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Enhancement of Distribution System using Improved Real-Coded Genetic Algorithm

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Abstract- Distributed generation (DG) implementation into power networks offers several technical and environmental advantages. These advantages include lessening power losses, improving voltage profiles, boosting power system reliability, and offering an easy determination to rapidly growing load needs. On the other hand, installing these DG units might have negative consequences if their distribution is not adequately sized. This research paper aims to allocate DGs optimally while improving the distribution network's voltage profile with decreased power losses. Several approaches have been developed to determine the optimal allocation of DGs in distribution networks. Genetic Algorithm (GA) is one of the most used artificial, naturally inspired approaches. Recently an improved version of the GA was introduced that is called Improved Real Coaded Genetic Algorithm (IRGA) as a powerful optimization algorithm. The IRGA was utilized as a solution tool in this research. Two DG types were considered in this study, the first is DGs capable of injecting active power only while the second is DGs capable of injecting active and reactive power. The attained results show that the developed IRGA can successfully identify the optimum solutions by minimizing power loss and improving the voltage profile, outperforming other current literature approaches. Also, power losses and voltage profile enhancement have improved significantly as the number of DG units has increased.

Keywords Distributed generation, optimal allocation, active power loss, voltage profile, improved real coded genetic algorithm.

Nomenclature

DG	Distributed generation	Max_it	Maximum number of iterations
P_L	Total Active Power Loss (MW)	SBX	Simulated Binary Crossover.
Q_L	Total Reactive Power Loss (MVAr)	DGI	DGs Inject Active power only.
V_P	Voltage Profile.	DGII	DGs Inject both Active and Reactive power.
VD_t	Total voltage deviation (pu)	Xi	Starting Population
GA	Genetic Algorithm	N_p	The size of the population
IRGA	Improved real-coded genetic algorithm.	μ_m	The mutation distribution index
P_{DGi}	DG active power generation (MW).	p_m	Mutation probability
Q_{DGi}	DG Reactive power generation (MVAr).	L_{DGi}	Location of DG.
SLD	Single Line Diagram.	RDN	Radial Distribution Network.

1. Introduction

Electricity utility operators are constantly looking for new generational techniques and technologies to improve the energy's consistency and quality. A section of the most recent generation of technical advancements is referred to as distributed generation (DG). The primary driver for adopting DG units is to deploy more easily installed modular generating units close to the load centers, as opposed to the old methods of doing so, which included upgrading transmission lines and building new centralized power plants. There are several financial, technological, and environmental benefits of using DGs. The technological advantages include improving power quality, lowering line loss, cutting peak load, strengthening voltage stability, control, or profile, and boosting system security and dependability. Reductions in power, gasoline, and transportation expenses as a result of the use of renewable resources might be included as economic improvements. Distributed generation's socio-technical effects have also been examined and presented in [1]. Installing DG in the distribution system has various benefits outside just reducing power losses, such as Improving both voltage profile and power factor, putting off the need to expand the network, and constructing new transmission and distribution lines to satisfy increased electricity demand. Due to its minimal emission, it is regarded as ecologically benign. Some DG solutions, like solar and wind energy, produce no waste at all, it is easy to set up and run either independently or as a backup generation after a brief period of installation, and in remote locations with typically unreliable networks, DG units are very helpful. Due to the many benefits of this technology, electric power utilities are incorporating DG technology to change their infrastructure. However, placing DG units, especially big ones, in some locations may have detrimental effects on the distribution network, including voltage rise and instability in addition to circuit breaker failure because of the bidirectional power flow. It's critical to choose the optimal DG units allocation to maximize the benefits of DG and minimize any potential drawbacks [2]. By allocating DG units optimally, the vast majority of economic and technical gains may be realized. On the other side, improper DG placement may lead to high power loss, voltage increase, and poor system stability [3]. Optimum locations for DG units are found to reduce the losses in [4]. Regarding the improvement in voltage stability, the optimal installation location has also been found [5]. The analytical methodologies for the optimal allocation of DGs in relation to network losses were investigated in [6]. To determine the best placement, capacity, and number of DGs in the distribution network, a more sophisticated stochastic fractal search algorithm with chaos has been developed in Ref. [7]. Several optimization algorithms were used to determine the best allocation of DGs in electrical systems [8]. Later, the genetic algorithm-based optimum DG allocation additionally the unknown parameters of the generation side were taken into account [9]. The enhanced particle swarm method was used to allocate dispersed energy resources simultaneously [10]. An implementation of evolutionary methods has been resolved for optimal DG placement and size, consisting of a genetic-fuzzy algorithm [11]. A combination of analytic methods with genetic algorithm in [12]. A Mathematical, heuristic, and analytical methods [13]. General algebraic modeling system method [14]. The Trader Inspired Algorithm (TIA) is implemented for identifying the optimal placement and capacity of multiple types of RESs-DGs, taking into account multi-objectives and actual uncertainties [15]. A combination of GA and PSO [16]. A determination of the DGs and capacitors optimal placement and size using the Grasshopper method [17]. Table 1, introduces an overview of previous research about the best locations, proposed methodologies, and Principal features of the suggested model for DGs allocation.

Table. 1. A thorough review of earlier reported methodologies for optimal DG allocation

Ref.	Objective	Proposed Methodology	Case Study	Principal Features of the Suggested Model
[18]	Studying the importance of demand-side responses in the best distribution network deployment of DGs	A novel analytical method	IEEE-33	Investigating the impact of response to demand and voltage-dependent demand methods on optimum DG allocation.
[19]	DGs and capacitors Optimal allocation	Spring search algorithm	IEEE-33	Another goal of the problem that gives environmental benefits is to investigate pollutant gas emissions.
[20]	Multi-objective of DGs and electric vehicle station allocation	Non-dominated sorting NSGA -II	IEEE-118	The simultaneous distribution of DGs and stations will provide significant benefits to all parties concerned.
[21]	Allocation of the number of DGs in distribution systems	Sine Cosine method and chaos map theory	IEEE 33 and 69	In comparison to existing optimization methods with quick convergence properties, two suggested optimization methods were combined and resulted in efficiency and reliability.
[22]	DGs optimal location and capacity.	SA-PSO	IEEE-33	The problem takes into account several indices, including investment cost, power loss, yearly power cost, and environmental cost.

Despite the concise portrayal in the literature, the No Free Lunch theorem [23] directs the authors to the likelihood that employing modern optimization methods could enhance the DGs optimal location and capacity in distribution networks. The proposed Improved Real Coded Genetic Algorithm (IRGA) introduced an innovative approach to enhance the efficacy of the real-coded genetic algorithm. This approach entails the incorporation of a directional mutation operator, complemented by a directional crossover operator. These evolutionary mechanisms leverage directional cues to steer the exploration process toward the most promising regions within the variable space. Hence, this motivates the authors to employ it in this study for the optimal allocation of multiple DGs in radial distribution systems.

The ensuing list outlines the contributions of the paper:

- Mathematical modeling formulation of the DGs optimal allocation.
- Utilization of IRGA to reach DGs optimal allocation of DG seeking for total active power loss maximum reduction and maximum voltage profile improvement.
- Investigation of different scenarios of multiple DGs employment in different scale standard IEEE test networks.
- Comparison of literature reported results, and IRGA in terms of converged fitness functions.

The rest of the research paper is structured as follows: Section 2 introduces the problem formulation and provides guidelines for the optimal allocation of DGs in power distribution networks. Section 3 elaborates on the IRGA algorithm's mathematical formulation. The outcomes and pertinent discussions are presented in Section 4. Ultimately, Section 5 encapsulates the paper's conclusive remarks.

