# A GA/IPSO BASED APPROACH FOR SYSTEM LOSS REDUCTION AND VOLTAGE PROFILE IMPROVEMENT EMPLOYING ARITHMETIC CROSSOVER AND MUTATION.

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**Abstract**

Reduction of system losses and improvement of voltage profile is one of the key aspects in power system operation. Though many methods are used to achieve this aspect, Distributed Generation (DG) has found increased usage nowadays due to its many advantages. Majority of algorithms proposed in this area have emphasized on real power losses only in their formulations. In modern practical power systems reactive power injection plays a critical role in voltage stability control, thus the reactive power losses need to be incorporated in optimizing DG allocation for voltage profile improvement. This paper aims at solving this problem by proposing a hybrid of GA and IPSO to optimize DG location and size while considering both real and reactive power losses. The hybrid technique aims at inheriting the good traits from the two techniques while avoiding the undesirable ones. Arithmetic crossover and mutation has being employed in the proposed algorithm.

**Key words:** Distributed Generation (DG), Particle Swarm Optimization (PSO), Genetic Algorithm (GA), system loss reduction, voltage profile improvement.

## 1. Introduction

### *1.1 Distribution systems*

Electricity networks are in the era of major transition from stable passive distribution networks with unidirectional electricity transportation to active distribution networks with bidirectional electricity transportation. Radial distribution networks without any DG units are considered passive since the electrical power is supplied by the national grid system to the customers embedded in the distribution networks. They become active when DG units are added to the distribution system leading to bidirectional power flows in the networks [1]. In an active distribution network the amount of energy lost in transmitting electricity is less as compared to the passive distribution network, because the electricity is generated very near to the load center. Active Distribution Network has several advantages like reduced line losses, voltage profile improvement, reduced emission of pollutants, increased overall efficiency, improved power quality and relieved T&D congestion. Hence, utilities and distribution companies need tools for proper planning and operation of Active Distribution Networks. The most important benefits are reduction of line losses and voltage stability improvement. These are crucially important in determining the size and location of DG unit to be placed in the distribution networks. Studies indicate that poor selection of location and size of a DG in a distribution system would lead to higher losses than the losses without DG [2]

The main motive behind applying DGs in the power distribution are energy efficiency or rational use of energy, deregulation or competition policy, diversification of energy sources, availability of modular generating plant, ease of finding locations for smaller generators, shorter construction time and lower capital costs for smaller plants, and its proximity of the generation plant to heavy loads, which can reduce the transmission costs. The DG when connected to network can provide a number of benefits. Some of the benefits are power losses reduction, energy undelivered costs reduction, preventing or delaying network expansion [3, 4]. Other benefits are peak load operating costs reduction, improved voltage profile and improved load factor [5]. In addition to providing benefits, DG can also have negative impacts on network. These impacts include frequency deviation, voltage deviation and harmonics on network [6]. The increase of power losses is another effect that may occur [7]. Thus careful considerations need to be taken when sizing and locating DGs in distribution systems.

**1.2 *DG placement and sizing optimization***

Traditionally load growth is forecasted by distribution companies until a predetermined amount is reached, whereby a new capacity must be added to the network . This new capacity is usually the addition of new substations or expanding existing substations capacities and their associated new feeders or both. However, the flexibility, technologies, technical & monetary benefits and concepts of DG planning is challenging this state of matter and gaining credibility as a solution to the distribution planning problems with the prohibitively high cost of power curtailment in the changing regulatory and economic scenarios. This enhances DG as an attractive distribution planning option that avoids causing degradation of power quality, reliability and control of the utility systems. Quinta et al. (1993) [8] and Khator and Leung (1997) [9] reported that the distribution system planning problem is to identify a combination of expansion projects for the least cost network investment that satisfies load growth requirements without violating any system and operational constraints.

Usually, DGs are integrated with the existing distribution system and lots of studies are done to find out the best location and size of DGs to produce utmost benefits. The main characteristics that are considered for the identification of an optimal DG location and size are the minimization of transmission loss, maximization of supply reliability and maximization of profit of the distribution companies (DISCOs). Due to extensive costs, the DGs should be allocated properly with optimal size to enhance the system performance in order to minimize the system loss as well as to get some improvements in the voltage profile while maintaining the stability of the system. The effect of placing a DG on network indices usually differs on the basis of its type, location and load at the connection point. Thus interconnection planning of DG to electrical network must consider a number of factors. The factors include DG technology; capacity of DG unit; location of DG connected and network connection type [5].

