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# An improved gravitational search algorithm for optimal placement and sizing of renewable distributed generation units in a distribution system for power quality enhancement

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**Abstract:** Distributed generation (DG) is an important element to be considered in distribution planning since it plays a major role in stability and power quality improvement. This paper presents a new method for determining optimal sizing and placement of DG in a distribution system. A multi-objective function is formed to minimize the total losses, average total voltage harmonic distortion (THD<sub>v</sub>) and voltage deviation in the distribution system. The improved gravitational search algorithm (IGSA) is proposed as an optimization techniques and its performance is compared with other optimization techniques such as particle swarm optimization (PSO) and gravitational search algorithm (GSA). The load flow algorithm from MATPOWER and harmonic load flow was integrated in MATLAB environment to solve the proposed multi-objective function. Finally, the proposed algorithm is tested on the radial 69-bus distribution system with three case studies. The results show that the IGSA performs better than PSO and GSA by giving the best fitness value and the fastest average elapsed time.

Key words:

Harmonic distortion, distributed generation, improved gravitation search algorithm, optimization, loss reduction.

### 1 Introduction

The existence of renewable DGs in the distribution system may lead to several benefits such as voltage support, improved power quality, loss reduction, improved utility system reliability and deferment of investments into new or upgraded transmission and distribution infrastructure [1]. However, when DG is connected to a distribution system, it may contribute to harmonic propagation in the system depending on the type of DG unit and the power converter technology [2]. DG can be classified into two types, namely, inverter-based DG and non-inverter-based DG [3]. Examples of inverter-based DG are photovoltaic systems, wind turbine generators, fuel cells, and micro turbines, which uses power converters as interfacing devices to the grid. On the other hand, small hydro synchronous generators and induction generators are considered to be non-inverter-based DG units.

DGs are to be installed at the distribution system level of the electric grid and should be placed close to the load center. The impact of DG on power losses, voltage profile, short circuit current, harmonic distortion and power system reliability are usually tested separately before connecting it to the distribution system. The achievement of the benefits from DGs depends greatly on how optimally they are installed. Studies have indicated that approximately 13% of the generated power is consumed as losses at the distribution level [4]. Another problem in the distribution system is the voltage profile, which tends to drop below tolerable operating limits along distribution feeders as load increases. This arises due to the growing electricity demand, which requires the upgrading of the distribution system infrastructure [5]. Hence, to reduce the power losses and to improve both the voltage profile and the THD<sub>v</sub>, an appropriate planning must be carried out before integrating DG into power systems. In this process, several factors need to be considered, such as the technology to be used, the number of the units, the capacity of the units, the optimal location, and the type of network connection.

In the literature, several methods have been applied to determine optimal location and size of DG in a distribution system. The analytical method used for optimal DG placement and sizing is only accurate for the developed model and it can be very complicated for solving complex systems. The power flow algorithm has been used to find the

optimum DG size at each load bus by assuming that each load bus is allowed to have a DG unit [6, 7]. However, this method is ineffective because it requires large number of load flow computations. Analytical methods can also be used to place the DG in radial or meshed systems [8]. In this method, separate expressions for radial and meshed systems are required and complex procedures based on phasor current are applied to solve the DG placement problem. Nonetheless, this method only determines the optimum DG placement but not the optimum DG size as it considers a fixed DG size.

Another popular method used in optimal placement and sizing of DG in distribution systems is by means of metaheuristic technique which applies an iterative process that can act as a guide for its subordinate heuristics in order to powerfully find the optimal or near-optimal solutions of the optimization problem [9]. It intelligently combines different concepts derived from artificial intelligence to improve the performance. Some of the techniques that adopt meta-heuristics concepts include genetic algorithm (GA), Tabu search, particle swarm optimization (PSO), ant colony optimization (ACO) and gravitation search algorithm (GSA). GA is part of evolutionary algorithm which uses evolutionary mechanism such as selection, crossover and mutations [10]. It has been considered as a widely used optimization search method employed in finding accurate and near-optimal solutions in multi-objective optimization problems. In [11-13], a GA was adopted for finding the optimal size and site of DG units in power distribution systems. It is considered appropriate for solving multi-objective problems such as DG allocation and gives satisfactory solutions. However, the disadvantage of GA is that it requires long computational time with prolonged convergence time [14, 15].

