Power Loss Reduction in the Active Distribution Network by Doubly Fed Induction Generator (DFIG) Placement and Sizing Using Ordinary Particle Swarm Optimization (PSO) and an hybrid of Genetic Algorithm (GA) and PSO (HGAPSO).

Peter Musau Moses, Dr. Nicodemus Abungu Odoro, Prof. J. Mwangi Mbutia

Abstract— Due to the increased importance of DFIGs in optimization of real and reactive power losses and the maintenance of voltage profile, the general methods of DG placement and sizing in the existing literature cannot be of practical importance. In DFIG, in this paper, a pure PSO method used in general DG is compared with a HGAPSO in the siting and sizing of DFIG with the objective of minimizing power losses. The corresponding Combined participation factors are assigned using the DFIG Domain Distributed Slack Bus Model and a comparison made on the two schemes of loss minimization. The obtained results for the real and reactive power losses and voltage profile illustrate the DFIG need in the modern power system.

Keywords— Distributed Generator (DG), Doubly Fed Induction generator (DFIG), Hybrid GAPSO (HGAPSO), Genetic Algorithm (GA), Particle Swarm Optimization (PSO).

I. INTRODUCTION

The electric distribution system is the most extensive part of the electrical system, and consequently, it is the mainly responsible for energy losses [1]. Therefore, the use of optimization techniques in the design of this subsystem can lead to significant economic gains, obtaining networks which minimize the immediate costs (those related to installation and reconductoring) and further costs (costs related to energy losses and system maintenance) [2–4]. It is well known that distribution systems are in constant evolution, subject to load increasing in different places at different times, which leads to the need of successive system expansions [5, 7, 8].

Since the last few years, the interest in the placement of DG in utility networks has increased due to its effective role in reducing the power loss of the distribution networks so as to serve remote loads.

In recent years, the power industry has experienced significant changes on the distribution power system primarily due to the implementation of smart-grid technology and the incremental implementation of distributed generation. Distributed Generation (DG) is simply defined as the decentralization of power plants by placing smaller generating units closer to the point of consumption, traditionally ten mega-watts or smaller. While DG is not a new concept, DG is gaining widespread interest primarily due to increase in customer demand, advancements in technology, economics, deregulation, environmental and national security concerns.

The distribution power system traditionally has been designed for radial power flow, but with the introduction of DG, the power flow becomes bidirectional. As a result, conventional load flow analysis tools and techniques are not able to properly assess the impact of DG on the electrical system. The presence of DG on the distribution system creates an array of potential problems related to safety, stability, reliability and security of the electrical system. Distributed generation on a power system affects the voltage, power flow, short circuit currents, losses and other power system analysis results. Whether the impact of the DG is positive or negative on the system will depend on the location and size of the DG. This paper will go very specific to study the placement and sizing of the DFIG.

Proper management of DG reduces Green house Gas (GHG) emissions, improves efficiency, helps deferring system upgrades, improves reliability and enhances the energy security. As voltage increases at the end of a feeder, demand supply imbalance during fault condition, decline in power quality, increase in power losses, and reduction of reliability levels may occur, if DGs are not properly allocated [9, 10].
To overcome these problems, solution methodologies and techniques are suggested by various authors to solve the problem of optimal allocation of DGs in the utility network. The exact allocation of DGs is achieved by considering all feasible combinations of sizes and sizes of DGs in the system. The number of alternatives could however, be very large as the number of variables of the problem (i.e. number of DGs and number of nodes of the system) increases.

**A. General DG placement and sizing methods: A review**

Distributed generation utilization is an effective alternative for reducing this cost by generation near the load points. In recent years, several studies have considered techniques for locating DG units on distribution systems.