2. Problem Mathematical Formulation

2.1. Fitness Function

There are two single objective functions in this study: The first is to achieve maximum reduction in the total active power loss of the system f_1 as in Eq. (1), The second is to achieve maximum reduction in the voltage deviation f_2 as in Eq. (2). According to the distribution network's various equality and inequality restrictions [24].

$$f_1 = \min(P_L) \tag{1}$$

$$f_2 = \min(VD_t) \tag{2}$$

Total losses in active power are calculated in Eq. (3), and total losses in reactive power are calculated in Eq. (4) [25]

$$\mathrm{P_L} = \sum_{i=1}^{N_{line}} \{ (\mathrm{I_i^t})^2 * \mathrm{R_i} \} \tag{3}$$

$$\mathrm{Q_L} = \sum_{i=1}^{N_{line}} \{ (\mathrm{I_i^t})^2 * \mathrm{X_i} \} \tag{4}$$

where, $\mathrm{P_L}$ is a total loss in system active power in MW, $\mathrm{Q_L}$ is total loss in system reactive power in MVAr, and $\mathrm{I_i^t}$ is the i^{th} line's current in kA at time t; N_{line} is the system lines's number; R_i is i^{th} line resistance in Ω, and X_i is i^{th} line reactance in Ω. A single-line diagram (SLD) of the Radial Distribution Network (RDN) is shown in Fig. 1, The bus p is the sending end while bus q is considered as the receiver end bus.

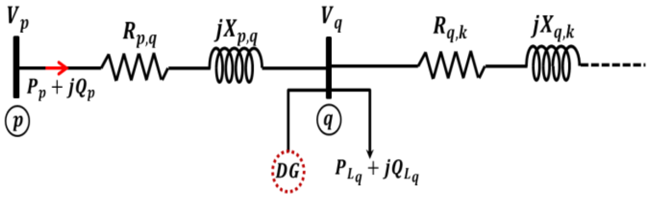

Fig.1. SLD of RDS with DG placement.

The voltage deviation (VD), which shows the closeness of the bus voltages to the nominal voltage value, is computed as follows in Eq. (5) [26][27].

$$VD_t = \sum_{i=1}^{NB} |V_i - V_i^{ref}| \tag{5}$$

where VD_t is the total system voltage deviation, V_i is the voltage of bus i , V_i^{ref} is the reference voltage at bus i while NB refers to the total number of buses.

2.2. Constraints

The objective problem put forward has two different sorts of constraints, which are as follows:

2.2.1. *Power balance constraints*

The total output power of a power system equals the total demand power plus any losses in the system power. It can be defined in Eq.(6) for active power and Eq. (7) for reactive power [26].

$$P_G + \sum_{i=1}^{N} P_{DG,i} = P_d + P_L \tag{6}$$

$$Q_G + \sum_{i=1}^{N} Q_{DG,i} = Q_d + Q_L \tag{7}$$

where, P_G is the main substation-injected active power and Q_G is the main substation-injected reactive power, N is the number of DGs, P_{DGi} is the generation of active power by i^{th} DG and Q_{DGi} is the generation of active power by i^{th} DG, P_d is the total active power demand of the system and Q_d is total reactive power demand of the system, P_L is the total loss in active power of the system and Q_L is total loss in the reactive power of the system.

2.2.2. *Voltage constraints*

In this research, voltage restrictions can be expressed by Eq. (8).

$$V_{min} \le |V_i| \le V_{max} \tag{8}$$

where, V_{min} is the bus voltage minimum limit which value is 0.95 pu and V_{max} is the bus voltage maximum limit which value is 1.05 pu. That restriction requires that the level of voltage at all buses after connection of DG fall within the range of 0.95 and 1.05 pu [28]–[30].

2.2.3. *DG constraints*

Two types of DGs will be used in this study; the first is DGI, which is capable of injecting active power only into the network. The second DGII added reactive and active power to the system. The amount of total real power P_{DGi} that the units of DG are be mounted, shall deliver less than or equal to the amount of total active power loads of the distribution system. Minimum and maximum generation limitations for DG units are indicated by Eq. (9) and Eq. (10) [31].

$$P_{DGi}^{min} \leq P_{DGi} \leq P_{DGi}^{max} \tag{9}$$

$$Q_{DGi}^{min} \leq Q_{DGi} \leq Q_{DGi}^{max} \tag{10}$$

DG sites cannot be at slack buses, and these limitations are specified in Eq. (11) [7].

$$2 \leq L_{DGi} \leq N_{bus} \tag{11}$$

where L_{DGi} stands for the locations of the i^{th} DG.

3. Improved Real Coaded Genetic Algorithm

The Improved Real Coded Genetic Algorithm (IRGA) is an improved version of the genetic algorithm that is used to solve engineering optimization problems [32]. For each minimization issue, GA contributes to the worldwide optimal solution. Due to the complexity of binary representation when dealing with persistent search spaces of increasing dimensions Real-coded genetic algorithm (RGA) has been used. This study makes use of polynomial mutation and Simulated Binary Crossover (SBX). IRGA investigates one-to-one difficulties in order to improve confluence speed and result rate. The child population competes with the parent population one on one. The five IRGA platforms are as follows: the first is an initialization, the second is parent population selection, the third is the crossover, the fourth is a mutation, and the last one is the selection of both parent and child populations.

3.1. *Initialization*

The starting population (Xi) of control factors was chosen at random from a set of evenly distributed control factors spanning their upper and lower boundaries, and presented in Eq. (12).

$$x_{i,j}^{0} \sim U\left(x_j^{min}, x_j^{max}\right), \quad i \in N_p, j \in n \tag{12}$$

where, $x_{i,j}^{0}$ is the i^{th} population's initial j^{th} variable, x_j^{max} and x_j^{min} are maximum and minimum values for the j^{th} choice variable, $U(x_j^{min}, x_j^{max})$ is a symmetrical random parameter with a range of $[x_j^{min}, x_j^{max}]$, n is the selection variables number in an individual, N_p is the size of the population.

3.2. *Parent Population Selection*

Here, to pick the parent from the pairing pool, the selection method of binary tournament is used. A pair of chromosomes are chosen at random from the list of population and their objective function values are analyzed. The chromosome that wins, or one that has the minimal value for the objective function, remains in the pairing pool. This procedure is continued until the pairing pool is full of the chromosomes.

3.3. *Simulated Binary Crossover (SBX)*

SBX is an operator used to generate child populations (x_1' , x_2')from a pair of parents (x_1 , x_2). This operator creates them in three steps, First, create the random number u within 0 and 1, then compute γ, the polynomial probability distribution is used as in Eq. (13) and Eq. (14).

$$\beta = 1 + \frac{2}{x_2 - x_1} \min[(x_1 - x^{min}), (x^{max} - x_2)] \tag{13}$$

$$\gamma = \begin{cases} (u\alpha)^{\frac{1}{\mu_c+1}}, & if \ u \leq 1/\alpha \\ \left(\frac{1}{2-u\alpha}\right)^{\frac{1}{\mu_c+1}}, & otherwise \end{cases} \tag{14}$$

where, μ_c is the distribution index for SBX, and is capable of acquiring any positive value, and it has two options, The higher value limits the generation of child populations to those that are close to their parents, and its low value permits the creation of a child population far from parents. α is the parameter computed as in Eq. (15)

$$\beta = \alpha = 2 - \beta^{-(\mu_c+1)} \tag{15}$$

The third step is to compute the intermediate populations x_{p1} and x_{p2} in Eq. (16), (17).