The Tabu search method was used by Nara at al. (2001), Golshan & Arefifar (2007), and Rugthaichararoencheep & Sirisumrannukul (2009) to determine optimal DG size and location [16-18]. Tabu search is an optimization tool that has the ability to avoid entrapment in local minima by using a flexible memory system. This approach explores its memory structures to effectively and economically direct the search to attractive regions in the solution space. However, the drawback of this method is that some assumptions cannot be satisfied or approximated in most practical application [19]. PSO is swarm intelligence technique applied in modelling social behaviour to guide swarms of particles towards the most promising regions of the search space [20]. Interestingly, PSO adopted by Ardakani et al. (2007) can be easily implemented and usually results in faster convergence rates than GA [21]. However, its application is limited as it is only efficient in solving unconstrained optimization problems [22]. Amanifar and Hamedani in 2011 applied PSO technique with sensitivity analysis for solving the optimal DG placement and sizing problem by minimizing the total system cost, reducing losses and THD and improving the voltage profile [4]. The advantage of this combined method is that the search space is reduced, which eventually increases the speed of the optimization process. However, this method does not give optimal result of DG placement and sizing simultaneously. Ant Colony Optimization (ACO) algorithms utilize the concept of a population of ants, to collectively solve the optimization problem under consideration. Each ant searches for minimum cost based on its private information and the information available in the local node it visits. As a matter of fact, each ant of the colony is complex enough to find a feasible solution; nevertheless, a collective interaction among these ants would yield better quality result [23]. Falaghi and Haghifam (2007) adopted the ACO algorithm to achieve the minimum investment cost of DG and the minimum total operation cost of the system as the objective function in determining the optimal number and location of DG sources in distribution systems [24]. The merits of the ACO algorithm are that it is reliable. Conversely, the demerits of ACO are that it is hard to analyse theoretically and it gives uncertain convergence time [25].

Gravitational search algorithm (GSA) which is based on the Newtonian gravity in which every particle in the universe attracts every other particle with a force that is directly proportional to the product of their masses and inversely proportional to the square of the distance between them [26]. Mistry et al. and Kadir et al. adopted the GSA technique for determining optimal placement and sizing of DG in distribution system [27, 28]. There are some weaknesses in the GSA process for searching the best solution [29, 30].

This paper proposes a new and improved gravitational search algorithm (IGSA) for determining the optimal placement and sizing of DG in a radial distribution system by minimizing the losses, THD<sub>v</sub> and voltage deviation. The assumption has been made in this simulation where the distribution system is a balanced system due to the installation of single-phase renewable DG units (rooftop PVs solar) are similar for each phases. Several researchers have employed the 69-bus system for evaluating the optimal placement and sizing of DG due to the balanced and the simplicity of the system [18, 22, 31]. Thus, the methodology is then tested in a 69-bus radial distribution system. To minimize the objective functions, the proposed algorithm is integrated with MATPOWER Newton-Raphson load flow algorithm [32] and harmonic load flow algorithm [33]. Though, this proposed technique also can be used to evaluate the unbalanced system by using the several simulation tools such as Forward/Backward power flow algorithm and Digsilent Power Factory [34, 35]. The improved technique has been compared with others optimization techniques such as PSO and GSA in three case studies. The result of the proposed technique exhibits the highest performance in getting the best fitness and fastest average elapsed time. The results also show the efficiency of the proposed technique in minimizing the total losses, average  $THD_v$  and voltage deviation.

# 2. Problem Formulation

A multi-objective optimization technique, formulated as a constrained non-linear integer optimization problem, is proposed for DG placement, sizing and controlling DG voltage at a distribution system. The objective is to minimize the total power loss, the average THD<sub>v</sub> and the voltage deviation. The fitness function is given by Eq. (1):

$$F_{\min} = \gamma \times P_{loss} + \beta \times THD_{v} + \chi \times V_{dev}$$
<sup>(1)</sup>

where *F* is the fitness function,  $P_{loss}$  is the total power loss (%),  $\gamma$  is the coefficient factor for total power loss,  $THD_{\nu}$  is the average  $THD_{\nu}$  (%) at all system busbars,  $\beta$  is the coefficient factor for  $THD_{\nu}$ ,  $V_{de\nu}$  is the voltage deviation (%) at all system busbars and  $\chi$  is the coefficient factor for  $V_{de\nu}$ . The total real power loss is defined by