In EI-hattam and Salma [10], an analytical approach has been presented to identify appropriate location to place single DG in radial as well as loop systems to minimize losses. But, in this approach, optimal sizing is not considered. Loss Sensitivity Factor method (LSF) applied by Graham *et al.*, [11] is based on the principle of linearization of the original nonlinear equation (loss equation) around the initial operating point, which helps to reduce the amount of solution space. Optimal placement of DG units is determined exclusively for the various distributed load profiles to minimize the total losses. They have iteratively increased the size of DG unit at all buses and then calculated the losses; based on loss calculation they ranked the nodes. Top ranked nodes are selected for DG unit placement. Ashwani Kumar and Wenzhong Gao [12] presented a multi-objective optimization approach for determining optimal location of DGs in deregulated electricity markets with a aim of improving the voltage profile and reducing the line losses. This approach combined the use of power flow and power loss sensitivity factors in identifying the most suitable zone and then optimized the solution by maximizing the voltage improvement and minimizing the line losses in the network. This work did not consider reactive power loss in optimization.

T. N. Shukla, S.P. Singh and K. B Naik (2010) [13] used GA to optimally locate DG for minimum system losses in radial distribution networks. The problem was formulated as an optimization problem with minimization of real power loss subject to equality and inequality constraints and solution is obtained using GA. The appropriate location is decided on the basis of active power loss sensitivity to real power injection through DG. They demonstrated that the benefit increases with increased number of locations within certain locations beyond which it is uneconomical. This formulation considered active power losses only. The Genetic Algorithm (GA) based method to determine size and location of DG unit was also used in Ault and McDonald (2000) and Caisheng and Nehrir (2004) [14, 15]. They addressed the problem in terms of cost, considering that cost function may lead to deviation of exact size of the DG unit at suitable location. J. J. Jamian and others (2012) [16] implemented an Evolutionary PSO for sizing DGs to achieve power loss reduction. They argued that though EPSO and PSO give same performance in finding the optimal size of DG, EPSO can give superior results by having less iteration and shorter computation time. Besides that, EPSO avoids the problem of being trapped in a local minimum by selecting the survival particles to remain in the next iteration. Yustra, Mochamad Ashari and Adi Soeprijanto (2012) [17] proposed a method based on Improved PSO (IPSO) for optimal DG allocation with the aim of reducing system losses. IPSO generated more optimal solution than PSO and SGA methods using active power losses reduction parameter. However, IPSO method needed more iterations to converge compared to the other two methods. M. Vatankhah and S.M. Hosseini (2012) [18] proposed the use of new coding in PSO which included both active and reactive powers of DGs to achieve better profile improvement by optimizing the size and location of the DGs. In their proposed method, four set of weighing factors are chosen based on the importance and criticality of the different loads. Their results showed that the weighting factor had a considerable effect on voltage profile improvement. Arash Afraz and others (2012) [19] also proposed a PSO based approach to optimize the sizing and sitting of DGs in radial distribution systems with an objective of reducing line losses and improving voltage profile. The proposed objective function was a multi-objective one considering active and reactive power losses of the system and the voltage profile. In their research they considered a DG generating active power only.

S. Chandrashekhar Reddy, P. V. N. Prasad and A. Jaya Laxmi (2012) [20], proposed a hybrid technique which includes genetic algorithm (GA) and neural network (NN) for identification of possible locations for fixing DGs and the amount of power to be generated by the DG to achieve power quality improvement. They argued that by fixing DGs at suitable locations and evaluating generating power based on the load conditions, the power quality of a system can be improved. In this work only real power loss was considered. M. Abedini and H. Saremi (2012) [21] presented a combination of GA and PSO for optimal DG location and sizing in distribution systems with load uncertainity. The combined method was implemented for the 52 bus system to minimize real power losses and increase voltage stability. The proposed method was found to produce better results compared to either of the two methods. They only considered active power losses. They also optimized the location and size of a DG generating active power only.

