Therefore, the mutation operator is introduced, which is actually applied after the particle position is updated and hence modifies the position vector. The mutation operator increases the explorative behaviour with all the particles at beginning of search space. Later as the number of iteration increases, the effect of this operator decreases. Hence, this operator helps in maintaining the particles within the search space. The pseudocode of mutation operator is presented in Algorithm 1.

Algorithm 1. Pseudocode for mutation operator

% mu = mutation rate % rr = reducing rate % iter = current iteration % maxiter = maximum iteration % varmax = particle's upper boundary % varmin = particle's lower boundary
1: **initialize** reducing rate (rr)
rr = (1 − (iter − 1)/(maxiter − 1))^(1/mu)
2: **if** rand < rr
3: **function** mutation_factor (particle, rr, varmax, varmin)
4: Calculate mutation range (m_range)
m_range = (varmax − varmin) × rr
5: Assign particle's upper and lower bounds
ub = particle + m_range
lb = particle − m_range
6: Verify particle's upper and lower bounds
if ub > varmax **then** ub = varmax
if lb < varmin **then** lb = varmin
7: Assign new values to particle within upper and lower bounds
particle = unifrnd (lb, ub)
8: **end function**

The main input parameters for the advanced-PFNDMOPSO need to be pre-defined, such as maximum number of iteration $(Maxiter = 200)$, population size $(NPOP = 200)$, repository size $(NREP = 50)$, weight of inertia $(w = 0.5)$, inertia weight damping rate $(w_{damp} = 0.99)$, personal and global learning coefficient $(C_1 = 1 \; and \; C_1 = 2)$, number of grids per dimension $(NGrid = 7)$, inflation rate $(alpha = 0.1)$, leader selection parameter $(beta = 2)$, deletion selection parameter $(gama = 2)$ and mutation rate $(\mu = 0.1)$. The complete algorithm is shown in Figure 3 and explained as follows:

Input data: random population $POP\,(i)$, fitness function $POP\,(i)\,.\,Objectives$, up-date velocity $POP\,(i)\,.\,Vel$ and position $POP\,(i)\,.\,Position$ at certain number of iteration with Equations (22)–(25) respectively.

$$\begin{aligned} POP(i).Vel \quad &= w \times POP(i).Vel + C_1 \times rand() \times \\ &(POP(i).Pbest - POP(i)) + C_2 \times rand() \times (REP(h) - POP(i)) \end{aligned} \tag{22}$$

$$POP(i).Position = POP(i).Position + POP(i).Vel \tag{23}$$

$$POP(i).Position = \max(POP(i).Position, Var_{\min}) \tag{24}$$

$$POP(i).Position = \min(POP(i).Position, Var_{\max}) \tag{25}$$

Result: Pareto-optimal solution u^k.

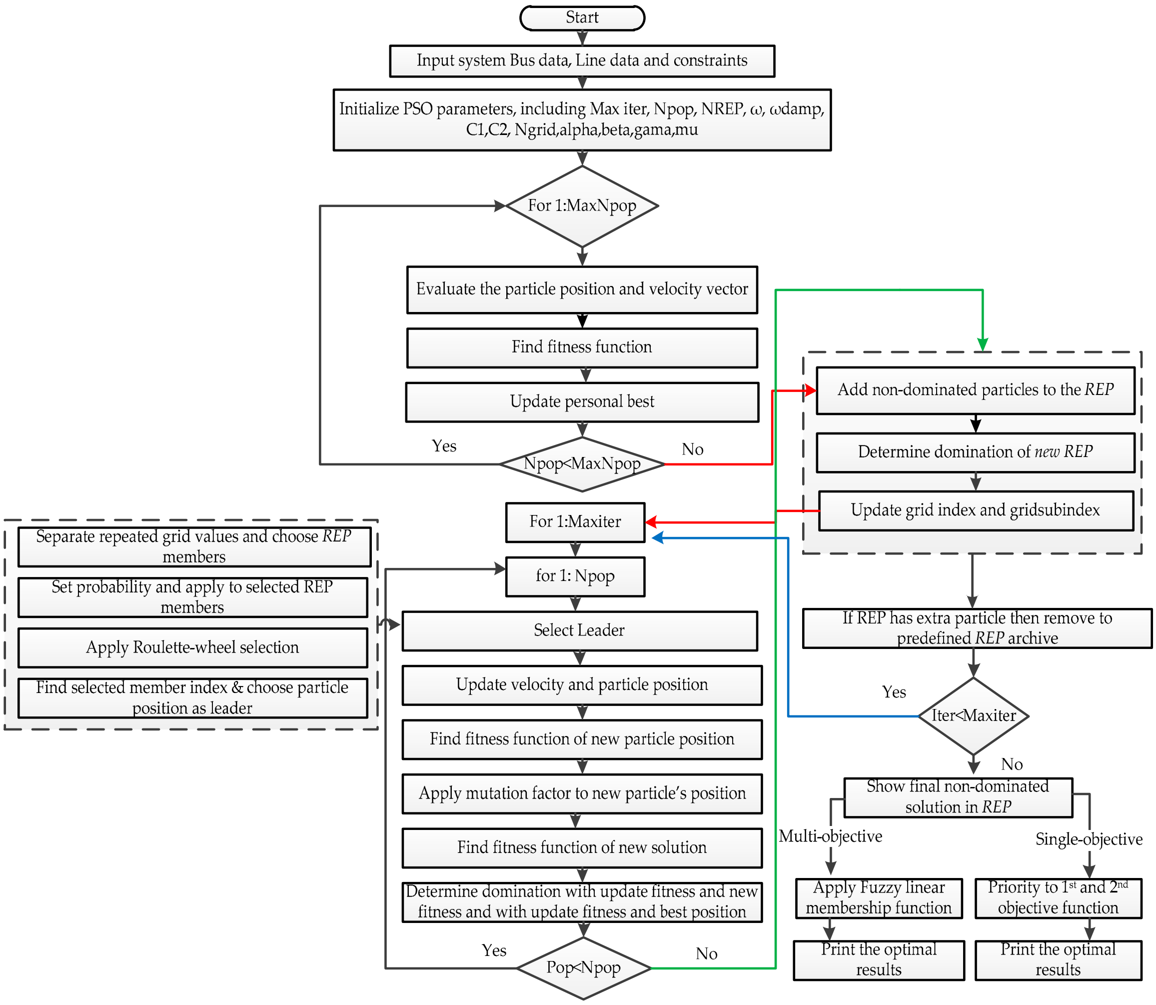

Figure 3. Flow chart for optimal DG configuration using proposed method.