$$x_{p1} = 0.5\,[\,(x_1 + x_2) - \gamma(\,|\,x_2 - x_2\,|)] \tag{16}$$

$$x_{p2} = 0.5\,[\,(x_1 + x_2) + \gamma(\,|\,x_2 - x_2\,|)] \tag{17}$$

3.4. *Polynomial Mutation*

The polynomial probability distribution function is defined in three steps. First, create the random number u within [0,1] then calculate the parameter σ as in Eq. (18).

$$\sigma = \begin{cases} [2u + (1-2u)(1-\varphi)^{\mu_m+1}]^{\frac{1}{\mu_m+1}} - 1, & if \ u \leq 0.5 \\ 1 - [2(1-u) + 2(u-0.5)(1-\varphi)^{\mu_m+1}]^{\frac{1}{\mu_m+1}}, & otherwise \end{cases} \tag{18}$$

where, μ_m is the mutation distribution index and obtains any positive value, the parameter φ can be calculated as in Eq. (19).

$$\varphi = \frac{\min\left[x_p - x^{min}\right), (x^{max} - x_p)]}{(x^{max} - x^{min})} \tag{19}$$

The third step is the computation of the mutated offspring as in Eqs. (20,21).

$$x_1' = x_{p1} + \sigma\,(x^{max} - x^{min}) \tag{20}$$

$$x_2' = x_{p2} + \sigma\,(x^{max} - x^{min}) \tag{21}$$

To change the perturbation, μ_m and p_m can be variegated as in Eqs. (22,23).

$$\mu_m = \mu_{m\,min} + iter \tag{22}$$

$$p_m = \frac{1}{n} + \frac{iter}{iter\_max}\ \left(1 - \frac{1}{n}\right) \tag{23}$$

where n is the choice variable number, $\mu_{m\,min}$ is the lowest for μ_m , and p_m is mutation probability. The objective's value has been calculated for each offspring.

3.5. *Selection Between Parent and Offspring*

To compare the objective function value of each parent (x_i) with the corresponding offspring (x_1') in order to achieve diversity for each parent (x_i). The objective function of lower population value between parent and offspring is continued in the following iteration as in Eq. (24).

$$x_i = \begin{cases} x_i' , & if\ \ f(x_i') \le f(x_i) \\ X_i , & otherwise \end{cases} ,\ i \in N_p \tag{24}$$

The procedure was repeated until the number of iterations reached its maximum value. A flowchart of employing IRGA in the optimal allocation of DGs is presented in Fig. 2.

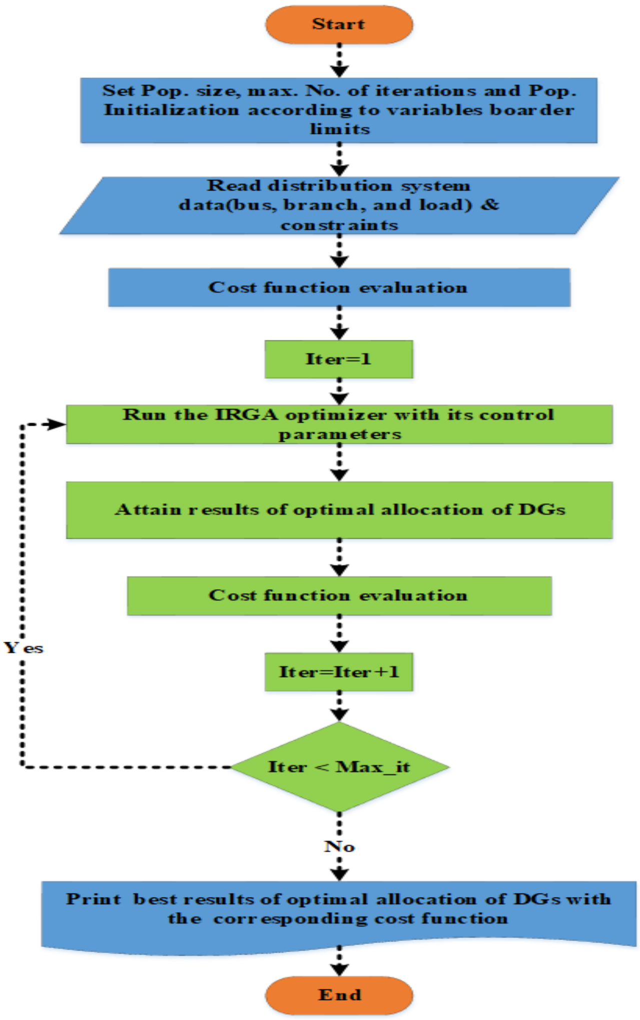

Fig. 2. Flowchart of IRGA.

4. Results and Discussion

The IEEE radial system's 33-bus and 69-bus are used for the implementation of the IRGA for single and multiple DG units with two types of DGs, DGI- DGs which deliver active power only, DGII - DGs which deliver both active and reactive power. The suggested approach applies to any number of DGs, but for this study, the number of DGs is limited to three as reported in many literatures. For all the test systems, bus 1. is taken as a slack bus. The proposed IRGA is employed via the MATLAB R2021b platform using an Intel ® core TM i5-1035G1 CPU @ 1.00GHz,1.19 GHz, with an 8.00 GB RAM setup Laptop. The MATPOWER package is used to calculate the power flow of each case**.** Table 2, Presents a summary of all studied cases in this research.

Table 2. Summary of Study Cases

Cases	IEEE-33 bus system				IEEE-69 bus system			
	P_L Reduction		VD Reduction		P_L Reduction		VD Reduction	
	DG I	DG II	DG I	DG II	DG I	DG II	DG I	DG II
Case 1	✓	✓						
Case 2			✓	✓				
Case 3					✓	✓		
Case 4							✓	✓

4.1. *The IEEE 33-Bus system*

Single-line diagram of this system is shown in Fig. 3, The total load of this system is 3715 kW and 2300 kVAr. System total generation was 3917.677 kW and 2435.14 kVAr, with a total loss in active power of 203 kW and reactive power of 140 kVAr. While the initial value of VD is 1.7009 pu. General details concerning this system are provided in Table 3. The system line and bus data as well as the system limitations can be retrieved in Ref. [33].

Table 3. The IEEE- 33 Node Data

No. of buses	33
Lines	32
Generators/Feeders	1
Transformers	0
Loads bus (PQ)	32
shunt capacitors	0
Slack bus	1
PV buses	0

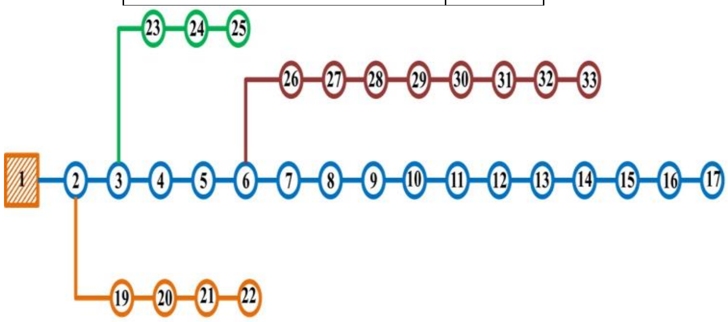

Fig 3. Single line diagram of the IEEE 33-node.

4.1. *Case1: Power Loss Reduction*

Considering maximum lessening in total loss of system active power as an objective function in this case, seeking the allocation of DGs while the two DG types are considered.

After the implementation of IRGA to define the optimal capacity and placement of DGs, the results are presented in Table 4.