## 2. Formulations

### 2.1 *Objective function*

The multi-objective index for the performance calculation of distribution systems for DG size and location planning with load models considers the below mentioned indices by giving a weight to each index.

#### 2.1.1 *Real power loss reduction index*

Real Power Loss Reduction Index (PLRI) is expressed as:

$$PLRI = \frac{P_{L(base)} - P_{L(DGi)}}{P_{L(base)}} \tag{1}$$

#### 2.1.2 *Reactive power loss reduction index*

Reactive Power Loss Reduction Index (QLRI) is expressed as;

$$QLRI = \frac{Q_{L(base)} - Q_{L(DGi)}}{Q_{L(base)}} \tag{2}$$

#### 2.1.3 *Voltage profile improvement index*

The Voltage Profile Improvement Index (VPII) is defined as;

$$VPII = \frac{1}{[\max\limits_{i=2}^{n} \frac{|V_{(nom)}| - |V_{(DGi)}|}{|V_{(nom)}|}]} \tag{3}$$

#### 2.1.4 *Multi-objective based problem formulation*

In order to achieve the performance calculation of distributed systems for DG size and location the Multi-Objective Function (MOF) is given by;

$$MOF = w_1 PLRI + w_2 QLRI + w_3 VPII \tag{4}$$

Where;

$w_1$ , $w_2$ and $w_3$ are the respective weights assigned to each factor.

The sum of the absolute values of the weights assigned to all the impacts should add up to one.

That is; $|w_1| + |w_2| + |w_3| = 1$ (5)

These weights are indicated to give the corresponding importance to each impact indices for penetration of DG with load models and depend on the required analysis. The weights vary according to engineer's concerns. In this research work, more emphasizes is given to real power loss reduction since this results to a considerable decrease in total cost. Though this is not to mean that the other two factors are not important, thus the weights are assigned as follows;

$w_1 = 0.5$, $w_2 = 0.2$ and $w_3 = 0.3$

Thus the MOF is given by;

$$MOF = 0.5PLRI + 0.2QLRI + 0.3VPII \tag{6}$$

**2.2 *Operational constraints formulation***

The above formulated multi-objective function is minimized subject to various operational constraints so as satisfy the electrical requirements for the distribution network.

2.2.1 *Load balance constraint*

For each bus, the following load regulations should be satisfied;

$$P_{gni} - P_{dni} - V_{ni}\sum_{j=1}^{N} V_{nj} Y_{nj} \cos(\delta_{ni} - \delta_{nj} - \theta_{nj}) = 0 \tag{7a}$$

$$Q_{gni} - Q_{dni} - V_{ni}\sum_{j=1}^{N} V_{nj} Y_{nj} \sin(\delta_{ni} - \delta_{nj} - \theta_{nj}) = 0 \tag{7b}$$

2.2.2 *Real power generation limit*

This refers to the upper and lower real power generation limit of generators at bus-i.

$$P_{gi}^{\min} \le P_{gi} \le P_{gi}^{\max}, i = 1,2,\ldots N_g \tag{8}$$

2.2.3 *Reactive power generation limit*

This refers the upper and lower reactive power generation limit of generators and other reactive sources at bus-i.

$$Q_{gi}^{\min} \le Q_{gi} \le Q_{gi}^{\max}, i = 1,2,\ldots N_q \tag{9}$$

2.2.4 *Voltage limit*

The voltage must be kept within standard limits at each bus.

$$V_i^{\min} \le V_i \le V_i^{\max}, i = 1,2,\ldots. N_b \tag{10}$$

2.2.5 *DG real power generation limit*

This includes the upper and lower real power generation limit of distributed generators connected at bus-i.

$$P_{DGi}^{\min} \le P_{DGi} \le P_{DGi}^{\max}, i = 1,2,\ldots N_{DG} \tag{11}$$

2.2.6 *DG reactive power generation limit*

This includes the upper and lower reactive power generation limit of distributed generators connected at bus-i.

$$Q_{DGi}^{\min} \le Q_{DGi} \le Q_{DGi}^{\max}, i = 1,2,\ldots N_{DG} \tag{12}$$

## 3. Review of Optimization Techniques used

**3.1 *Genetic algorithm***

Genetic Algorithm simulates the biological processes that allows the consecutive generations in a population to adapt to their environment. Genetic Algorithms are unconstrained optimization methods, which model the evolutionary adaptation in nature. The Genetic Algorithm initiates the mechanism of the natural selection and evolution and aims to solve an optimization problem with objective function *f*(*x*). Where;

$x = x_1, x_2, \cdots, x_N$ is the N-dimensional vector of optimization parameters.