Steps:

1. Initialization: initialize the population.
2. For $i = 1$ *to* Max.
3. Initialize $POP\ (i)\ .\ Position$.
4. Initialize the velocity of each particle.
5. For $i = 1$ *to* Max.
6. Initialize $POP\ (i)\ .\ Vel$.
7. Run load flow and find the fitness function of each particle in population.
8. Update the personal best *Pbest*.
9. Determine domination among the particles and save the non-dominated particles in repository archive (*REP*). The new generated solutions are added to repository and the dominated solutions are removed from repository.
10. Find the leader (global best) from *REP* of every particle.
11. In order to select the leader from members of the repository front, firstly the member of repository front is gridded and then the roulette wheel technique is used so that cells with lower congestion have more chance to be selected. Finally, one of the selected grid's members is chosen randomly.
12. Update the speed of each particle using Equation (22).
13. Update the new position of each particle (personal best) using Equations (23)–(25).
14. Run load flow and find the fitness function of each particle in population.

15. Apply mutation factor.
16. Add non-dominated solution set of the recent population in the repository.
17. Determine the domination among the particles and save the non-dominated particles in repository archive REP.
18. Check the size of the repository. If the repository exceeds the predefined limit, remove the extra members.
19. If the convergence of algorithm occurs, the operation will stop, otherwise, go to step 6.
20. The rest of the members in the repository will be taken for the final solution.
21. For single-objective, the priority is given to only that objective function.
22. For multi-objective, the optimal compromise solution will be chosen.

5. Fuzzy Decision Model

In order to get the best compromise solution from non-dominated Pareto-front solution, fuzzy decision model is proposed. For every solution in kth Pareto-front, the linear membership function α_i^k is introduced, which represents the proper goal of ith objective function. Figure 4 shows the linear membership function trend and mathematically can be expressed in Equation (26).

$$\alpha_i{}^k = \begin{cases} 1 & \text{if } f_i \leq f_i{}^{\min} \\ \frac{f_i{}^{\max} - f_i{}^k}{f_i{}^{\max} - f_i{}^{\min}} & \text{if } f_i{}^{\min} < f < f_i{}^{\max} \\ 0 & \text{if } f_i \geq f_i{}^{\max} \end{cases} \tag{26}$$

where $f_i^{\min}$ and $f_i^{\max}$ are the minimum and maximum values of ith objective function in all non-dominated solutions respectively. The value of membership function α generally varies between 0 *to* 1, if $\alpha_i = 0$, then the solution shows the incompatibility with set and if $\alpha_i = 1$, then the solution shows full compatibility. The degree of preference of each non-dominated solution k can be found using normalized membership value α^k as follows:

$$\alpha^k = \frac{\sum\limits_{i=1}^{N_{obj}} \alpha_i^k}{\sum\limits_{k=1}^{M_{nd}} \sum\limits_{i=1}^{N_{obj}} \alpha_i^k} \tag{27}$$

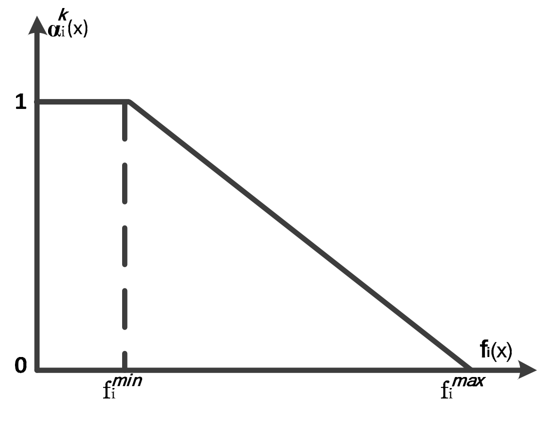

Figure 4. Linear fuzzy-decision model.

6. Case Studies

This section provides the optimal placement and sizing of single and multiple distributed generation resources using the advanced-PFNDMOPSO method. Two case studies are performed as single-objective and multi-objective optimization for power loss reduction and voltage stability improvement. In single objective optimization, the priority is given to 1st and 2nd objective function after getting pareto-results obtained from proposed model. In multi-objective optimization, the trade-off between these two functions has been taken out. The proposed model is tested on IEEE 33 bus system. The technical specification for this test system are taken from ref. [2]. The base case values for both case studies are 1 MVA and 12.66 kV respectively. Each case study is further investigated with different types of DGs. The DG types are demarcated as; Type-1: Active power DG, Type-2: Reactive Power DG and Type 3: Active-Reactive power DG. The size of real power DG should be in range of $p_{DG}^{\min} = 0$ MW, $p_{DG}^{\max} \leq 2$ MW and the size reactive power DG should be in range of $Q_{DG}^{\min} = 0$ MVAr, $Q_{DG}^{\max} = 2$ MVAr, the voltage limits for Type-1 and Type-3 are $V_{\min} = 0.95$ (p.u) and $V_{\max} = 1.05$ (p.u), whereas, the voltage limits for Type-2 are $V_{\min} = 0.92$ (p.u) and $V_{\max} = 1.05$ (p.u) respectively. Each type of DG is further processed with installation of single and multiple number of DGs as shown in Figure 5.

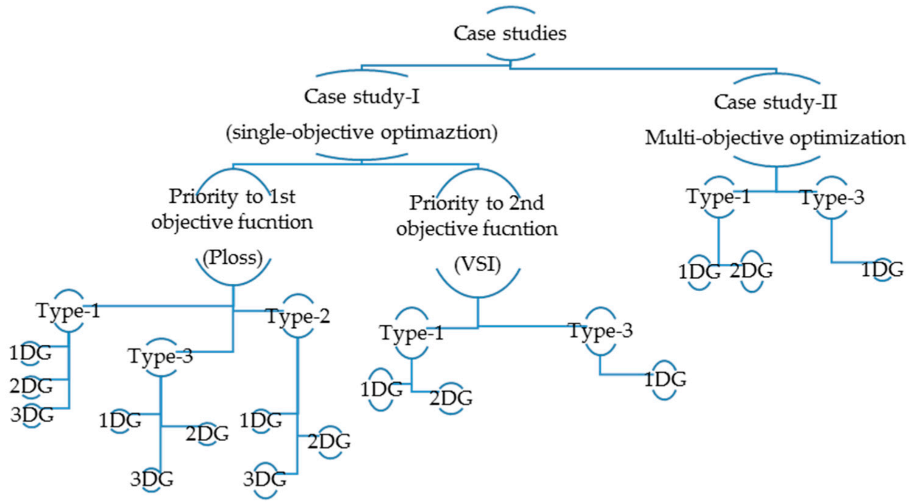

Figure 5. The conceptual framework of case studies.