In the case of DGI, DG is operating at the unity power factor, optimal allocation of a single DG in the test system contributes a 48.785 % reduction in P_L and reduces the VD from 1.7009 pu to 0.8296 pu. While installation of two DGs at the same time reduces P_L by 57.6797 % and reduces the VD to 0.6471 pu. However, placing three DGs at the same time reduces P_L by 64.799 % and reduces the VD to 0.5872 pu. In the case of DGII, the allocation of a single DG in the test system contributes a 69.354 % reduction in P_L and reduces the VD to 0.5258 pu. In case of Placing two DGs at the same time reduces P_L by 85.916 % and reduces the VD to 0.1958 pu, though placing three DGs at the same time reduces P_L by 94.2514 % and reduces the VD to 0.1237 pu. A comparison of the suggested method's findings with existing approaches in the literature for three DG in the type of DGII is tabulated in Table 5. The IRGA outperforms the other competing algorithms in determining the optimal location and size of the DG. Also, Fig.4, shows the impact of DG units in active power loss minimization on the network while Fig.5, and Fig.6, demonstrate the IRGA's convergence properties after the network has been expanded to include one, two, and three DGs of type DGI and DGII respectively.

Table 4. Comparative results of multiple DG applications in the IEEE- 33 bus system for Case 1

	DG I						DG II					
Item	Single DG	Double DGs		Triple DGs			Single DG	Double DGs		Triple DGs		
DG location	6	13	30	14	24	30	6	12	30	13	24	30
DG size (kW)	2575.3	846.4	1158.7	754	1099.4	1071.4	2543.9	960.7	1088.5	778.9	1072.7	1035.3
DG size (kVAr)	0	0	0	0	0	0	1500	455	1040.2	366.8	516.8	1014.3
P_L (kW)	104	85.9		71.5			62.2	28.6		11.7		
Q_L (kVAr)	74.8	58.6		49.4			48.8	20.4		9.7		
P_L reduction %	48.785	57.6797		64.799			69.354	85.916		94.2514		
Q_L reduction %	46.58	58.178		64.72			65.1662	85.4523		93.0628		
VD (p.u)	0.8296	0.6471		0.5872			0.5258	0.1958		0.1237		

Table 5. Results comparison for case 1 in the IEEE-33 node with Three DGII for various methods

Algorithm	I-DBEA[34]	LSFSA[35]	EGWO-PSO[36]	AREP-EGWO-PSO[36]	Proposed IRGA
DG location	13 / 24 / 30	6 / 18 / 30	13 / 24 / 30	14 / 24 / 31	13 / 24 / 30
DG size (kW)	749 1042 1239	1383 552 1063	779 1072 1036	780 1103 937	778.9 1072.7 1035.3
DG size (kVAr)	464 645.76 767.85	857.09 342.09 658.779	353.55 549.2 998.55	339.6 565.08 877	366.8 516.8 1014.3
P_L (kW)	14.57	26.7	11.95	15.5	**11.7**

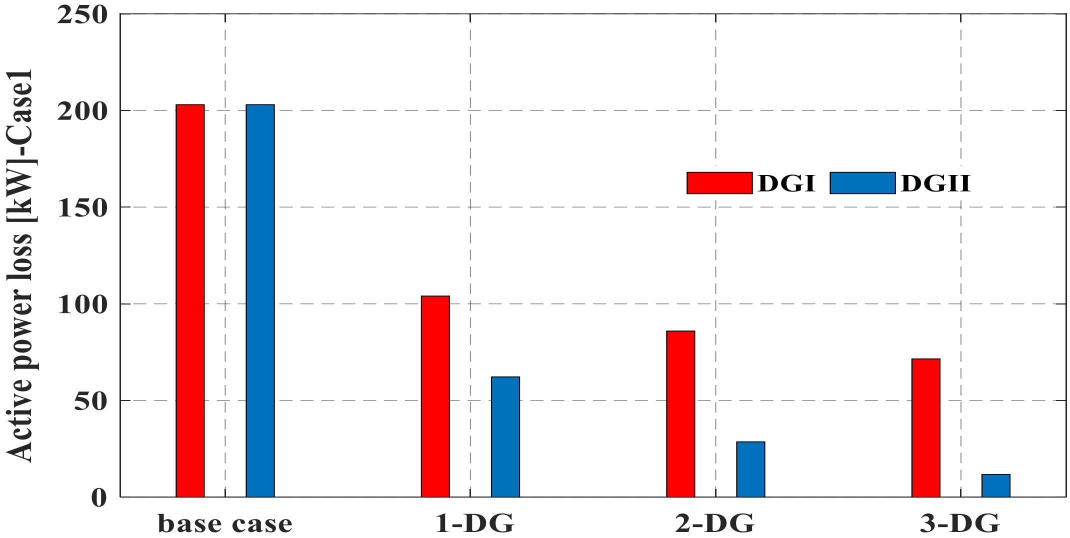

Fig. 4. comparison of reduction in active power loss for Case-1 in IEEE-33 node system.

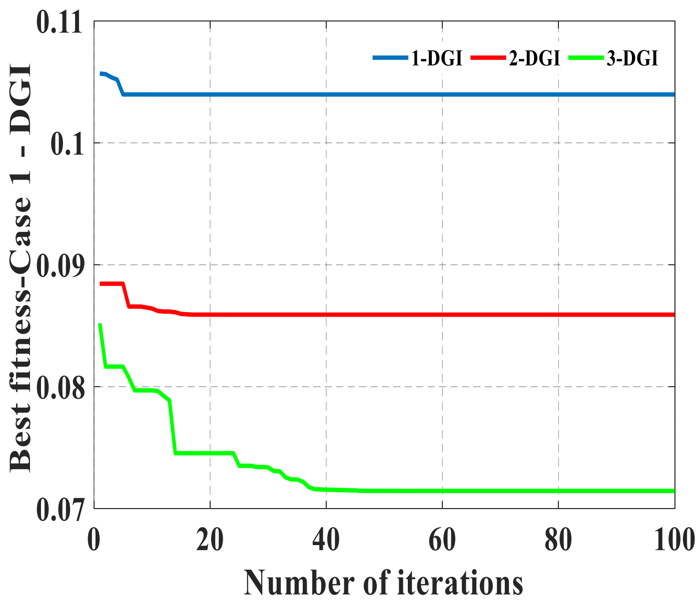

Fig. 5. Convergence properties of IRGA for DGI.

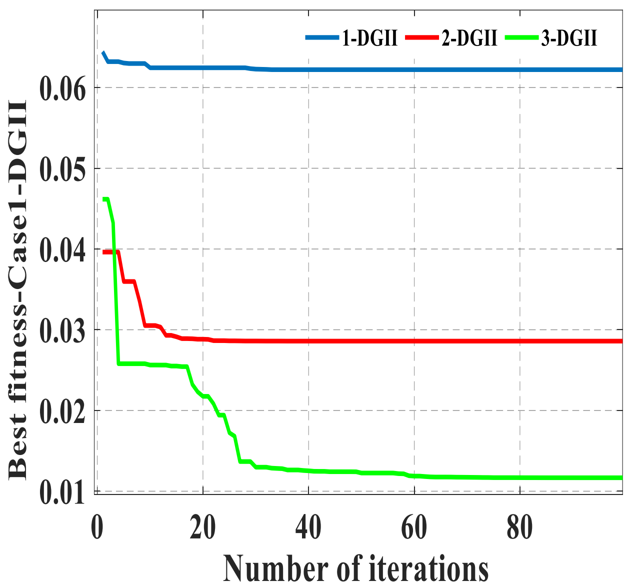

Fig. 6. Convergence properties of IRGA for DGII.