Genes and chromosomes are the basic building blocks of the GA. The conventional standard GA (SGA) encodes the optimization parameters into binary code string. A gene in SGA is a binary code. A chromosome is a concatenation of genes that takes the form;

$$Chromosome = [g_1^1 g_2^1 \cdots g_{L1}^1, g_1^2 g_2^2 \cdots g_{L2}^2, \ldots., g_1^N g_2^N \cdots g_{LN}^N] = [x_1 x_2 \cdots x_N]$$

Where; $g_j^i$ is a gene, $L_i$ is the length of the code string of the $i^{th}$ optimization parameter

$$x_k = [g_1^k g_2^k \cdots g_{Lk}^k]$$

GA is one of the effective parameter search techniques which are considered when conventional techniques have not achieved the desired speed, accuracy or efficiency. Genetic Algorithm has several advantages some of which include;

1. They require no knowledge of gradient information about the response surface.
2. They are resistant to becoming trapped in local optima therefore can be employed for a wide variety of optimization problems.
3. It can quickly scan a vast solution set.

4. Bad proposals do not affect the end solution negatively as they are simply discarded.
5. It doesn't have to know any rules of the problem - it works by its own internal rules.

### 3.2 *Particle swarm optimization*

Particle Swarm Optimization (PSO) is a population-based optimization method first proposed by Kennedy and Eberhart in 1995, inspired by social behavior of bird flocking or fish schooling [22]. The PSO algorithm starts with a population of particles with random positions in the search space. Each particle is a solution of the problem and has a fitness value. The fitness is evaluated and is to be optimized. A velocity is defined which directs each particle's position and gets updated in each iteration. Particles gradually move toward the optima due to their best position they have ever experienced and the best solution which group has experienced [23]. The velocity of a particle is updated due to three factors: the past velocity of the particle, the best position particle has experienced so far and the best position the entire swarm has experienced so far.

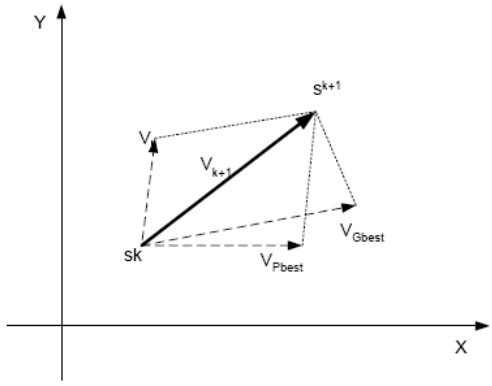


Fig. 1. Concept of a searching point by PSO

Mathematically the modification process may be expressed as follows:

$$V_{id}^{k+1} = wV_{id}^{k} + c_1 r(P_{best_{id}} - S_{id}^{k}) + c_2 r(G_{best_{id}} - S_{id}^{k}) \tag{13}$$

$$w_k = w_{\max} - \frac{(w_{\max} - w_{\min})}{k_{\max}}.k \tag{14}$$

$$S_{id}^{k+1} = S_{id}^{k} + V_{id}^{k+1} \tag{15}$$

Where,

$V_{id}^{k+1}$ is modified velocity of agent, $w$ is weight function for velocity of agent, $V_{id}^{k}$ is current velocity, $c_1$ and $c_2$ are weight coefficients for each term respectively, $r$ is a random number, $P_{best_{id}}$ is the particles best position, $S_{id}^{k}$ is current searching point, $S_{id}^{k+1}$ is the modified searching point, $V_{id}^{k+1}$ is modified velocity of agent i, $G_{best_{id}}$ is the groups best position, $w_{\min}$ and $w_{\max}$ are the minimum and maximum weights respectively, $k$ and $k_{\max}$ are the current and maximum iteration.