The one-line diagram of IEEE 33 bus system is given in Figure 6. The total real and reactive power demands are 3720 kW and 2300 kVAr respectively. The proposed methodology is carried out by simulation using Intel core i_5, 4096 MB RAM personal computer using MATLAB (2015a) software package [38].

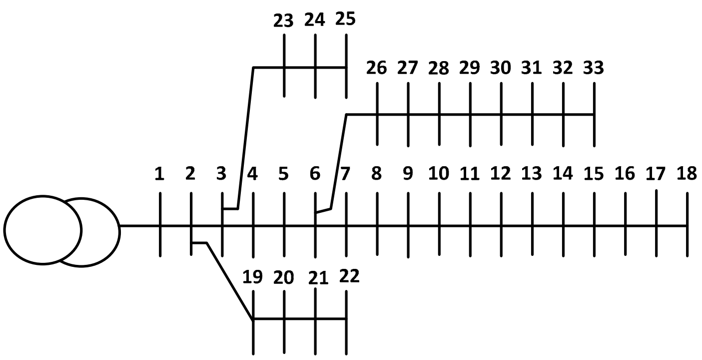

Figure 6. IEEE 33 radial distribution system.

6.1. Case Study-I: Single-Objective Optimization

The purpose of this case study is to validate competency of the proposed method for various types of distributed generators in the distribution system. For this, among the pareto results produced by the proposed method, the priority is given to only specific objective function i.e., power loss reduction (Ploss) or voltage stability improvement (VSI). However, other associated objective function values are also recorded.

6.1.1. Priority to 1st Objective Function (Ploss)

In this case, the priority is given only to a 1st objective function which is active power loss reduction (i.e., ploss). The optimal placement and sizing are found for three types of DGs and each having three numbers of DG units, i.e., Type-1 (1 DG), . . . , Type-1 (3 DG), Type-2 (1 DG), ..., Type-2 (3 DG) and Type-3 (1 DG), . . . , Type-3 (3 DG) respectively. The results of the proposed method are also compared with the literature that has worked for minimization of power loss. Table 1 is showing the optimal location, size and power loss reduction by each DG along with voltage stability improvement.

Table 1. Optimal placement and sizing of DG for case study-I as single-objective function with priority to 1st objective function.

DG-Type	DG No.	DG Location	DG Size (MW)	Ploss (kW)	VSI	Reduction in Ploss (%)
Base-case	-	-	-	211	25.125	
Type-1	1 DG	7	2.0	115.17	27.326	45.41
	2 DG	13, 31	1.1115, 1.4882	87.8	28.75	57.42
	3 DG	14, 24, 27	0.70027, 1.0089, 1.62850	79.4	29.05	62.37
Type-2	1 DG	30	1.2807	151.4	26.192	28.24
	2 DG	12, 30	0.44219, 1.2062	142.5	26.75	32.46
	3 DG	30, 30, 12	1.06288, 0.3525, 0.4533	140	26.83	33.64
Type-3	1-1 DG (P) 1-1 DG (Q)	8 30	1.911 1.253	64.78	29.19	69.29
	2-2 DG (P) 2-2 DG (Q)	15, 31 30, 20	0.8258, 1.1288 1.4424, 0.3717	40.2	30.025	80.94
	3-3 DG (P) 3-3 DG (Q)	20, 29, 13 12, 5, 33	0.447, 1.3574, 0.9058 0.663, 0.6557, 0.78976	34.5	31.173	83.64

It can also be seen that with the use of different types of DGs, the placement and sizing varies largely, which eventually affect overall objective functions. This revealed that with maximum (3) number of DG units of (Type-1, Type-2 and Type-3), the objective 1 is improved up to 62.37 percent, 33.64 percent, and 83.64 percent respectively. The results had revealed that integration of Type-3 DG gives better performance as compared to Type-1 and Type-2 DG.

The results of the proposed model are compared with Type-1 DG with following algorithms. The Type-1 DG with one DG unit is compared with flower pollination algorithm (FPA) [39], GA [6], grid search algorithm (GSA) [40] and PSO [2], for two-DG units with FPA [39] and for three-DG units with GA [41], PSO [41], genetic algorithm and particle swarm optimization algorithm (GA/PSO) [41], dynamic adoption of PSO (DAPSO) [42], parto frontier differential evolution (PFDE) [43] and loss sensitivity factor and simulated annealing (LSFSA) [44]. Table 2 shows the comparisons of proposed method with other algorithms.

It can be seen from Table 2 that with the use of only 1 DG, the proposed method gives better loss reduction compared to FPA [39]. However, when compared with analytical method (AM) [6], GSA [40] and PSO [41], optimization algorithms, the loss reduction by proposed method is same but the DG capacity is lesser. Similarly, for 2 DG the performance of proposed algorithm is better in terms of loss reduction and DG capacity as compared to FPA [39] algorithm. Moreover, for 3 DG, it can be seen that the loss reduction is maximum by the proposed method compared to other methods such as LSFSA [44], PFDE [43], DAPSO [42], GA/PSO [41], PSO [41], GA [41] reported in the literature.

Table 2. Comparison of the proposed method with other algorithms for Type-1 DG (1st objective function).

Method	DG Size & Location	Ploss (kW)	Method	DG Size & Location	Ploss (kW)
	1 DG			**2 DG**	
Proposed method	2.0 at 7 2.589 [x] at 06	115.17 111.0	Proposed method	1.2603 at 29 0.9277 at 13	87.8
AM [6]	2.600 at 06	111.0	FPA [39]	1.0339 at 12 1.0866 at 30	89.2
GSA [40]	2.600 at 06	111.0			
PSO [2]	2.600 at 06	111.0			
FPA [39]	2.000 at 07	115.17			
Method	**DG Size & Location**	**Ploss (kW)**	**Method**	**DG Size & Location**	**Ploss (kW)**
			3 DG		
Proposed method	0.70027 at 14 1.0089 at 24 1.62850 at 27	79.40	GA/PSO [41]	1.2000 at 32 0.8630 at 16 0.9250 at 11	103.40
LSFSA [44]	1.1124 at 06 0.4874 at 18 0.8679 at 32	82.80	PSO [41]	0.9816 at 13 0.8297 at 32 1.1768 at 08	105.30
PFDE [43]	0.9100 at 13 1.2500 at 26 0.8800 at 32	88.00	GA [41]	1.5000 at 11 0.4228 at 29 1.0714 at 30	106.30
DAPSO [42]	0.6810 at 10 0.600 at 18 0.7190 at 31	92.55			

[x] All constraints are appreciated except μ.