4.2. Case 2: Voltage Profile Enhancement

Considering the maximum enhancement of voltages at each node is an objective function in this case, seeking the allocation of DGs while the two DG types are considered. After the implementation of IRGA to define the optimal capacity and placement of DGs, The results are presented in Table 6.

Optimally placing a single DG in the network contributes to reducing the VD from 1.7009 pu to 0.389 pu and 2 DG to 0.1138 pu while placing 3 DGs reduces the VD to 0.0625 pu. In the case of DG II, the optimal allocation of a single DG in the test system contributes a 56.99 % reduction in P_L and reduces the VD from 1.7009 pu to 0.2834 pu. When Placing two DGs at the same time reduces P_L by 58.7418 % and reduces the VD to 0.1144 pu while placing three DGs at the same time reduces P_L by 80.69 % and reduces the VD to 0.06 pu. An illustration of how adding multiple DG units to the network for both DGI and DGII leads to a reduction in VD is presented in Fig.7, The convergence characteristics of the IRGA upon utilizing one, two, and three DGs of type DGI and DGII are presented on Fig.8, and Fig.9, respectively. Also, Fig.10, and Fig.11, demonstrate how the voltage profile improves in corresponding to multiple DG units. The three DGs from type DGII significantly improved the system voltage profile.

Table 6. Comparative results of multiple DG applications in the IEEE- 33 bus system for Case 2

	DG I						DG II					
Item	Single DG	Double DGs		Triple DGs			Single DG	Double DGs		Triple DGs		
DG location	9	14	28	13	24	29	8	13	28	13	24	29
DG size (kW)	3000	674.3	2912.4	542.7	1390.6	2110.6	3000	541.3	2579.1	529.6	1287.5	1805.8
DG size (kVAr)	0	0	0	0	0	0	1467.1	583.1	184.6	709.2	414.3	396.2
P_L (kW)	155.9	145.1		113.6			87.3	83.8		39.2		
Q_L (kVAr)	113.2	104.4		80.4			68.3	62.5		30.6		
P_L reduction %	23.179	28.5118		44.033			56.99	58.7418		80.6934		
Q_L reduction %	19.119	25.4569		42.549			51.205	55.3374		78.1246		
VD (p.u)	0.389	0.1138		0.0625			0.2834	0.1105		**0.06**		

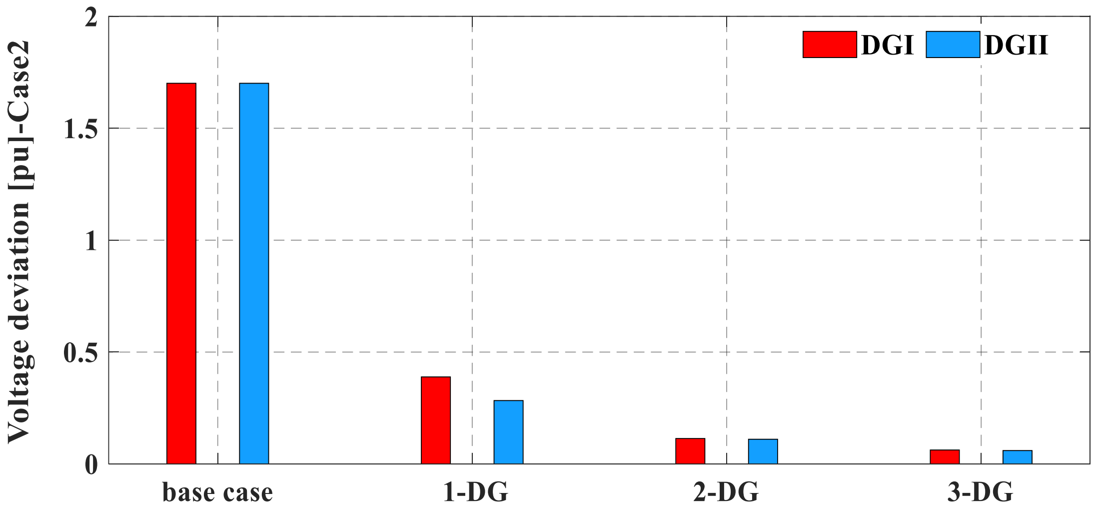

Fig. 7. Comparison of reduction in voltage deviation for Case-2 in the IEEE-33 node system.

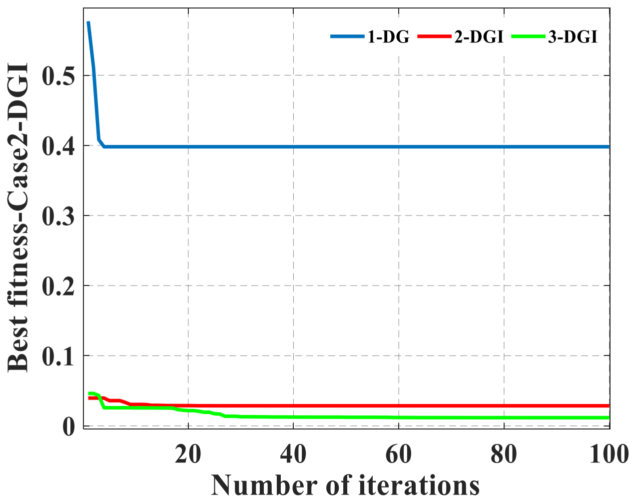

Fig. 8. Convergence properties of IRGA for DGI.

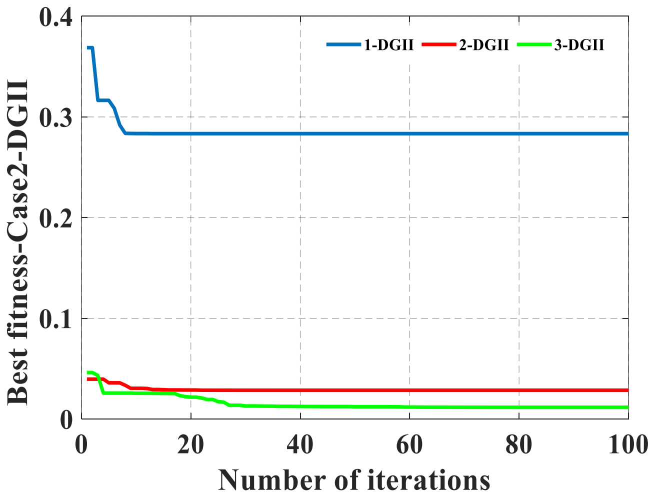

Fig. 9. Convergence properties of IRGA for DGII.

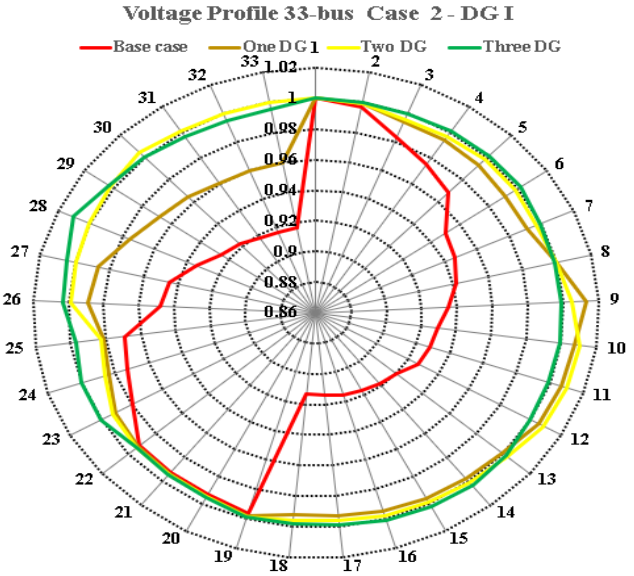

Fig. 10. The enhancement of voltage profile compared to the number of DGI.