PSO has many advantages which include.

1. During the development of several generations, only the most optimist particle can transmit information onto the other particles, and the speed of the researching is very fast.
2. Calculation in PSO is very simple. Compared with the other developing calculations, it occupies the bigger optimization ability.
3. PSO adopts the real number code, and it is decided directly by the solution. The number of the dimension is equal to the constant of the solution.

The only major disadvantage of PSO is;

1. The method easily suffers from the partial optimism, which causes the less exact at the regulation of its speed and the direction.

### 3.3 *Arithmetic crossover and mutation*

In the proposed algorithm crossover and mutation is applied both in GA and PSO sections. These operators help in avoiding pre-mature convergence/partial optimism and thus improving the performance of PSO. In GA For each crossover operation a scalar $\lambda \in (0,1)$.is generated randomly between 0 and 1 and used to compute the children as shown

$$X_{c1} = \lambda X_{p1} + (1-\lambda) X_{p2}$$
$$X_{c2} = \lambda X_{p2} + (1-\lambda) X_{p1} \qquad (16)$$

For a given child $X_{cl}^{k} = X_{l1}^{k},,, X_{lj,,,}^{k} X_{lm}^{k}$ where; $l = 1,2,...,N;\ j = 1,2,...,m$ if the element $X_{lj}^{k}$ is selected for mutation, the resulting offspring is $X_{cl}^{k} = X_{l1}^{k},,, X_{lj,,,}^{k*} X_{lm}^{k}$

Where; $X_{lj}^{k*} = X_{lj}^{k} + \Delta X_{lj}^{k}$

$\Delta X_{lj}^{k}$ is randomly selected from the two possible choices:

$$\Delta X_{lj}^{k} = r(X_{lj}^{\max} - X_{lj}^{k})(1 - \frac{k}{k_{\max}}) \text{ or } \Delta X_{lj}^{k} = r(X_{lj}^{\min} - X_{lj}^{k})(1 - \frac{k}{k_{\max}})$$

*r* is a random number In between 0 and 1

In the same case for PSO if $S_{c1}$ and $S_{c2}$ are selected as parents the children are obtained using the below equations;

$$S_{c1} = \lambda S_{p1} + (1-\lambda) S_{p2}$$
$$S_{c2} = \lambda S_{p2} + (1-\lambda) S_{p1} \qquad (17)$$

For a given child $S_{cl}^{k} = S_{l1}^{k},,, S_{lj,,,}^{k} S_{lm}^{k}$ where; $l = 1,2,...,N;\ j = 1,2,...,m$ if the element $X_{lj}^{k}$ is selected for mutation, the resulting offspring is $S_{cl}^{k} = S_{l1}^{k},,, S_{lj,,,}^{k*} S_{lm}^{k}$

Where; $S_{lj}^{k*} = S_{lj}^{k} + \Delta S_{lj}^{k}$

$\Delta S_{lj}^{k}$ is randomly selected from the two possible choices:

$$\Delta S_{lj}^{k} = r(S_{lj}^{\max} - S_{lj}^{k})(1 - \frac{k}{k_{\max}}) \text{ or } \Delta S_{lj}^{k} = r(S_{lj}^{\min} - S_{lj}^{k})(1 - \frac{k}{k_{\max}})$$

## 4. The Proposed GA/IPSO Algorithm

The proposed algorithm is implemented in the following steps:

1. Get system data by reading the power system parameters.
2. Employ Newton-Raphson method for load flow studies to calculate system base case power loss.
3. Input both GA and IPSO control parameters.
4. Set bus count $i = 1$
5. While $i \leq n$

   (i) Set iteration count $k = 1$

   (ii) While $k \leq k_{\max}$

      a) Initialize N chromosomes with random values to represent possible DG sizes. $P_{DGi}^{\min} \leq P_{DGi} \leq P_{DGi}^{\max}, i = 1,2,... n_{DG}$ and $Q_{DGi}^{\min} \leq Q_{DGi} \leq Q_{DGi}^{\max}, i = 1,2,... n_{DG}$.
      b) Evaluate each chromosomes fitness using the multi-objective.
      c) Using roulette wheel selection method select two chromosomes ($X_{p1}$ and $X_{p2}$).
      d) Perform crossover and mutation based on the probabilities $P_{cross}$ and $P_{mut}$

e) Create a new population by repeating steps (iii) and (iv) while accepting the newly formed children until the new population is complete.