The voltage profile and voltage stability are two main parameters of the radial distribution system. The voltage profile of each node defines the performance of the system, whereas, the voltage stability indicates the ability of a system to maintain its stability. Optimal placement and sizing of DG along with power loss reduction increases the voltage profile and voltage stability of each bus of the system. The results of both parameters for single-objective optimization with priority to 1st objective function are depicted in Table 3.

Table 3. The voltage profile and voltage stability of the system for 1st objective function.

DG Type	DG No.	Voltage (p.u)		Voltage Stability (p.u)	
		Min	Max	Min	Max
	Base Case	**0.9037 at 18**	**1.00 at 1**	**0.6669 at 18**	**1.00 at 1**
Type-1	1 DG 2 DG 3 DG	0.9424 at 18 0.9647 at 18 0.9728 at 18	1.00 at 1 1.00 at 1 1.00 at 1	0.7888 at 18 0.8661 at 18 0.8953 at 18	1.00 at 1 1.00 at 1 1.00 at 1
Type-2	1 DG 2 DG 3 DG	0.9160 at 18 0.9295 at 18 0.9297 at 18	1.00 at 1 1.00 at 1 1.00 at 1	0.6984 at 18 0.7405 at 18 0.7410 at 18	1.00 at 1 1.00 at 1 1.00 at 1
Type-3	1 DG 2 DG 3 DG	0.9492 at 18 0.9859 at 18 1.0051 at 18	1.00 at 1 1.00 at 1 1.00 at 1 & 33	0.8116 at 18 0.9449 at 18 1.020 at 18	1.00 at 1 1.00 at 1 1.00 at 1

The base case voltage profile values for IEEE 33 bus is 0.9037 p.u at bus 18 before installing the DG. However, it can be seen that with the installation of Type-1 DG the voltage profile can be improved up to 0.9728 p.u. With the installation of Type-2 DG, it can be improved up to 0.9297 p.u and with the installation of Type-3 DG, it can be improved up to 1.0 p.u respectively. Similarly, for voltage stability the base case values are 0.6669 p.u without installation of DG. The installation of Type-1 DG also improves voltage stability by 0.8953 p.u. The installation of Type-2 and Type-3 DG can improve the voltage stability up to 0.7410 p.u and 1 p.u respectively.

Before adding the distributed generation sources in IEEE 33 bus system, the substation bus has highest voltage profile of 1.00 p.u, however, the bus 18 has lowest voltage profile. After integrating DG, it can be seen that the Type-1 and Type-3 increases more voltage profile as compared to Type-2 DG. Similarly, Figures 7 and 8 shows the voltage profile of each bus of the system.

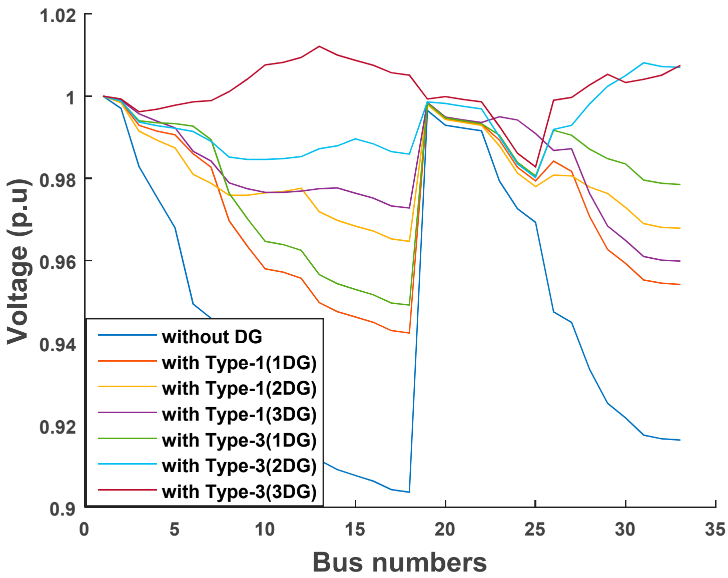

Figure 7. Voltage profile for 33 bus with Type-1 and Type-3 DG for 1st objective function.

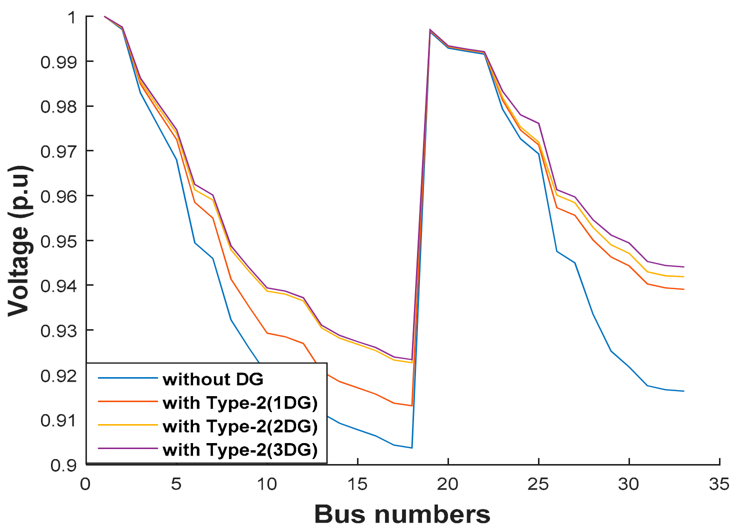

Figure 8. Voltage profile for 33 bus with Type-2 DG for 1st objective function.

It can be seen from Figures 9 and 10 that the voltage stability of substation bus is highest. However, the bus 18 and bus 65 has lowest values without adding the distributed generation sources. After integrating DG, similar to voltage profile, the voltage stability is also increased more by Type-1 and Type-3 DG as compared to Type-2 DG.