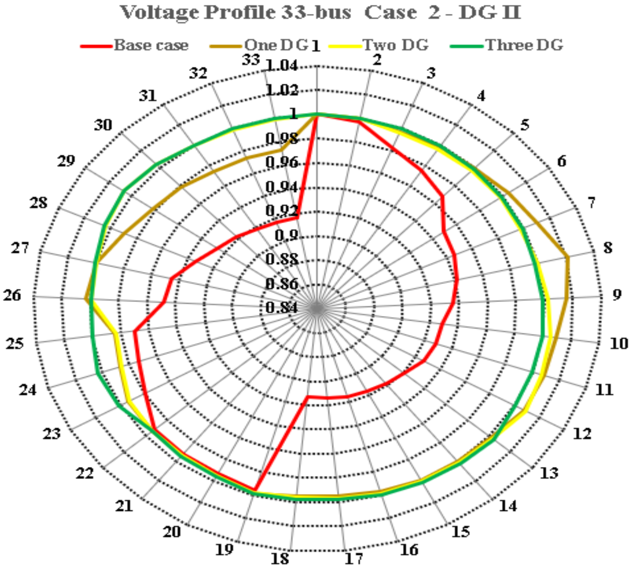

Fig. 11. The enhancement of voltage profile compared to the number of DGII.

4.3. The IEEE 69-Bus System

The single-line diagram of this system is shown in Fig. 12, The total load of this system is 3802.1 kW and 2694.7 kVAr. System total generation is 4027.1 kW and 2796.865 kVAr, with a total loss in active power of 225 kW and reactive power of 100 kVAr. While the initial value of VD is 1.8369 pu. General details concerning this system are provided in Table 7. The system line and bus data as well as the system limitations can be retrieved in Ref. [33].

Table 7. The IEEE 69 -bus test system data

Number of buses	69
Lines or branches	68
Generators/Feeders	1
Loads bus (PQ)	68
shunt capacitors	0
Slack bus	1
PV buses	0

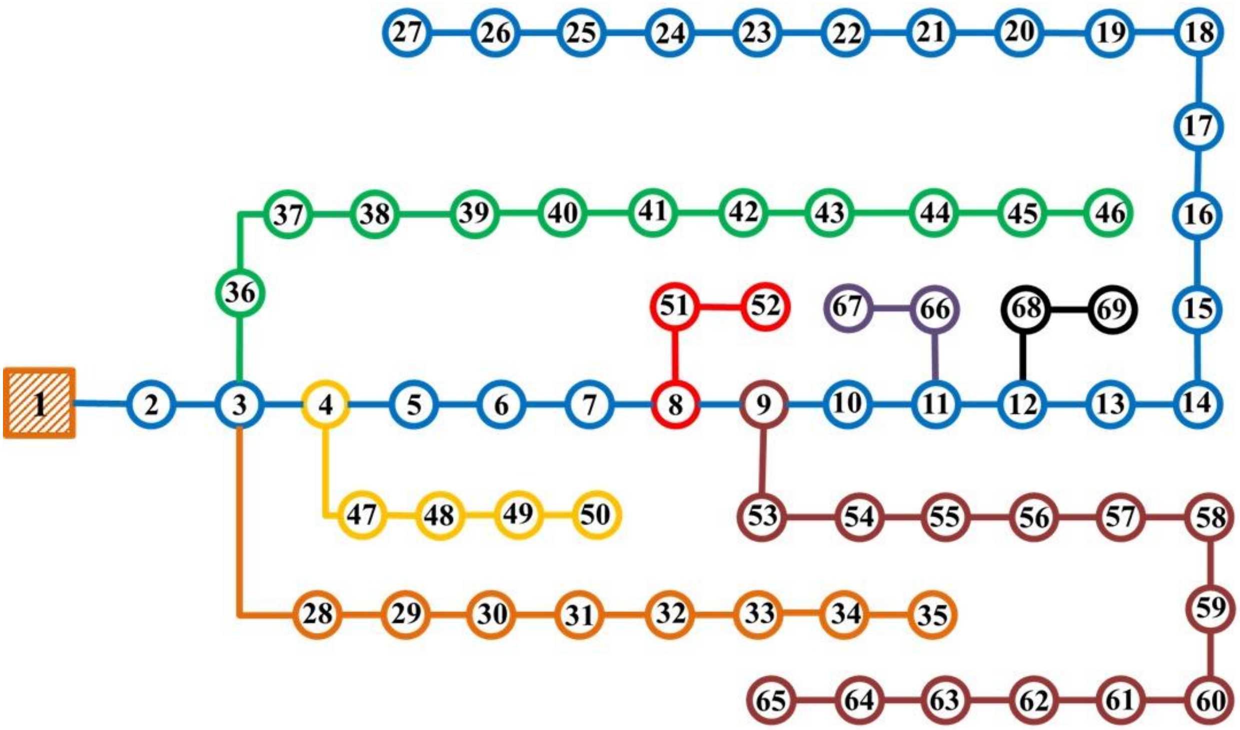

Fig.12. IEEE 69-Node single line diagram.

4.4. Case 3: Power Loss Reduction

Total active power loss minimization is considered an objective function in this case seeking the allocation of DGs while the two DG types are considered. After the implementation of IRGA to define the optimal capacity and placement of DGs, the results are presented in Table 8.

Table 8. Comparative results of multiple DG applications in the IEEE- 69 node system for Case 3

	DG I						**DG II**					
Item	Single DG	Double DGs		Triple DGs			Single DG	Double DGs		Triple DGs		
DG location	61	17	61	11	18	61	61	17	61	11	18	61
DG size (kW)	1872.7	531.5	1781.5	526.8	380.4	1719	1828.5	522.3	1734.7	494.5	379.19	1674.38
DG size (kVAr)	0	0	0	0	0	0	1300.6	353.4	1238.5	353.8	251.5	1195.5
P_L (kW)	83.2	71.7		69.4			23.2	7.2		4.3		
Q_L (kVAr)	40.5	35.9		35			14.4	8		6.8		
P_L reduction %	63.0116	68.1435		69.1429			89.7	96.798		98.103		
Q_L reduction %	59.4639	64.058		65.038			85.62	91.9547		93.2414		
VD (p.u)	0.872	0.4997		0.4493			0.5868	0.1299		0.0645		

In this case, the DG is operating at the unity power factor. The placement of one DG optimally in the network results in a 63.0116% reduction in P_L and a reduction in VD from 1.8369 pu to 0.872 pu. Installing two DGs at the same time decreases P_L by 68.1435% and the VD to 0.4997 pu, while placing three DGs at the same time reduces P_L by 69.1429% and the VD to 0.4493pu. In the scenario of DG II, optimally using a single DG in the network reduces P_L by 89.7% and reduces the VD from 1.8369 pu to 0.5868 pu. Inserting two DGs at the same time decreases P_L by 96.7% and VD to 0.1299 pu, however, adding three DGs reduces P_L by 98.103% and VD to 0.0645 pu. A comparison of the suggested method's findings with existing approaches in the literature for three DG in the type of DGII is tabulated in Table 9. The IRGA outperforms the other competing algorithms in determining the optimal location and size of the DG. Also, the impact of DG units in active power loss minimization on the network is shown in Fig.13, While Fig.14, and Fig.15, demonstrate the IRGA's convergence properties after the network has been expanded to include one, two, and three DGs of type DGI and DGII respectively.