Rau and War[22] have used gradient and second order method to minimize loss, line loading and reactive power requirements in the Distribution network. Willis[23] investigated loss minimization using analytical based 2/3 rule assuming a constant power source and a uniformly distributed load. Hybrid and Constraint Based Multi Objective Programming (HCBMOP) and GA method was proposed by Celli et al.[24] to minimize the cost of network upgrading, power losses and energy required by customer. He later used the method to minimize the cost of network upgrading, cost of energy losses and DG network acceptability index[25] with the DG fully considered as a valid planning alternative. Carpinelli et al.[26] used the method proposed in [24] for a peak load with constant growth rate and a constant power source to minimize the cost of losses and to improve voltage quality and harmonic distortions. Karnaiah et al.[27] used GA and Multiple Attribute Making Decision (MAMD) approach on a PQ model DG to investigate its technical attributes such as reactive power flows, voltage variation and active loss as well as the economic attributes which include line congestion, capital cost and emission.

Elh aftam et al.[27] used an Heuristic Iterative Search method to minimize the cost of investment and operation of DGs, loss and energy required by customers, which Satish et al.[28] later applied to minimize DG investment and operation losses and energy purchased from the main grid.

Falahizadeh et al.[29] use Ant Colony Optimization (ACO) on a time varying load to minimize investment cost, operation cost and energy buying from transmission grid. Further Soroudi and Elson[30] used Particle Swarm Optimization on a multi-load level to minimize the cost of active losses, investment and operation cost of DG and emission cost.

The other methods used include analytical approach[28], simulated annealing[31,32,58], optimal power flow[33], sensitivity analysis[34], fast sequential quadratic programming[35] and NSGA II and max-min approach[36]. All these methods have not take care of the intermittent renewables and therefore in practice they are inaccurate.

GA with decision making approach is used by Carpinelli et al.[37] to minimize the cost of power losses and network upgrading. For a wind generator with a peak load and constant load growth, Ochoa et al.[38] used multi objective optimization with NSGA for a wind generator with a time varying load to maximize the integration of DG and energy export, minimizing losses and short circuit level.

Several analytical approaches were also proposed in the literature[39-43]. GA based methods and PSO technique was also presented[44,45,48]. EP based method and FL based method are also presented in[49] and[50]. The other methods like probabilistic based MINLP[59], probabilistic based MC simulation[60], ABC[42], DLF[61], and OFP[51,52,53] are also presented by various authors. The hybrid based methods, like GA-PSO, GA-TS, and Fuzzy-GA are suggested by[54-56], respectively.

**B. DFIG placement and sizing importance**

Distributed generation has been growing rapidly in power systems. Studies by the Electric Power Research Institute (EPRI) and the Natural Gas Foundation indicate that 60% or higher of new generation will be distributed generation by 2030 with 30% being wind based using the commercially viable DFIG[11,12], hence such wind based distributed generation will play an important role in power systems.

Since DFIGs are located close to the load centers, they have the following benefits: Voltage control and support, System reliability enhancement, Real and reactive power losses reduction, Transmission and distribution release and infrastructural expansion deferment and lastly, flexibility in more energy management. In order to achieve these mentioned benefits, the DFIGs must be carefully installed and operated and the behaviors of distribution systems with DFIGs must be accurately analyzed. However the inclusion of large number of DFIGs within the distribution systems will change the distribution system analysis, planning, operation and control presented in the existing literature.
C: Objective

The main objective of this paper is to use HGAPSO in the placement and sizing of the DFIG with the aim of reducing real and reactive power losses. The results will be compared with those of ordinary PSO and the combined participation factors assigned to the various buses using DFIG domain. Distributed slack bus model

II. DFIG Placement and Sizing Using HGAPSO

A: The need for HGAPSO

Particle Swarm Optimization

Swarm Intelligence (SI) is an innovative distributed intelligent paradigm for solving optimization problems that originally took its inspiration from the biological examples by swarming, flocking, and herding phenomena in vertebrates. Particle Swarm Optimization (PSO) incorporates swarming behaviors observed in flocks of birds, schools of fish, or swarms of bees, and even human social behavior, from which the idea is emerged [13,14,15]. PSO is a population-based optimization tool, which could be implemented and applied easily to solve various function optimization problems. As an algorithm, the main strength of PSO is its fast convergence, which compares favorably with many global optimization algorithms like Genetic Algorithms (GA) [16] Simulated Annealing (SA) [17,18] and other global optimization algorithms. For applying PSO successfully, one of the key issues is finding how to map the problem solution into the PSO particle, which directly affects its feasibility and performance.