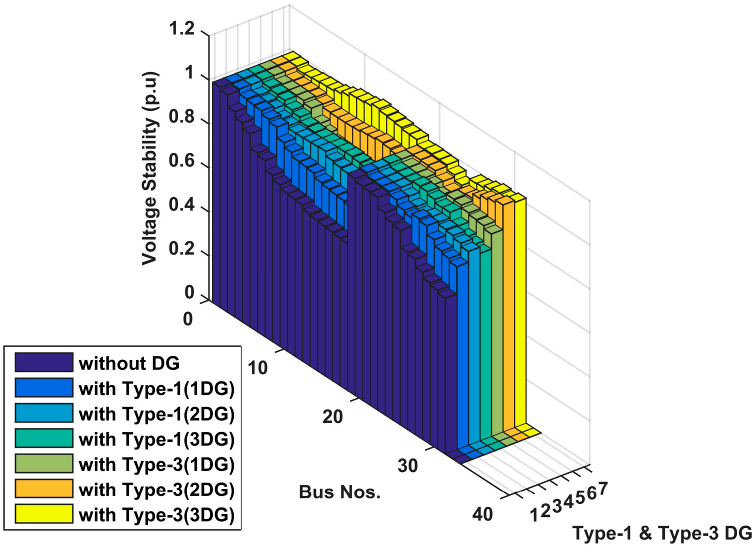

Figure 9. Voltage stability for 33 bus with Type-1 and Type-3 DG for 1st objective function.

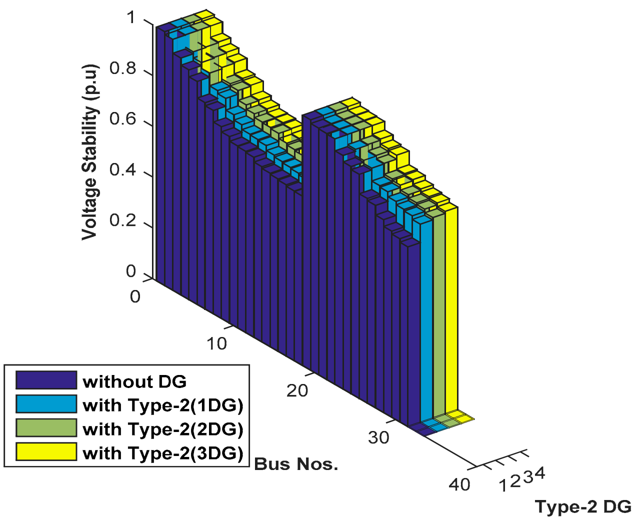

Figure 10. Voltage stability for 33 bus with Type-2 DG for 1st objective function.

6.1.2. Priority to 2nd Objective Function (VSI)

Among the pareto results observed by the proposed method, priority is given to the second objective function, which is voltage stability improvement. The detailed discussion is available for two types of DGs i.e., Type-1 (1 DG and 2 DG) and Type-3 (1 DG) in Table 4.

It can be seen that by giving priority to VSI, a significant VSI had been improved. The results show that with Type-1 (2 DG) VSI is improved upto 27.62 percent, whereas, with Type-3 (1 DG) it is improved by 31.23 percent.

Table 4. Optimal placement and sizing of DG for case-1 as single-objective function with priority to 2nd objective function.

DG-Type	DG No.	DG Location	DG Size (MW)	Ploss (kW)	VSI	Reduction in VSI (%)
Type-1	1 DG	16	1.999	194.9	29.767	18.47
	2 DG	14, 30	1.972, 1.860	188.7	32.067	27.62
Type-3	1-1 DG (P)	15	1.956	179.4	32.974	31.23
	1-1 DG (Q)	10	2.0			

The results for VSI as an objective function are also validated against backtracking search algorithm (BSA) [19] as shown in Table 5.

Table 5. Comparison of the proposed method with other algorithms for Type-1 (1 DG) and Type-3 (1 DG) for 2nd objective function.

Parameters	Type-1 (1 DG)		Type-3 (1 DG)	
	Proposed Method	BSA	Proposed Method	BSA
DG Size (MVA)	1.984 at 10	1.857 at 11	1.975 at 13 + j2 at 8	1.618 + j1.895 at 11
$V_{\min}$ (p.u)	0.9440 at 33	0.9438 at 33	0.9629 at 33	0.9604 at 33
$V_{\max}$ (p.u)	0.9982 at 2	0.9981 at 3	1.049 at 15	1.0049 at 11
$VSI_{\min}$	0.7974 at 33	0.7934 at 33	0.8630 at 33	0.8507 at 33
$VSI_{\max}$	0.9927 at 2	0.9926 at 2	1.229 at 13	1.2058 at 12
$1/\sum VSI$	29.240	29.237	32.53	32.051
P_{loss} (kW)	133.0	133.01	137.6	138.74
Q_{loss} (kVAR)	94.1	93.53	106.3	105.35

For Type-1 (1 DG) and Type-3 (1 DG), the proposed method gives better results in voltage stability improvement as compared to BSA presented in [19]. The voltage stability improvement by proposed method is higher as at 29.767 and 32.974 as compared to BSA 29.237 and 32.051 respectively. Even the VSI values were deeply checked in relating to power loss as referred by BSA. It is realized that the outcomes are higher even in this case as compared to BSA. Moreover, the minimum and maximum voltage profile and voltage stability of the proposed method are also upfront.

By giving priority to VSI as an objective function, the significant voltage profile and voltage stability improvement had been observed. The results of both parameters are depicted in Table 6.

Table 6. The voltage profile and voltage stability of the system for 2nd objective function.

DG Type	DG No.	Voltage (p.u)		Voltage Stability (p.u)	
		Min	Max	Min	Max
	Base Case	**0.9037 at 18**	**1.00 at 1**	**0.6669 at 18**	**1.00 at 1**
Type-1	1 DG	0.9440 at 18	1.00 at 1	0.7974 at 18	1.00 at 1
	2 DG	0.9836 at 25	1.037 at 14	0.9360 at 25	1.159 at 14
Type-3	1 DG	0.9629 at 33	1.052 at 13	0.86303 at 31	1.229 at 13

It can be seen that with installation of Type-1 (1 DG) and Type-1 (2 DG), the minimum voltage profile can be improved upto 0.9440 p.u and 0.9836 p.u respectively. Whereas, with installation of Type-3 (1 DG) it can be improved upto 0.9629 p.u. Similarly, the installation of DG improves voltage stability as 0.7974 and 0.9360 with Type-1 (1 DG) and Type-1 (2 DG) respectively. The installation of Type-3 (1 DG) can improve the voltage stability upto 0.86303. The voltage profile and voltage stability on each bus can be realized in Figures 11 and 12 respectively.

It can be seen from Figure 11 and in Figure 12 that the voltage profile and voltage stability of all buses satisfy the minimum voltage profile and voltage stability standard. However, Type-3 (1 DG) gave more improvement in results as compared to Type-1 DG.