$$P_{loss} = \sum_{i=1}^{n} P_{loss_{i}} = 1, 2, 3, ..., n$$
(2)

where *n* is the number of lines. The average  $THD_v$  is defined by

$$THD_{V} = \frac{\sum_{i=1}^{m} THD_{V_{i}}}{m}$$
(3)

where *m* is the number of buses. The  $V_{dev}$  is defined by

$$V_{dev} = \frac{V_{iref} - V_i}{V_i} \tag{4}$$

where  $V_{iref}$  is reference voltage at bus *i* and  $V_i$  is the actual voltage at bus *i*.

The total power loss, the average  $THD_v$  and voltage deviation should be minimized according to the network power flow equations at fundamental and harmonic frequencies. Generally, multi-objective methods provide a set of optimal solutions. For this paper, the sum of the coefficient factor method is used to decide the relative importance of the objectives in order to obtain the best optimization solution. The coefficient factor for total power loss is assumed to be 0.4 while the average  $THD_v$  and voltage deviation are considered as 0.3. The factor for power loss is considered greater than  $THD_v$  and voltage deviation because the reduction of power loss in distribution networks has a significant impact on economic and technical prospects.

The inequality constraints involve those associated with the bus voltages and the DG to be installed. The bus voltage magnitudes are to be kept within acceptable operating limits throughout the optimization process, as follows:

$$V_{\min} \le \left| V_i \right| \le V_{\max} \tag{5}$$

where  $V_{\min}$  is the lower bound of bus voltage limits,  $V_{\max}$  is the upper bound of the voltage limits, and  $|V_i|$  is the root mean square (RMS) value of the *i*<sup>th</sup> bus voltage.

The total harmonic level at each bus is to be less than or equal to the maximum allowable harmonic level, as expressed as follows:

$$THD_{vi} (\%) \le THD_{v\max}$$
(6)

where  $THD_{vmax}$  is the maximum allowable level at each bus (5%).

#### 3. Proposed Algorithm

With the growing use of DGs in distribution systems, several techniques have been used to solve power system optimization problems. In this paper, the IGSA is used to determine the optimal placement and sizing of DG in a

distribution system. The Newton-Raphson loadflow algorithm from MATPOWER and harmonic loadflow are integrated into this optimization technique in order to obtain the minimum fitness functions for the total power loss, average THD<sub>v</sub> and voltage deviation.

3.1 Gravitational search algorithm

Gravitational search algorithm (GSA) was developed by Rashedi et al. in 2009. It is based on metaphor of gravitational kinematics. This algorithm is based on the Newtonian gravity: "Every particle in the universe attracts every other particle with a force that is directly proportional to the product of their masses and inversely proportional to the square of the distance between them" [26]. The computational procedures of the GSA technique are described as follows [26]:

i. The position of the *i*<sup>th</sup> agent is given in Eq.(7):  

$$X_{i} = (x_{i}^{1}, \dots, x_{i}^{d}, \dots, x_{i}^{n}), \text{ for } i = 1, 2, \dots, N$$
(7)

where  $x_i^d$  presents the position of  $i^{th}$  agent in the  $d^{th}$  dimension.

And the detail position of each  $i^{th}$  agent is given in Eq. (8)

$$x_i^n = \left[ \text{(Size, V_control, Location)}_1, \text{(Size, V_control, Location)}_2, \text{(Size, V_control, Location)}_N \right]$$
(8)

where  $x_i^n$  is the position of each  $i^{th}$  agent, Size is the DG size, V\_control is the voltage control of DG and Location is the location of the DG.

ii. Update gravitational constant (G) is given in Eq.(9):

$$G(t) = G_0 \times \frac{T - t}{T} \tag{9}$$

where G(t) is the value of the gravitational constant at time t.  $G_0$  is the value of the gravitational constant at the first cosmic quantum-interval of time  $t_0$ .