f) Replace old population with new population for a further run of algorithm.

g) Update the iterations counter $k = k + 1$

(iii) Stop and store result (Location, size). Location is the bus (*i*) under consideration and size is the chromosome with the best fitness in the last iteration.

(iv) Increment bus count $i = i + 1$

6. Use GA results stored as initial IPSO particles.
7. Calculate the fitness value for each particle using the multi-objective function. The fitness value of each particle during the first iteration becomes its $p_{best}$. The best fitness value among all the $p_{best}$ is denoted as $q_{best}$
8. Set iteration count $iter = 1$
9. While $iter \le iter_{\max}$

(i) Modify the velocity of each particle element.

(ii) Then generate the new position for each particle element.

(iii) Compute the fitness value of each new particle and update pbest and qbestas shown;.

$$p_{best(j)}^{k+1} = \begin{cases} p_{best(j)}^{k} \text{..........} if \; MOF_j^{k+1} \prec MOF_j^k \\ f_j^{k+1} \text{..........} if \; MOF_j^{k+1} \ge MOF_j^k \end{cases}$$

$$q_{best}^{k+1} = \begin{cases} q_{best}^{k} \text{..........} if \; MOF^{k+1} \prec MOF^k \\ p_{best(j)}^{k+1} \text{..........} if \; MOF^{k+1} \ge MOF^k \end{cases} \tag{18}$$

(iv) Using roulette wheel selection method select two chromosomes ($S_{p1}$ and $S_{p2}$).

(v) Perform crossover and mutation based on the probabilities $P_{cross}$ and $P_{mut}$

(vi) Create a new population by repeating steps (iv) and (v) while accepting the newly formed children until the new population is complete.

(vii) Update the iteration counter, $iter = iter + 1$

10. Stop. The particle that generates the latest $q_{best}$ is the optimal solution.
11. With the latest $q_{best}$ in the network calculate system power loss and bus voltages.

## 5. Results and Analysis

### 5.1 *System loss reduction*

The above proposed method was implemented in Matlab 2009. The distribution test system used is the radial 33 bus system. The system has 32 sectionalizing branches, 5 tie switches, nominal voltage of 12.66KV and a total system load 3.72 MW and 2.3 MVAR. Shulka et al (2010) [13] reported the base case system loss of 216.00KW. This value was obtained using backward sweep power flow method. Shulka et al work was only concerned with active power and thus gave only real power losses. It was important to consider other works which gives both active and reactive power losses and thus K. Varesi (2011) [24] work was chosen in this case. This work gives a base case real power loss of 211KW and reactive power loss of 143KVAR on the 33-bus test system using distribution load flow method. Thus for comparison purposes the real and reactive power losses of the 33-bus test system before DG installation were taken to be 216KW and 143KVAR respectively. The comparison of the results obtained for real and reactive power losses is done in Table 1 below.

Table 1: Real and Reactive Power Losses Comparison

| METHODOLOGY | OPTIMAL LOCATION | DG SIZE | | POWER LOSS | | LOSS REDUCTION | | %LOSS REDUCTION | |
|---|---|---|---|---|---|---|---|---|---|
| | | $P_{DG}$ $(KW)$ | $Q_{DG}$ $(KVAR)$ | $P_L$ $(KW)$ | $Q_L$ $(KVAR)$ | $\Delta P_L$ $(KW)$ | $\Delta Q_L$ $(KVAR)$ | $\%\Delta P_L$ | $\%\Delta Q_L$ |
| **Backward Sweep Power Flow [13]** | (No DG) | (No DG) | (No DG) | 216 | — | — | — | — | — |
| **Distribution Load flow [24]** | (No DG) | (No DG) | (No DG) | 211 | 143 | — | — | — | — |
| **Heuristic [13]** | Bus 6 | 2490 | — | 132.83 | — | 83.17 | — | 38.50 % | — |
| **GA[13]** | Bus 6 | 2380 | — | 132.64 | — | 83.36 | — | 38.59 % | — |
| **PSO 1 [24]** | Bus 6 | 2591 | — | 112 | 83 | 104 | 60 | 48.15 % | 41.96 % |
| **PSO 2 [24]** | Bus 6 | 2551 | 1755 | 68 | 55 | 148 | 88 | 68.52 % | 61.54 % |
| **Proposed GA/IPSO** | Bus 6 | 2563.4 | 1739.6 | 66.23 | 55.42 | 149.77 | 87.58 | 69.34 % | 61.24 % |