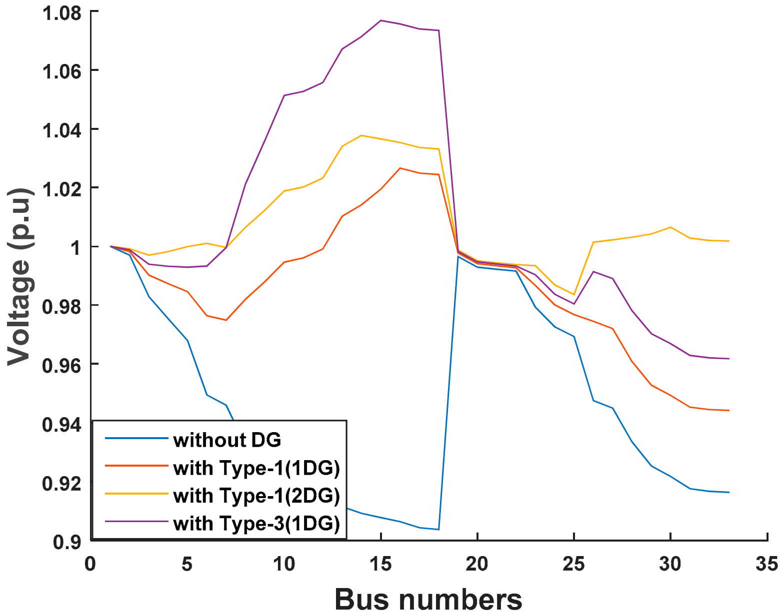

Figure 11. Voltage profile for 33 bus with Type-1 (1 DG and 2 DG) and Type-3 (1 DG) for 2nd objective function.

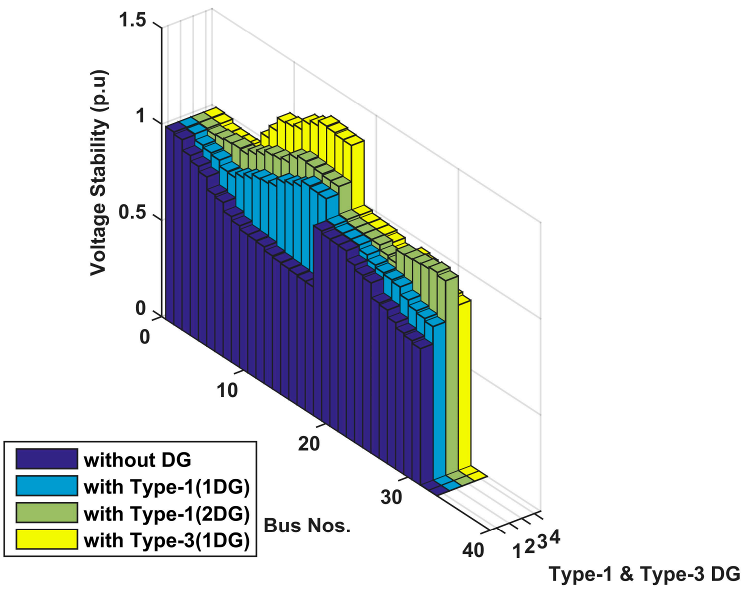

Figure 12. Voltage stability for 33 bus with Type-1 (1 DG and 2 DG) and Type-3 (1 DG) for 2nd objective function.

6.2. Case Study-II: Multi-Objective Optimization

In this case study, the two important objective functions such as power loss reduction and voltage stability are optimized simultaneously. A list of pareto solution is recorded, after getting the simulation results of the proposed method. Then, pareto based fuzzy decision-making technique is applied for choosing the best compromise solution set from them. In this case, two types of DGs, i.e., Tyep-1 and Type-3 are included, to realize the optimal results. Table 7 shows the optimal compromise results when

Type-1 of 1DG is used. Furthermore, the efficacy and performance of the proposed method are also compared with BSA and GA algorithms [19]. The pareto solutions of Type-1 (1 DG) is portrayed in Figure 13.

Table 7. Optimal compromise results of proposed method in comparison with BSA and GA for Type-1 (1DG) in multi-objective optimization case.

Parameters	Base Case	Proposed Method	BSA	GA
$DG\ Size$ (MVA)	-	1.874 + j0 at 9	1.632 + j0 at 10	1.415 + j0 at 10
V_{min} (p.u)	0.9037 at 18	0.9439 at 33	0.9408 at 33	0.9378 at 33
V_{max} (p.u)	0.9970 at 2	0.9982 at 2	0.9980 at 2	0.9979 at 2
$VSI_{\min}$	0.6669 at 18	0.7970 at 31	0.7834 at 33	0.7735 at 33
$VSI_{\max}$	0.9881 at 2	0.99269 at 2	0.9921 at 2	0.9916 at 2
$1/\sum VSI$	Proposed 25.125 BSA/GA-25.554	28.40	28.765	28.361
P_{loss} (kW)	211	124.5 (40.99%)	125.54 (40.46%)	123.55 (41.40%)
Q_{loss} (kVAR)	143	88	87.25	84.47

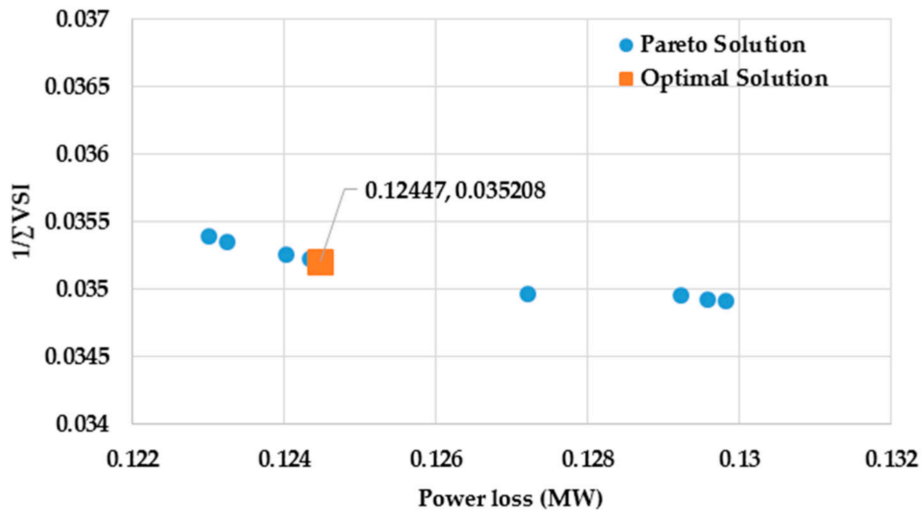

Figure 13. Pareto-solution and optimal compromise solution for Type-1 (1 DG).