iii. Update mass (*M*). Give weighting in the range between 0 and 1, correspond to their fitness as given in Eq.(10)-(11):

$$m_{i}(t) = \frac{fitness_{i}(t) - worst(t)}{best(t) - worst(t)}$$
(10)

$$M_{i}(t) = \frac{m_{i}(t)}{\sum_{j=1}^{N} m_{j}(t)}$$
(11)

where  $fitness_i(t)$  represent the fitness value of the agent *i* at time *t*, worst(t) and best(t) are defined as maximum and minimum fitness, respectively.

iv. Update  $k_{best}$  which is given in Eq.(12):

$$k_{best} = K_{best\_final} + \left[\frac{T-t}{T} \times (100 - K_{best\_final})\right]$$
(12)

v. Calculate total force (F) as given in Eq.(13)-(16):

$$F_{ij}^{d} = G \times \frac{M_i \times M_j}{R_{ij} + \varepsilon} \times (x_j^d - x_i^d)$$
(13)

$$R_{ij} = \left\| X_i, X_j \right\|_2 = \sqrt{\sum_{d=1}^{D} (x_j^d - x_i^d)^2}$$
(14)

$$\varepsilon = small\ coefficien\ t, 2^{-52}$$
(15)

To give a stochastic characteristic, the total force that acts on agent *i* in a dimension *d* be a randomly weighted sum of  $d^{th}$  components of the forces exerted from other agents is given in Eq. (16):

$$F_i^d(t) = \sum_{j \in Kbest, j \neq i}^N rand_j F_{ij}^d(t)$$
(16)

where  $rand_j$  is a random number in the interval between 0 to 1.

vi. Calculate acceleration factor  $\alpha$  which is given in Eq.(17):

$$a_i^d = \frac{F_i^d}{M_i} \tag{17}$$

vii. Update velocity *v* as given in Eq.(18):  $v_i^d(t+1) = rand_i \times v_i^d(t) + a_i^d(t)$ 

(18)

where  $rand_i$  is the random variable in the interval (0,1). This random number will gives a randomized characteristic to the search.

viii. Update position x as given in Eq.(19):  

$$x_i^d(t+1) = x_i^d(t) + v_i^d(t+1)$$
(19)

# 3.2 Improved Gravitational Search Algorithm

In GSA concept, the performance of the agents is considered by their masses. All the agents attract each other by the gravity force, whereas this force causes a global movement of all agents toward the agents with heavier masses [26]. The heavy masses were resultant to good solutions of the problem. In other words, each mass represents a solution, and the algorithm is piloted by appropriately adjusting the gravitational and inertia masses. By descend of time, the masses will be attracted by the heaviest mass which it represents an optimum solution in the search space. The achievement of the GSA depends on the two contradictory objectives which are exploration and exploitation. The exploration is the ability of expanding global investigation of the search space, while the exploration is the ability of finding the optima around a good solution. In premier iterations, the algorithm must use the exploration fades in to allow the found solution to be superior.

However, there were some weaknesses of the GSA in the searching process for the best solution. The first weakness was the controlling the balance between exploration and exploitation where more exploration will affect the premature convergence while the exploitation affects the convergence rate [29]. The second weakness was the best agent is still exploring the global space even it was at the best position [30]. To tackle these weaknesses, we propose an improved gravitational search algorithm (IGSA) which aims to improve the quality of the solution and to get the fastest convergence. In the propose IGSA, the chaotic dynamics is applied for the purpose of improvement in the searching behavior and to avoid the premature convergence. Due to the simplicity of execution and its unique capability to escape from being trapped in local optima (premature convergence), chaos has been an innovative optimization technique and chaos-based searching algorithms have stimulated strong benefits [36]. In this paper, the well-known logistic equation [36] as typical chaotic system, is employed for constructing the IGSA. The logistic equation is described as follows:

$$\phi(t+1) = \rho \times \phi(t) \times (1 - \phi(t)), \ 0 \le \phi(1) \le 1$$
(20)

where  $\phi$  is the chaotic value,  $\rho$  is a control parameter and has a real value in the range of 0 and 4, and *t* is the iteration number. The behavior of the system represented by Eq. (20) is greatly changed with the variation of  $\rho$ . The value of  $\rho$ determines whether  $\phi$  stabilizes at a constant size, oscillates within limited bounds, or behaves chaotically in an unpredictable pattern. Fig. 1 shows the chaotic dynamics when  $\rho = 4$  and  $\phi = 0.55$  [36].