Genetic Algorithm

Genetic Algorithms are a family of computational models inspired by evolution. These algorithms encode a potential solution to a specific problem on a simple chromosome-like data structure and apply recombination and mutation operators to these structures so as to preserve critical information. An implementation of a genetic algorithm begins with a population of (usually random) chromosomes. One then evaluates these structures and allocates reproductive opportunities in such a way that those chromosomes which represent a better solution to the target problem are given more chances to reproduce than those chromosomes which are poorer solutions. This is called survival of the fittest. The goodness of a solution is typically defined with respect to the current population.

The genetic algorithm can be viewed as two stage process. It starts with the current population. Selection is applied to the current population to create an intermediate population.

Then recombination and mutation are applied to the intermediate population to create the next population. The process of going from the current population to the next population constitutes one generation in the execution construction of the intermediate population is complete and recombination can occur. This can be viewed as creating the next population from the intermediate population. Crossover is applied to randomly paired strings with a probability denoted Pc. A pair of strings is picked with probability Pm for recombination. These strings form two new strings that are inserted into the next population. After recombination, mutation operator is applied. For each bit in the population, is mutated with some low probability Prm. Typically the mutation rate is applied with less than 1% probability. In some cases mutation is interpreted as randomly generating a new bit in which case, only 50% of the time will the mutation actually change the bit value.

After the process of selection, recombination and mutation, the next population can be evaluated. The process of evaluation, selection, recombination and mutation forms one generation in the execution of a genetic algorithm. In this paper, the mutation genetic operator is used to introduce divergence to the PSO so as to escape the local maxima.

Hybrid PSO with GA(HGAPSO)

The drawback of PSO is that the swarm may prematurely converge. The underlying principle behind this problem is that, for the global best PSO, particles converge to a single point, which is on the line between the global best and the personal best positions. This point is not guaranteed for a local optimum [19]. Another reason for this problem is the fast rate of information flow between particles, resulting in the creation of similar particles with a loss in diversity that increases the possibility of being trapped in local optima. A further drawback is that stochastic approaches have problem-dependent performance. This dependency usually results from the parameter settings in each algorithm. The different parameter settings for a stochastic search algorithm result in high performance variances. In general, no single parameter setting can be applied to all problems. Increasing the inertia weight (w) will increase the speed of the particles resulting in more exploration (global search) and less exploitation (local search) or on the other hand, reducing the inertia weight will decrease the speed of the particles resulting in more exploitation and less exploration. Thus finding the best value for the parameter is not an easy task and it may differ from one problem to another.
Therefore, from the above, it can be concluded that the PSO performance is problem-dependent. The problem-dependent performance can be addressed through hybrid mechanism. It combines different approaches to be benefited from the advantages of each approach.

To overcome the limitations of PSO, hybrid algorithms with GA are proposed. The basis behind this is that such a hybrid approach is expected to have merits of PSO with those of GA. One advantage of PSO over GA is its algorithmic simplicity. Another clear difference between PSO and GA is the ability to control convergence. Crossover and mutation rates can subtly affect the convergence of GA, but these cannot be analogous to the level of control achieved through manipulating the inertia weight. In fact, the decrease of inertia weight dramatically increases the swarm’s convergence. The main problem with PSO is that it prematurely converges [19] to stable point, which is not necessarily maximum. To prevent the occurrence, position update of the global best particles is changed. The position update is done through some hybrid mechanism of GA. The idea behind GA is due to its genetic operators crossover and mutation. By applying crossover operation, information can be swapped between two particles to have the ability to fly to the new search area. The purpose of applying mutation to PSO is to increase the diversity of the population and the ability to have the PSO to avoid the local maxima.