It can be seen that with the use of 1 DG of Type-1, the PFNDMOPSO method gives acceptable results in loss reduction and voltage stability improvement as compared to the BSA and GA algorithms [19]. Specifically, power loss reduction by the proposed method is higher as 49.99 % as compared to BSA 40.46%. However, GA marginally reduces more power loss as compared to the proposed method. Similarly, for voltage stability the proposed method gives higher voltage stability than the GA and BSA. Moreover, the minimum and maximum voltage profile and voltage stability of the proposed method also give higher in results as compared to BSA and GA.

In order to check the validity and performance of the proposed method, the proposed method is extended by hosting 2 DG for Type-1 and 1 DG for Type-3. The numerical outcomes of Type-1 (2 DG) and Type-3 (1 DG) and its compared results with BSA and GA are shown in Table 8. The pareto-optimal solutions of these Type-1 (2 DG) and Type-2 (1 DG) are shown in Figures 14 and 15 respectively.

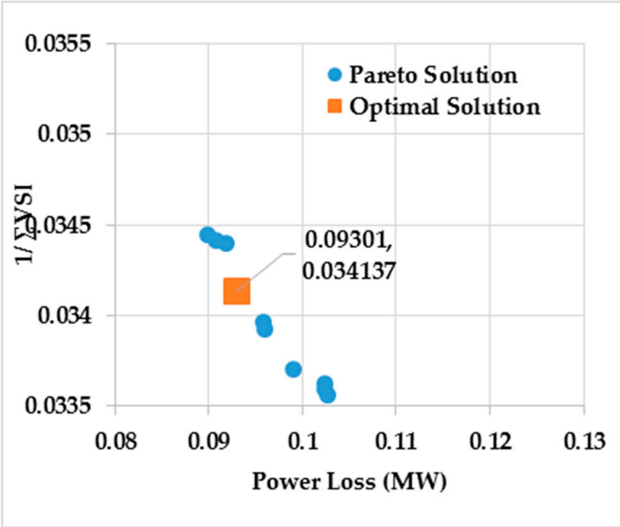

Figure 14. Pareto-solution and optimal compromise solution for Type-1 (2 DG).

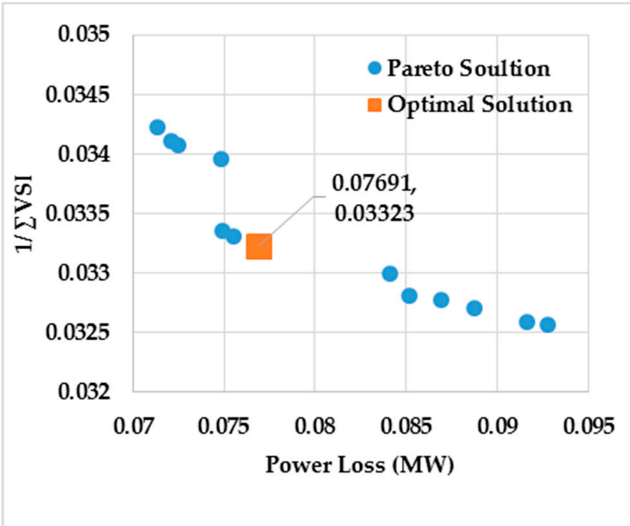

Figure 15. Pareto-solution and optimal compromise solution for Type-3 (1 DG).

Table 8. Optimal compromise results of multi-objective function for Type-1 (2 DG) and Type-3 (1 DG).

Parameters	**Type-1 (2 DG)**			**Type-3 (1 DG)**		
	Proposed Method	**BSA**	**GA**	**Proposed Method**	**BSA**	**GA**
DGSize (MVA)	1.1155 at 11	1.126 + j0 at 13	1.139 + j0 at 13	1.991 at 9 + j1.60 at 33	1.858 + j1.493 at 8	1.802 + j1.152 at 2
	1.4882 at 29	0.730 + j0 at 31	0.0717 + j0 at 31			
$V_{\min}$ (p.u)	0.9766 at 33	0.9631 at 33	0.9627 at 33	0.9825 at 33	0.9578 at 33	0.9541 at 33
$V_{\max}$ (p.u)	0.9986 at 2	0.9982 at 2	0.9982 at 2	1.00 at 9, 10, 11	1.0125 at 8	1.0045 at 8
$VSI_{\min}$	0.9129 at 31	0.8503 at 31	0.8497 at 31	0.9353 at 31	0.8417 at 33	0.8287 at 33
$VSI_{\max}$	0.9944 at 2	0.9927 at 2	0.9927 at 2	1.0 at 9, 10, 11	1.0269 at 9	0.9945 at 9
$1/\sum VSI$	29.293	29.284	29.291	30.085	30.276	29.798
P_{loss} (kW)	93.0 (55.92%)	93.39 (55.71%)	93.85 (55.49%)	76.9 (63.55%)	85.73 (59.34%)	82.71 (60.77%)
Q_{loss} (kVAR)	65.0	63.41	63.72	58.6	66.08	61.51

For Type-1 (2 DG), the proposed method gives better results in loss reduction and voltage stability improvement as compared to BSA and GA algorithms [19]. Specifically, power loss reduction by proposed method is higher as at 55.92% as compared to BSA 55.71% and GA 55.49% respectively. Similarly for voltage stability, the proposed method gives higher outcomes as 29.293 compared to BSA 29.284 and GA 29.291. Moreover, the minimum and maximum voltage profile and minimum and maximum voltage stability of the proposed method are higher in results as compared to BSA and GA.

For Type-3 (1 DG), the power loss reduction by the proposed method is higher as at 63.55% as compared to BSA 59.34% and GA 60.77% respectively. However, voltage stability of the proposed method gives higher outcomes as 30.085 compared to BSA 30.276 and GA 29.798. Moreover, the minimum and maximum voltage profile and voltage stability of the proposed method in this are also higher in results as compared to BSA and GA.

Voltage Profile and Voltage Stability for Case Study-II

The Figures 16 and 17 shows the voltage profile and voltage stability analysis for multi-objective optimization case.