Fig. 1 Chaotic value using logistic map 300 iteration

The new equation for gravitational constant is obtained by multiplying Eq. (9) and (20) as follows:  $G(t) = \phi \times G \times \frac{T-t}{2}$ 

$$G(t) = \phi \times G_0 \times \frac{T}{T}$$
(21)

Fig. 2 provides a fair comparison between the conventional and proposed gravitational constant. As shown in Fig. 2, although the conventional gravitational weight decreases monotonously from  $G_{max}$  to  $G_{min}$ , the new gravitational decreases and oscillates simultaneously for total iteration when  $\rho = 4$  and  $\phi = 0.55$ .



115. 2 Comparison of the conventional and endone gravitational constant

In GSA, too much dependence on the random variables in the calculation will create less significant impact for the implementation of the gravitational theory on the search algorithm. Thus, the random variable in Eq. (16) is removed as to reduced too much reliance on randomize exploration process [30]. Based on the conventional GSA, the gravitational force acting on the particular agent depends on other masses,  $M_k$  and distance between other agents to the particular agents,  $R_{ij}$ . These two elements are given by a decision parameter,  $\gamma$  in quantum binary gravitational search algorithm (QBGSA) [30]. However, in this study, these two elements are used to get the decision parameter of  $\lambda$ . Thus  $\lambda$  can be obtained using the following conditions in Eq. (22)-(23):

$$\lambda_i^k = \begin{cases} 1, \text{ if } M(k) > M(i) \text{ and } R_{ik} \le \tau \\ 0, \text{ otherwise} \end{cases}$$
(22)

Where  $\tau$  is the maximum distance of the *i*<sup>th</sup> agent to the *k*<sup>th</sup> agent.

$$F_{ij}^{d} = \lambda_{i}^{k} \times G \times \frac{M_{i} \times M_{j}}{R_{ij} + \varepsilon} \times (x_{j}^{d} - x_{i}^{d})$$
(23)

In this study,  $\tau$  is set as 30% of the *i*<sup>th</sup> agent. That means, the attraction force by a far agent is very small and can be neglected. On the other hand, the lighter agent can be moved easily as compared to the heavier agent due to the initial mass action against the motion [30]. As a result, only the heavier *k*<sup>th</sup> agent can give effective acceleration on *i*<sup>th</sup> agent. The flow chart of IGSA algorithm

is shown in Fig.3. The detail process of optimal DG placement, sizing and voltage control was handle simultaneously is depicted in Fig. 4.



Fig. 3. Flow chart of the IGSA algorithm



Fig 4. The simultaneous process of DG placement, sizing and voltage control using IGSA

## 3.3 MATPOWER Newton-Raphson loadflow and harmonic loadflow

The growing number of DG units may contribute to harmonic distortion in power system networks. Therefore, harmonic analysis tool is very important for distribution system analysis and design. It can be used to assess the harmonic distortion in the voltage and current at various buses and can also determine the existence of unsafe

resonance phenomena in the power system. Generally, harmonic analysis algorithms can be divided into two categories. The first category is based on transient-state analysis techniques, such as time domain analysis and wavelet analysis [37, 38]. The second category is steady-state analysis, which is based on load flow programs and the use of frequency-based component models [39]. Steady-state based algorithms are more efficient compared to transient state based algorithms due to their large-scale power system application and less computational time [33, 40].

This study aims to determine optimal placement and sizing and of DGs in a distribution system. Thus, the fitness function of the losses and the voltage deviation are obtained from the *MATPOWER Newton-Raphson* loadflow [32]. While for the fitness of THDv can be obtained from the harmonic loadflow [33] in which the flow chart of the harmonic loadflow is depicted in Fig.5. The MATPOWER loadflow algorithm and the harmonic loadflow were integrated with the IGSA in order to determine the optimal parameters with the goal of minimizing the power loss, average THD<sub>v</sub> and voltage deviation. The proposed IGSA technique is used to find the best solution of the formulated problem.