There are three different hybrid approaches are proposed [19]. In PSO-GA (Type 1), the ghost particle position does not change its position over some designated time steps, the crossover operation is performed on the ghost particle with chromosome of GA. In this model both PSO and GA are run in parallel. In PSO-GA (Type 2), the stagnated ghost particles are change their positions by mutation operator of GA. Lastly, in PSO-GA (Type 3), the initial population of PSO is assigned by solution of GA. The total numbers of iterations are equally shared by GA and PSO. First half of the iterations are run by GA and the solutions are given as initial population of PSO. Remaining iterations are run by PSO. In this paper, the PSO-GA type 2 is preferred since we are interested in changing the string of the DFIGs optimize the power losses, taking their capacities as a constant. The cross over genetic operator is not of any importance in this paper since the DFIGs are independent of each other hence PSO-GA Type 1 and Type 3 cannot be used.

PSO, which is stochastic in nature and makes use of the memory of each particle as well as the knowledge gained by the swarm as a whole, has been proved to be powerful in solving many optimization problems.

The hybrid PSO systems find a better solution without trapping in local maximum, and to achieve faster convergence rate. This is because when the PSO particles stagnate, GA diversifies the particle position even though the solution is worse. In PSO-GA, particle movement uses randomness in its search. Hence, it is a kind of stochastic optimization algorithm that can search a complicated and uncertain area. This makes PSO-GA more flexible and robust. Unlike standard PSO, PSO-GA is more reliable in giving better quality solutions with reasonable computational time, since the hybrid strategy avoids premature convergence of the search process to local optimum and provides better exploration of the search process.

B. The DFIG capability limit curve curves

The model of a DFIG used in this paper consists of a pitch controlled wind turbine and an induction generator [20,21]. The stator of the DFIG is directly connected to the grid, while the rotor is connected to the converter consisting of two back to back pulse width modulated (PWM) inverters, which allow direct control of the rotor currents.

Direct control of the rotor currents allows for the variable speed operation and reactive power control thus the DFIG can operate at a higher efficiency over a wide range of wind speeds and thus help in providing voltage support for the power grid. The characteristics make the DFIG ideal for use as a wind generator, whose equivalent circuit is shown in the figure 1.0.

![Fig 1: Equivalent circuit of a DFIG [20,21]](image)

The stator active and reactive power can be expressed in terms of the stator and rotor currents as [20,21]

\[ P_s = \frac{3}{2} V_s I_s \]

\[ Q_s = \frac{3}{2} V_s I_r \] ............................(1)
In the PQ plane, the equation (1) represents the circumference centered at the origin [0,0] with the radius equal to the stator speed apparent power. Equation (2) represents a circumference centered at [−3V_s^2/X_s,0] and radius equal to [3(X_m V_s)X_s]. Therefore, given the maximum rotor and stator allowable currents \( I_r \) and \( I_s \), the DFIG capability limits can be obtained. The composed DFIG capability limits curve is shown in Figure 2.4 where \( u_s \) is used instead of \( V_s \). Taking the steady-state stability of the DFIG into account, represented by the vertical line at \( [−3V_s^2/X_s,0] \) coordinate, it is obvious that the DFIG real and reactive power capability mainly depends on the maximum allowable rotor current.

From the Figure, the DFIG can operate at any point in the intersecting area within the given limits, when the available active power is far from its maximum, the amount of reactive power is high. The large reactive power control capability of the DFIG makes it possible to use DFIG as the continuous reactive power support to support system voltage control.