As it can be seen from the above table all the methods used for comparison gave bus number 6 as the most optimal location for the DG. The proposed methodology also chooses this same node as is most preferred DG location. It is also noted that the size of DG chosen by the proposed GA/IPSO algorithm lies within range when compared to sizes from other methods in comparison. Key interest is taken to PSO 2 which considers a DG generating both active and reactive power just like in the proposed methodology and gives a DG size of 2551KW for active power and 1755KVAR for reactive power. The proposed method gives a slightly higher value for the real part of 2563.4KW and a slightly lower value for the reactive power which is 1739.6KVAR. In terms of loss reduction the proposed method gives the highest real power loss reduction of 149.77KW which is around 69.34% of the total real power loss before DG installation. The reactive power loss comparison can be greatly compared to that of the PSO 2 method (the better method) with a reduction of 87.58KVAR which is about 61.24% of the total reactive power loss before DG installation.

### 5.2 *Voltage profile improvement*

Table 2 below gives a comparison between the bus voltages obtained after DG location using the proposed method and those obtained by other methods. The effect of sizing and locating DG using the proposed method can be clearly seen in Figure 1. Table 3 gives the percentage improvement on the lowest bus voltage.

Table 2: Comparison of Bus Voltages

| Bus No. | Load flow | PSO [24] | Proposed GA/IPSO |
|---|---|---|---|
| **1** | 1.000 | 1.000 | 1.000 |
| **2** | 0.998 | 0.998 | 0.998 |
| **3** | 0.982 | 0.995 | 0.997 |
| **4** | 0.979 | 0.995 | 0.997 |
| **5** | 0.965 | 0.994 | 0.998 |
| **6** | 0.945 | 0.990 | 1.000 |
| **7** | 0.942 | 0.988 | 0.998 |
| **8** | 0.931 | 0.975 | 0.985 |
| **9** | 0.925 | 0.969 | 0.980 |
| **10** | 0.921 | 0.963 | 0.972 |
| **11** | 0.920 | 0.962 | 0.972 |

| Bus No. | Load flow | PSO [24] | Proposed GA/IPSO |
|---|---|---|---|
| **12** | 0.918 | 0.961 | 0.971 |
| **13** | 0.911 | 0.954 | 0.966 |
| **14** | 0.914 | 0.953 | 0.964 |
| **15** | 0.908 | 0.951 | 0.962 |
| **16** | 0.907 | 0.950 | 0.961 |
| **17** | 0.905 | 0.948 | 0.960 |
| **18** | 0.904 | 0.947 | 0.959 |
| **19** | 0.998 | 0.998 | 0.998 |
| **20** | 0.996 | 0.996 | 0.996 |
| **21** | 0.995 | 0.995 | 0.995 |
| **22** | 0.994 | 0.994 | 0.994 |

| Bus No. | Load flow | PSO [24] | Proposed GA/IPSO |
|---|---|---|---|
| **23** | 0.98 | 0.99 | 0.992 |
| **24** | 0.975 | 0.984 | 0.986 |
| **25** | 0.970 | 0.981 | 0.982 |
| **26** | 0.948 | 0.989 | 0.998 |
| **27** | 0.945 | 0.987 | 0.998 |
| **28** | 0.934 | 0.978 | 0.986 |
| **29** | 0.926 | 0.968 | 0.979 |
| **30** | 0.921 | 0.965 | 0.977 |
| **31** | 0.919 | 0.961 | 0.972 |
| **32** | 0.918 | 0.960 | 0.971 |
| **33** | 0.917 | 0.960 | 0.971 |