Fig. 5. Flow chart of Flow chart of harmonic loadflow algorithm

#### 4. Results and discussion

The proposed method for DG placement and sizing is tested on the 69-bus radial distribution system as shown in Fig.6. The load and bus data of the 69-bus radial distribution system are indicated in [18]. The system loads are considered as spot loads, with the total being 3.8 MW and 2.69 MVAr. The MVA base of this test system is 100MW. The minimum and maximum voltage limits are set at 0.9 p.u and 1.05 p.u. The maximum iteration for the IGSA, PSO and GSA algorithm is chosen as 300. The only supply source in the system is the substation at bus 1, which is a slack bus with constant voltage. The proposed algorithm was implemented and coded in MATLAB computing environment.



Fig. 6. 69-bus radial distribution system

The inverter-based DGs will be acting as the harmonic producing device in the distribution system. The typical harmonic spectrum of inverter-based DG is provided in Table 1 [40].

Harmonic order	Inverter based DG (%)		
1	100		
5	0.1941		
7	0.1309		
11	0.0758		
13	0.0586		
17	0.0379		
19	0.0329		
23	0.0226		
25	0.0241		
29	0.0193		

Table 1. Harmonic spectrum of non-linear loads and inverter-based DG

The IGSA technique is applied to determine the optimal sizing and placement of DGs in the 69-bus radial distribution system, considering the harmonic propagation in the analysis. The total harmonic distortion levels of each DG unit are to be maintained within 5% according to the IEEE standard 519-1992 [41]. There are several assumption made with regards to the impact of DG installation on power loss, harmonic distortion and voltage deviation, in the 69-bus radial distribution system, as indicated below:

i. The renewable DGs used to generate DC source are rooftop PVs solar. However, due to lack of input data (fluctuates input data of PV) as well as the variation of loading conditions, the general renewable DG (with constant DC source) is considered in this research.

- ii. The simulation are implemented based on snapshot at the peak load condition. The peak load has more significant impact on the power losses compared to the average load condition.
- iii. The installation of rooftop PVs solar units are similar for each phase.
- iv. The cost is not considered in this simulation.
- v. The maximum penetration level of renewable DGs is 50% of the total connected load [42].
- vi. The renewable DG will inject only active power.
- vii. The maximum number of DG connected to the system is 3.
- viii. The base case system is free from harmonic source and harmonic distortion.

Before applying IGSA algorithm, the parameters are tuned to enhance the performance of the proposed algorithm. The initial gravity constant,  $G_o$  is set to 100 and the best applying force, Kbest is monotonously decrease from 100% (Kbest<sub>max</sub>) to 2.0% (Kbest<sub>min</sub>). The  $\tau$  is set as 30% of the *i*<sup>th</sup> agent. Population sizes of 50 were selected for the IGSA algorithm. The same population sizes are used for PSO and GSA algorithm. In GSA, the Kbest is similar to the IGSA. The boundary constraints for the control parameters such as DG size, DG placement and DG voltage control are as followed:

- i. 1.5MW  $\leq$  DG size  $\leq$  1.9MW
- ii. Bus  $2 \le DG$  placement  $\le Bus 69$
- iii.  $0.98 \le \text{DG}$  voltage control  $\le 1.02$

In this study, three cases are considered:

- i. A single DG is to be placed and sized optimally in the test system. As well as the bus voltage at the DG placement is required to be set optimally. A base case is conducted to calculate the real power loss and voltage deviation before the presence of DG.
- ii. The 2 DGs are required to be placed and sized optimally in the test system. The bus voltages of DGs are also set optimally.
- iii. The 3 DGs are to be placed and sized optimally in the distribution system. The bus voltages of DGs are also set optimally.

The best fitness value among the 30 simulation runs using the three optimization techniques for one DG installed in the 69-bus radial distribution test system are illustrated in Fig.7. Fig.8 and Fig.9 show the best convergence characteristics for two and three DGs installed in the distribution system, respectively. The results indicated that the IGSA gives the best fitness value compared to PSO and GSA.