Fig 2: DFIG Capability Limits Curve[20]

C: Problem formulation

The real power loss in the distribution system is very significant from the system operation point of view. The difference between the generated power and the power demand gives the power loss. That is:

\[
\sum_{i=1}^{n} P_{\text{loss}} = \sum_{i=1}^{n} P_G - \sum_{i=1}^{n} P_D
\]

Where

- \( P_G = \sum_{i=1}^{n} P_{\text{gen}} \) is the total real power loss
- \( \sum_{i=1}^{n} P_{\text{gen}} \) is the generated power
- \( \sum_{i=1}^{n} P_{D} \) is the power demand

The objective of the placement technique is to minimize the total real power loss. Mathematically, the objective function can be written as:

\[
\min_{P_r \in \mathbb{R}} P_r \quad \text{subject to} \quad P_r \geq P_{\text{min}}
\]

with

\[
P_r = \sum_{i=1}^{n} K_r \left( P_r, P_i, \text{cos}(\theta_i, \theta_j), K_r \right)
\]

where

- \( K_r \) is the real power participation factor,
- \( K_r \) is the reactive power participation factor
- \( P_i, P_j \) and \( Q_i, Q_j \) are the real and reactive power injections in bus "i" and "j", respectively
- \( R_{ij} \) is the resistance between bus "i" and "j"
- \( V_i \) and \( \theta_i \) are the voltage and angle at bus "i" respectively.

In the objective function, the network parameters are absorbed in the loss equation by the real and reactive participation factors formulated in [46].
The objective function is solved subject to the following constraint of DFIG domains and the power distribution system parameters:

(i) Power balance

\[ n \sum_{i=1}^{n} P_{do_{i}} - \sum_{i=1}^{n} P_{do_{i}} P_{l} \] .......(5)

(ii) DFIG active capability limits

\[ P_{max}^{do_{i}} \leq P_{do_{i}} \leq P_{max}^{do_{i}} \] .......(6)

(iii) DFIG reactive capability limits

\[ Q_{max}^{do_{i}} \leq Q_{do_{i}} \leq Q_{max}^{do_{i}} \]

(iv) Voltage constraints at the buses

\[ V_{min}^{i} \leq V_{i} \leq V_{max}^{i} \] .......(10)

(vi) Line thermal limit

\[ P_{e} \leq P_{e}^{max} \] .......(11)

D. HGAPSO based optimization algorithm

The HGAPSO based approach for solving the optimal sizing and placement of the DFIG is aimed at minimizing the distribution line real and reactive losses. In this paper, the reactive power output is obtained by means of the DFIG power curves after the active power output is known. The total active power output is obtained by the equation (5). Considering the capability limits of the DFIGs, the maximum of the reactive power that each DFIG can generate or absorb, the HGAPSO based approach for solving the problem to minimize the losses takes the following steps.

Step 1: Input the line and bus data and the bus voltage limit.

Step 2: Calculate the loss using distribution load flow based on backward forward sweep.

Step 3: Randomly generate an initial population (array) of particles with random initial positions and velocities on dimensions in the solution space. Set the iteration counter \( k = 0 \).

Step 4: For each particle, if the bus voltage is within the limits, perform mutation on the particle position, one by one, keeping the velocity fixed, then perform mutation on the velocity, keeping the position fixed. Other positions and velocities are obtained. Calculate the total losses as in equation (1) in each case.

Step 5: For each particle, compare its objective position and velocity with the individual best. If the objective value is lower than \( P_{best} \) set this value as the current \( P_{best} \) and record the corresponding particle position.

Step 6: Compare all components of the particle according to their fitness values. Choose the particle associated with the minimum \( individual \ best \ P_{best} \) of all the particles and set the value of this \( P_{best} \) as the current \( overall \ best \ G_{best} \).

Step 7: If the iteration number reaches the maximum limit, go to step 9. Otherwise set iteration index \( k = k + 1 \) and go back to step 4.

Step 8: Update the velocity and position of the particle.

Step 9: If the particle equals to the population size \( N \), print out the optimal solution of the targeted problem; otherwise set the particle to \( i = 1 \) and go to step 3.

Step 10: Assign Combined participation Factors to each particle taking into consideration the DFIG domains[46].
The best position includes the optimal locations and sizes of the DFIGs and the corresponding fitness value represents the minimum total real power loss.

IEEE 33 bus radial distribution test system.

IEEE recommended balanced distribution systems include the radial 16 Bus, 30 Bus, 33 Bus 94 Bus 69 Bus and 119 Bus systems[57], with the 33 Bus and the 69 Bus being commonly used for most simulations because they are balanced topologies.