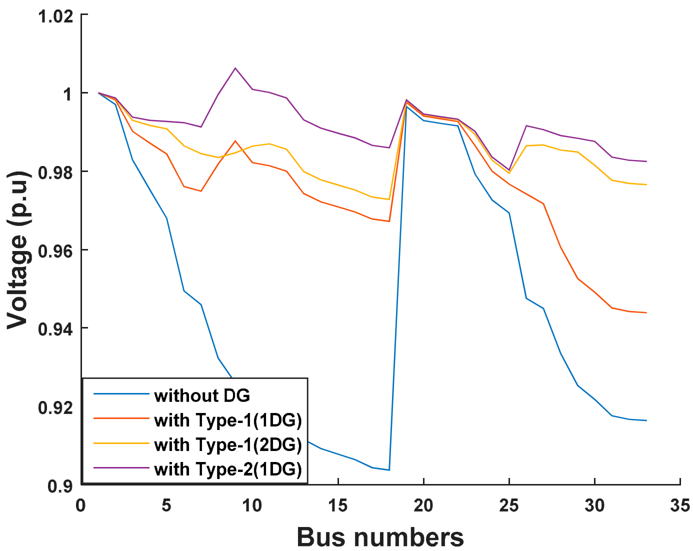

Figure 16. Voltage profile for Type-1 (1 DG and 2 DG) and Type-3 (1 DG).

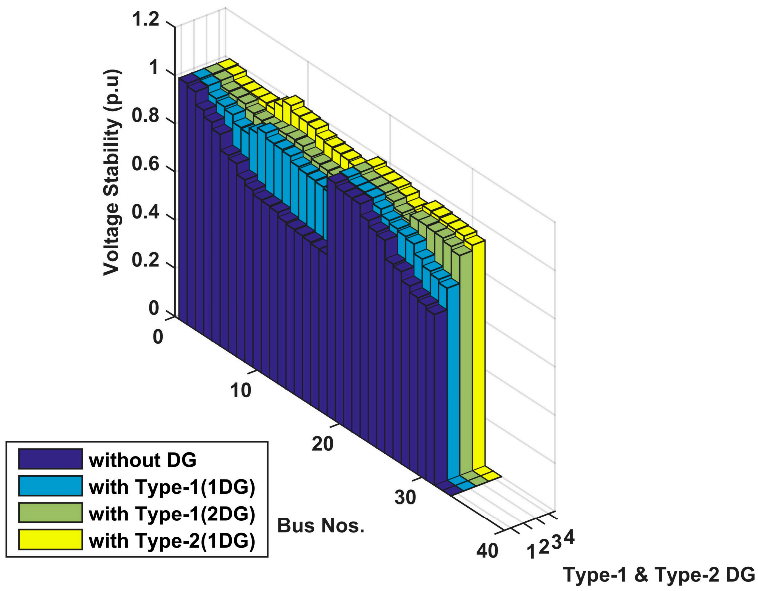

Figure 17. Voltage stability for Type-1 (1 DG and 2 DG) and Type-3 (1 DG).

It can be seen from Figure 16, that with the installation of Type-1 (1 DG) and Type-1 (2DG) the minimum voltage profile is improved upto 0.9439 p.u and 0.9766 p.u at bus 33 respectively, while maximum voltage profile is improved upto 0.9982 p.u and 0.9986 p.u at bus 2 respectively. With the installation of Type-3 (1DG), the minimum voltage profile is improved upto 0.9825 p.u at bus 33 and maximum voltage is improved upto 1.00 p.u at bus 9, 10 and 11 respectively.

Moreover, Figure 17 shows that with the installation of Type-1 (1 DG) and Type-1 (2 DG) the minimum voltage stability is improved upto 0.7970 p.u and 0.9129 p.u at bus 31 respectively, while maximum voltage stability is improved upto 0.99269 p.u and 0.9944 p.u at bus 2 respectively. With the installation of Type-3 (1 DG), the minimum voltage stability is improved upto 0.9353 p.u at bus 31 and maximum voltage is improved upto 1.00 p.u at bus 9,10 and 11 respectively.

The overall analysis shows that the voltage profile and voltage stability for both test systems at every node are improved, hence it can be concluded that the performance of the proposed methodology for optimal placement and sizing are better as compared to the literature algorithms.

7. Conclusions

In this manuscript, an advanced-PFNDMOPSO has been applied for optimal placement and sizing of distributed generation sources. The proposed method consists two case studies as single-objective optimization and multi-objective optimization for power loss reduction and voltage stability improvement. Three types of distributed generation sources i.e., active power DG, reactive power DG and active-reactive power DG (i.e., simultaneously placement Type-1 and Type-2) are proposed in the methodology. Furthermore, each case study consists of single and multiple numbers of DG(s). An advanced-non-dominated sorting MOPSO method is effectively utilized. For the case study-I, the preference is only given to only one objective function at a time (i.e., power loss reduction or voltage stability improvement). Whereas, for case study-II the optimal compromise results were chosen from trade-off solution using fuzzy decision model. The proposed methodology is tested on IEEE 33 bus system. The results of the proposed method are also compared with the literature algorithms. It can be concluded that the proposed method gives better results in terms of optimal placement and sizing of DG problem for both case studies. Additionally, the study also demonstrates that simultaneous installation of active and reactive power DG (Type-3) gives better performance in terms of power loss reduction, voltage stability and voltage profile improvement in the distribution system.

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Author Contributions: Perumal Nallagownden proposed the ideas of distributed generation in the distribution system and gave suggestions for the manuscript. Kumar Mahesh performed the simulation, analyzed the results critically and wrote this paper. Irraivan Elamvazuthi assisted in optimization algorithm and reviewed the manuscript.

Conflicts of Interest: The authors declare no conflict of interest.

Nomenclature

V	Volt
kW/MW	Kilo/mega watt
KVA/MVA	Kilo-volt/mega-volt ampere
KVar/MVar	Kilo-volt/mega-volt ampere reactive
$m1$, $m2$	$m1$ and $m2$ are buses name
i	i is the branch name connected between bus $m1$ and $m2$
p.u	Per unit
P_{DG}	Active power DG
$P_{DG}^{\min}$	min. value of Active power DG
$P_{DG}^{\max}$	max. value of Active power DG

Q_{DG}	reactive power DG
Q_{DG}^{min}	min. value of reactive power DG
Q_{DG}^{max}	max. value of reactive power DG
VSI	Voltage stability indicator
MOO	Multi-objective optimization
MOPSO	Multi-objective particle swarm optimization
DSTATCOM	Distribution static compensator
Obj-1	Objective-1
Obj-2	Objective-2
BA	Bat algorithm
ABC	Artificial bee colony
BSA	Backtracking search algorithm

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