Fig. 7 Convergence characteristic of GSA, PSO and IGSA algorithm for 1 DG in the 69-bus system



Fig.8 Convergence characteristic of GSA, PSO and IGSA algorithm for 2 DGs in the 69-bus system



Fig.9 Convergence characteristic of GSA, PSO and IGSA algorithm for 3 DGs in the 69-bus system

To further evaluate the effectiveness of the IGSA, 30 independent runs were conducted to measure the frequency of reaching the optimal or near optimal solution while maintaining the same stopping criterion (maximum iteration of 300). The statistical results for best fitness, worst fitness, average fitness, standard deviation and average elapsed time are summarized in the Tables 2 to 4 with 1, 2 and 3 DGs installed in the test system, respectively. For all cases, the IGSA technique has obtained the best optimal solution with the lowest standard deviation as indicated in bold. In terms of average elapsed time, the IGSA technique gives the optimal solution in the shortest time compared to PSO and GSA techniques as indicated in bold. Table 5 to Table 7 summarized the results of optimal placement, sizing and controlled voltage of DG in the test system for the three studied cases. The objective functions of this study are to minimize the power loss; voltage deviation and THD<sub>v</sub> as shown in Table 8. The base case power loss is 0.2298% and the base case average voltage deviation is 0.0272%.

Techniques	Worst Average fitness		Best	Std. devia	Std deviation			
	fitness	i erage inness	fitness			elapsed		
						time		
GSA	0.1961	0.1727	0.1628	0.0082	2	252.9133		
PSO	0.1818	0.1691	0.1691 0.1621		3	249.3032		
IGSA	0.1772	0.1643	0.1585	0.0041	l	239.1995		
Techniques	Table 3 Performance	and IGSA for 69-b	us system for 2 D	Gs tion	A			
rechniques	w orst fitness	Average innes	s Dest	Std. devia	uon	Average		
	Ittless		nuless			time		
GSA	0.1936	0.1168	0.0358	0.0483		265.8869		
PSO	0.1538	0.0995	0.0387	0.0347		260.7858		
IGSA	0.1655	0.0929	0.0346	0.0339	)	250.8889		
					a			
Techniques	I able 4 Performant	Average	and IUSA for 69-b	us system for 3 D Std. deviat	us ion	Average		
reeninques	fitness	fitness	fitness	Stu. ue viai	1011	elansed		
	inticss	intile 55	Inness			time		
GSA	0.2292	0.1461	0.0631	0.0460		268.5296		
PSO	0.2074	0.1082	0.0604	0.0389		266.8724		
IGSA	0.1854	0.1070	0.0548	0.0229		252.5867		
	Table 5 Optimization result	ts using GSA, PS	SO and IGSA algori	ithms for 1 DG in	the system			
	Size of DG1		1.8868	1.6679	1.7352			
	Controlled voltage of D	C1	1.0170	1.0079	1.0012			
	L ocation of DC1	01	54	1.0196	63			
	Location of DO1		54	14	03			
	Table 6 Optimization results	s using GSA, PS	O and IGSA algorit	thms for 2 DGs in	the system			
			GSA	PSO	IGSA			
	Size DG1		1.2969	1.3461	1.4880			
	Size DG2		0.3040	0.3403	0.3042			
	Controlled voltage of D	G1	1.0036	0.9880	0.9933			
	Controlled voltage of D	G2	0.9807	0.9801	1.0042			
	Location of DG1		67	67	63			
	Location of DG2		54	63	57			
	Table 7 Optimization result using GSA, PSO and IGSA algorithms for 3 DGs in the system							
	~ :		GSA	PSO	IGSA			
	Size DG1		1.3240	1.2469	1.3262			
	Size DG2		0.2362	0.2231	0.2970			
	Size DG3		0.2509	0.2009	0.2262			
	Controlled voltage of I	)Gl	0.9872	1.0043	1.0142			
	Controlled voltage of I	DG2	1.0107	0.9996	1.0086			
	Controlled voltage of I	<b>D</b> G3	1.0151	0.9856	0.9917			
	Location DG1		61	22	63			
	Location DG2		60	43	38			
	Location DG3		4	28	35			

DG availability	Optimisation	Losses (%)	Voltage deviation	THD <sub>v</sub>	Fitness
	Techniques		(%)	(%)	function
No DG in the system	-	0.2298	0.0272	0.0000	-
With 1 DG in the system	GSA	0.0290	0.0100	0.4941	0.1628
	PSO	0.0292	0.0105	0.4910	0.1621
	IGSA	0.0275	0.0107	0.4903	0.1585
With 2 DGs in the system	GSA	0.0299	0.0113	0.0681	0.0358
	PSO	0.0284	0.0104	0.0808	0.0387
	IGSA	0.0269	0.0087	0.0668	0.0346
With 3 DGs in the system	GSA	0.0218	0.0053	0.1760	0.0631
	PSO	0.0212	0.0072	0.1658	0.0604
	IGSA	0.0199	0.0078	0.1487	0.0548

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60.66% of the base case, respectively while the THD<sub>y</sub> increases to 0.4903%.