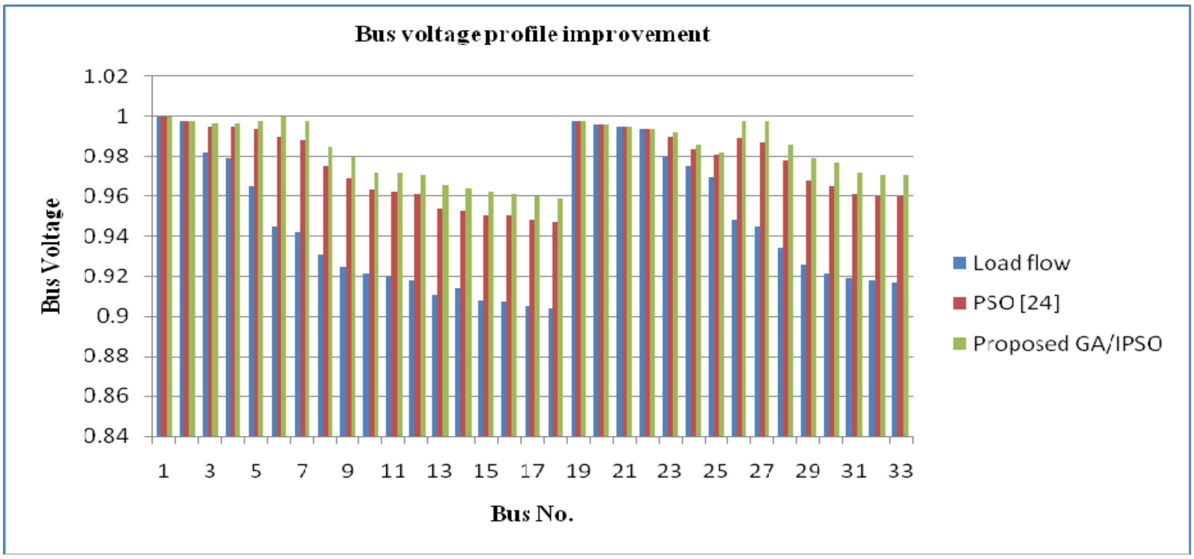


Figure 1: A figure showing bus voltage profile improvement

Table 3: Percentage Lowest Bus Voltage Improvement

| METHODOLOGY | LOWEST BUS VOLTAGE | % VOLTAGE IMPROVEMENT |
|---|---|---|
| **Load Flow** | 0.904 | — |
| **PSO [24]** | 0.947 | 4.757% |
| **Proposed GA/IPSO** | 0.959 | 6.084% |

From the results in Table 2 and Figure 1 it is vividly clear that the proposed methodology results to a better voltage profile improvement in the system. This is because the DG allocation by this methodology results to an improvement in the voltage of nearly all the buses in the system. Table 3 shows that the proposed methodology results to a 6.084% increase in the lowest bus voltage by increase it form 0.904 pu to 0.959 pu as compared to 4.757% given by the PSO method.

## 6. Conclusions

This paper gives the formulation and implementation of a GA/IPSO based algorithm for system loss reduction and voltage profile improvement in distribution systems by optimal location and sizing of a DG. The algorithm proposed has resulted to better results in terms of loss reduction and voltage profile improvement as compared to load flow, Heuristic, GA and PSO methods. Arithmetic crossover and mutation was employed in this methodology enabling the use of real coded GA chromosomes and PSO particles. GA algorithm was used for the first less iterations so as to utilize its advantage of exploring fast regions and avoid its disadvantage of lower convergence. The results of GA were used to initialize PSO particles so as to increase its convergence rate. Both crossover and mutation operators were also employed in improving the PSO. This ensured that the disadvantage of premature convergence for PSO is avoided.

As a result of utilizing the merits of these two optimization techniques while trying to avoid their demerits the proposed methodology resulted to a real power loss reduction of 69.34% and reactive power loss reduction of 61.24%. The placement of DG using this method also resulted to an increase in overall voltage profile with an increase of 6.084% in the lowest bus voltage.

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