Table 9. Results comparison for Case 3 in the IEEE-69 node with three DGII for various methods

Algorithm	I-DBEA [34]	LSFSA [35]	EGWO-PSO [36]	AREP-EGWO-PSO [36]	Proposed IRGA
DG location	16 59 61	18 60 65	11 18 61	18 60 65	11 18 61
DG size (kW)	1500 370 575	549 1195 312	495 379 1674	516 1312 455	494.5 379.19 1674.38
DG size (kVAr)	1275 314.5 488.75	466.65 1015.753 265.2	358.37 254.689 1211.9	346.75 984 317	353.8 251.5 1195.5
P_L (kW)	7.97	16.26	4.47	13.98	4.3

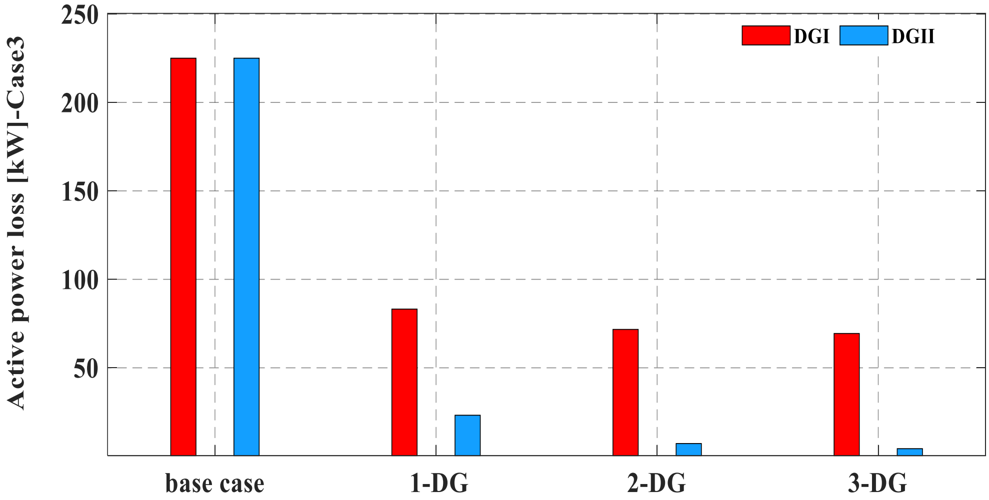

Fig. 13. Comparison of active power loss reduction, Case-3 - IEEE-69 node.

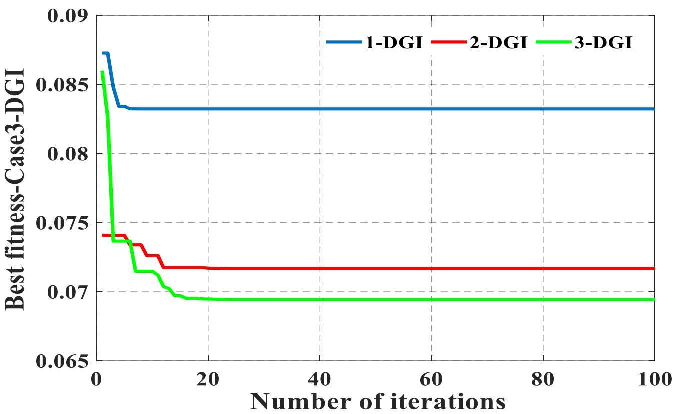

Fig. 14. The IRGA's convergence properties for DGI.

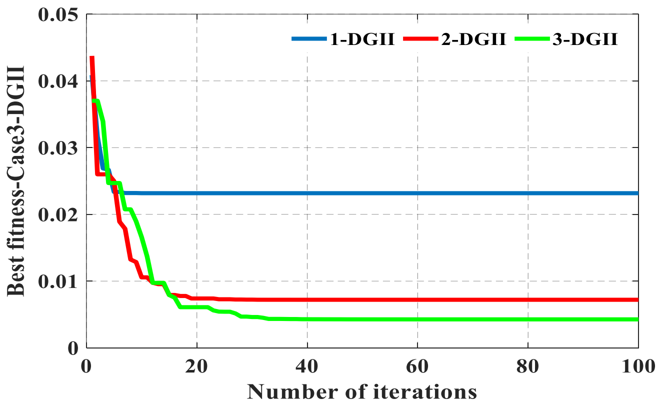

Fig. 15. The IRGA's convergence properties for DGII.

4.5. Case 4: Voltage Profile Enhancement

Considering the maximum enhancement of voltages at each node is an objective function in this case, seeking the allocation of DGs while the two DG types are considered. After the implementation of IRGA to define the optimal capacity and placement of DGs, the results are presented in Table 10.

Table 10. Comparative results of multiple DG applications in the IEEE- 69 node system-Case 4

	DG I						DG II					
Item	Single DG	Double DGs		Triple DGs			Single DG	Double DGs		Triple DGs		
DG location	59	13	61	21	61	66	57	14	61	20	61	66
DG size (kW)	3000	1231.7	2233.9	385.2	2203	987.9	3000	397.1	1593.7	221	1577.9	758.1
DG size (kVAr)	0	0	0	0	0	0	1500	334	1497	560.7	1445.5	100
P_L (kW)	127.1	90		83.7			91.9	51.2		11.4		
Q_L (kVAr)	57.1	42.8		40.8			39.7	24.4		9.2		
P_L reduction %	43.51	60.11		62.79			59.157	77.2326		94.94		
Q_L reduction %	42.94	57.22		59.198			60.32	75.603		90.755		
VD (p.u)	0.547	0.0827		0.0593			0.4438	0.0646		0.0429		

According to Table 10, when using the DGI type optimally, adding a single DG to the network contributes to a 43.51% reduced P_L and reduces the VD from 1.8369 pu to 0.547 pu. However, putting two DGs simultaneously decreases P_L by 60.11% and reduces the VD to 0.0827 pu, while simultaneously inserting three DGs reduces P_L by 62.79% and reduces the VD to 0.0593 pu. In the case of DG II, the optimal allocation of a single DG in the network contributes a 59.157 % reduction in P_L the VD from 1.8369 pu to 0.4438 pu. On the other hand, placing two DGs reduces P_L by 77.2326 % and reduces the VD to 0.0633 pu, while placing three DGs at the same time reduces P_L by 94.94 % and reduces the VD to 0.0429 pu. Fig.16, illustrates how the inclusion of multiple DG units in both categories, DGI and DGII, results in a decrease in voltage deviation. Fig.17, and 18, show the convergence behavior of the IRGA when utilizing one, two, and three DGs from DGI and DGII, respectively. Additionally, Fig.19, and 20, illustrate the enhancements in voltage profile according to the integration of multiple DG units. Notably, the incorporation of three DGs from the DGII category significantly enhances the overall system voltage profile.