Table 5 and Table 8 shows the results for the first case study with one inverter-based DG connected to the system. The proposed IGSA tends to converge steadily at bus 63 as the best candidate for optimal DG installation with the size of 1.7352MW and controlled voltage of 1.0013p.u. From the results of one DG installed shown in Table 8 and calculating the power loss and voltage deviation, the power loss and voltage deviation are reduced by 88.03% and

The results of the second case study with two DGs connected to the system are depicted in Table 6 and Table 8. From the results, the IGSA select buses 63 and 57 as the best candidates for optimal DG installation with the DG sizing of 1.488MW and 0.3042MW, respectively. Based on the results shown in Table 8 and the calculations of power loss and voltage deviation, the optimal two DG installations yield reduction of power loss and voltage deviation up to 88.29% and 68.01%, respectively of the base case while the THD<sub>v</sub> increases to 0.0668%.

The optimal planning of the three inverter-based DGs is analyzed based on the results shown in Table 7 and Table 8. Integrating three inverter-based DGs at buses 63, 38 and 35 with power ratings of 1.3262MW, 0.2970MW and 0.2262MW, respectively reduced the total power loss and voltage deviation up to 91.34% and 71.32%, respectively. However, the THD<sub>v</sub> is slightly increased to 0.1487% compared to the THD<sub>v</sub> in Case 2. From the results shown in Table 8, it is noted that installing the DG with optimal placement and sizing has significant impacts in terms of reduction of total power loss, voltage deviation and THD<sub>v</sub> in the distribution system. The power loss and voltage deviation are decreased dramatically when the numbers of DGs are increased at optimal locations and sizes. However, the THD<sub>v</sub> is the lowest when two DGs are connected to the distribution system. Table 8 also clearly shows that the proposed IGSA gives the best solution in term of fitness function value and average elapsed time compared to the GSA and PSO techniques.

Besides minimizing the power loss and  $THD_v$ , appropriate DG planning would improve the overall voltage profiles. Figures 10 to 13 shows the voltage profiles at all the 69 buses in the system considering pre and post DG integration. Figure 10 shows that the voltage at bus 63 is increased to 1.0013p.u after one DG is optimally installed in the system based on the IGSA results. Figure 11 illustrates the voltage profiles when two DGs are optimally installed in the system through IGSA, PSO and GSA techniques. It is noted that the voltage magnitudes are increased, especially at the bus where the DGs are installed. Figure 12 shows the voltage profiles when three DGs are installed in the system. The overall voltage profiles shows the increase in voltage magnitudes within the specified limits when DGs are installed at the optimal buses. Figure 13 shows the comparison of voltage profiles for different number of DGs installed based on the IGSA technique. By increasing the number of DGs at the optimal buses, the overall voltage profiles are significantly improved in which the voltage magnitudes are increased but within the specified limits.



Figure 10 Voltage magnitudes in the 69 bus radial distribution test system with one DG unit



Figure 11 Voltage magnitudes in the 69 bus radial distribution test system with two DG units



Figure 12 Voltage magnitudes in the 69 bus radial distribution test system with three DG units



Figure 13 Voltage magnitudes in the 69 bus radial distribution test system with different numbers of DG units using the IGSA technique

#### Conclusion

This paper presented a new method for determining optimal placement and sizing of DG units using the IGSA. In the studied optimization problem, the multi-objective function is to minimize the total power loss, voltage deviation and THD<sub>v</sub>. The results show that the proposed IGSA is effective in finding optimum size and locations of DGs in a power distribution system. The reduction of losses, voltage deviation and THD<sub>v</sub>, is clearly seen after optimizing the DG placement, sizing and controlling the voltages. The proposed IGSA performs better compared to the PSO and GSA in minimizing the losses, voltage deviation and THD<sub>v</sub>.

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