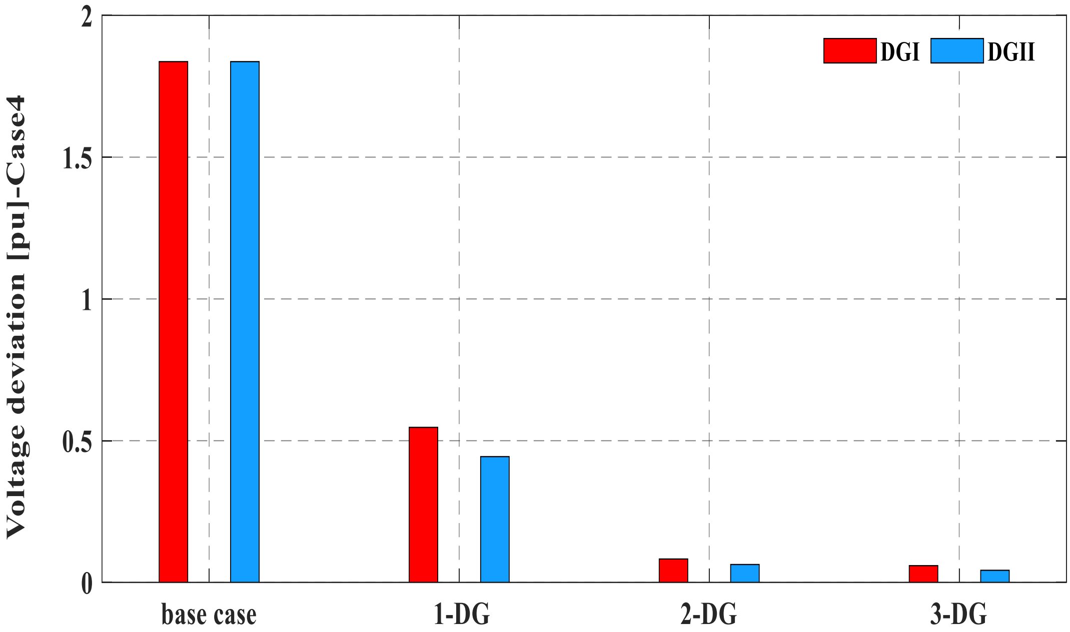

Fig. 16. Comparison of voltage deviation reduction for Case-4 in the IEEE-69 bus system.

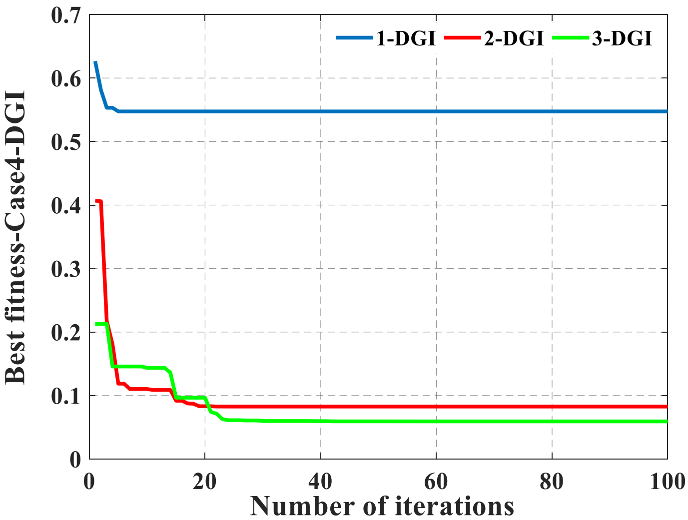

Fig. 17. The IRGA's convergence properties for DGI.

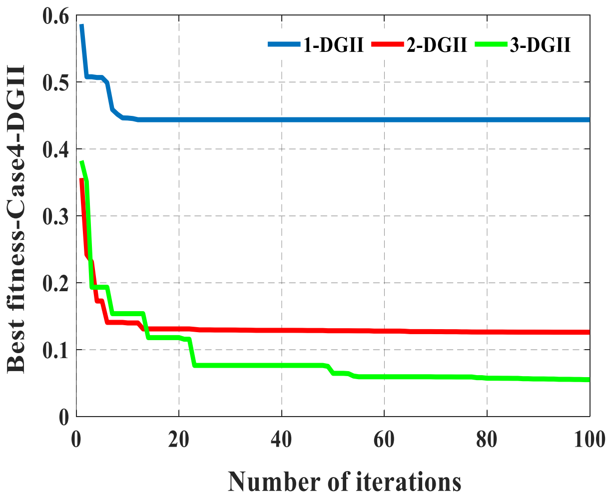

Fig. 18. The IRGA's convergence properties for DGII.

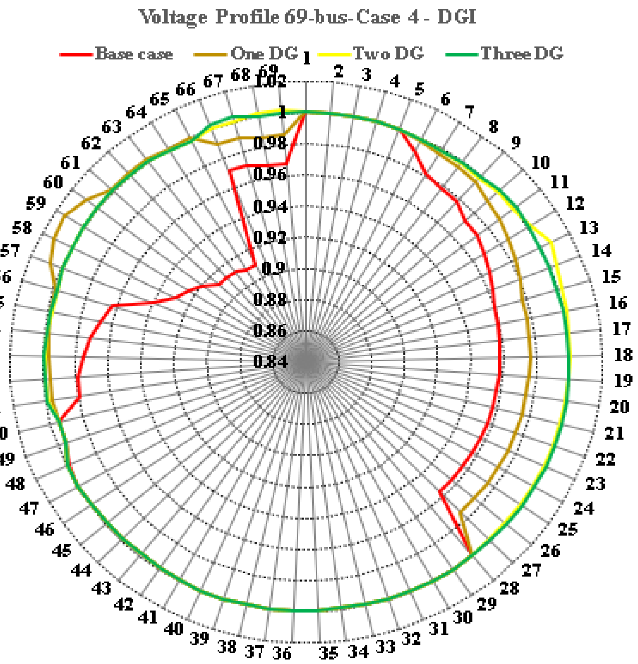

Fig. 19. the enhancement of voltage profile compared to the number of DGI.

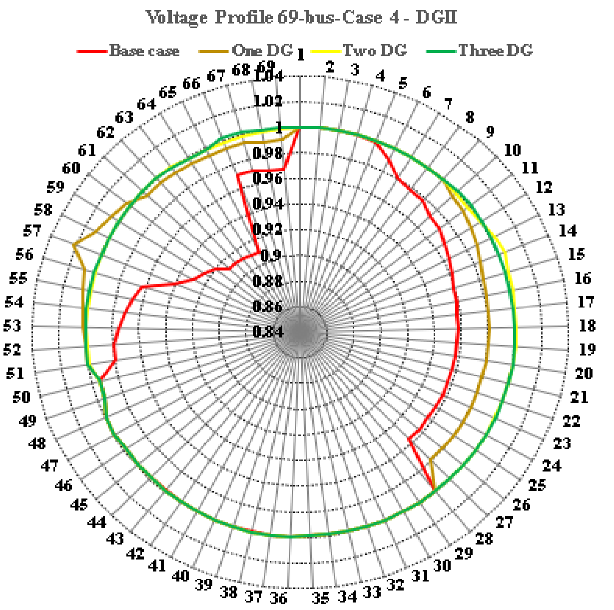

Fig. 20. The enhancement of voltage profile compared to the number of DGII.

5. Conclusion

In this study, the optimal allocation of single and multiple DG units in the distribution network is determined using an upgraded version of the Genetic Algorithm (GA) known as the Improved Real Coded Genetic Algorithm (IRGA). Investigations are also conducted into how the installation of DGs would affect key performance indicators and parameters like voltage profile and total loss in active and reactive power of the system. Active power loss reduction and Improvement of the voltage profile of the radial distribution network are the main objectives of installing DG units in this paper. The suggested technique is implemented on Two different IEEE standard bus systems which are IEEE 33 bus, and 69 bus. The results demonstrate the technique's applicability in diverse network systems. Also, the outcomes demonstrate a large decrease in the system's active and reactive power losses as well as an improvement in the voltage profile. If the optimum bus and DG value are established, it will demonstrate the benefits of DG penetration. The future research will be extended to include the availability, uncertainty, reliability and environmental factors related to DG deployment. Also, how scalable and adaptable are these units to different types of loads.

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