In this paper, the distribution test systems used is the radial 33 bus systems. The system has 32 sectionalizing branches, 5 tie switches, nominal voltage of 12.66 kV and a total system load 3.72 MW and 2.3 MVAR. The original total real power loss and reactive power loss in the system are 221.4346 kW (5.95%) and 150.1784 kVAR (6.53%). The network diagram is as shown in Figure 1.

![Figure 1: IEEE 33 Bus Radial Distribution System](image)

<table>
<thead>
<tr>
<th>Branch Number</th>
<th>Sending end bus</th>
<th>Receiving end bus</th>
<th>$P_R$ (kW)</th>
<th>$Q_V$ (kVAR)</th>
<th>$P_R$ (kW)</th>
<th>$Q_V$ (kVAR)</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>10</td>
<td>11</td>
<td>10</td>
<td>50</td>
<td>20</td>
<td>60</td>
</tr>
<tr>
<td>11</td>
<td>11</td>
<td>12</td>
<td>5</td>
<td>30</td>
<td>15</td>
<td>40</td>
</tr>
<tr>
<td>12</td>
<td>12</td>
<td>13</td>
<td>1</td>
<td>30</td>
<td>4</td>
<td>30</td>
</tr>
<tr>
<td>13</td>
<td>13</td>
<td>14</td>
<td>5</td>
<td>30</td>
<td>15</td>
<td>40</td>
</tr>
<tr>
<td>14</td>
<td>14</td>
<td>15</td>
<td>1</td>
<td>30</td>
<td>4</td>
<td>30</td>
</tr>
<tr>
<td>15</td>
<td>15</td>
<td>16</td>
<td>5</td>
<td>30</td>
<td>15</td>
<td>40</td>
</tr>
<tr>
<td>16</td>
<td>16</td>
<td>17</td>
<td>1</td>
<td>30</td>
<td>4</td>
<td>30</td>
</tr>
<tr>
<td>17</td>
<td>17</td>
<td>18</td>
<td>5</td>
<td>30</td>
<td>15</td>
<td>40</td>
</tr>
<tr>
<td>18</td>
<td>18</td>
<td>19</td>
<td>1</td>
<td>30</td>
<td>4</td>
<td>30</td>
</tr>
<tr>
<td>19</td>
<td>19</td>
<td>20</td>
<td>5</td>
<td>30</td>
<td>15</td>
<td>40</td>
</tr>
<tr>
<td>20</td>
<td>20</td>
<td>21</td>
<td>1</td>
<td>30</td>
<td>4</td>
<td>30</td>
</tr>
<tr>
<td>21</td>
<td>21</td>
<td>22</td>
<td>5</td>
<td>30</td>
<td>15</td>
<td>40</td>
</tr>
<tr>
<td>22</td>
<td>22</td>
<td>23</td>
<td>1</td>
<td>30</td>
<td>4</td>
<td>30</td>
</tr>
<tr>
<td>23</td>
<td>23</td>
<td>24</td>
<td>5</td>
<td>30</td>
<td>15</td>
<td>40</td>
</tr>
<tr>
<td>24</td>
<td>24</td>
<td>25</td>
<td>1</td>
<td>30</td>
<td>4</td>
<td>30</td>
</tr>
<tr>
<td>25</td>
<td>25</td>
<td>26</td>
<td>5</td>
<td>30</td>
<td>15</td>
<td>40</td>
</tr>
<tr>
<td>26</td>
<td>26</td>
<td>27</td>
<td>1</td>
<td>30</td>
<td>4</td>
<td>30</td>
</tr>
<tr>
<td>27</td>
<td>27</td>
<td>28</td>
<td>5</td>
<td>30</td>
<td>15</td>
<td>40</td>
</tr>
<tr>
<td>28</td>
<td>28</td>
<td>29</td>
<td>1</td>
<td>30</td>
<td>4</td>
<td>30</td>
</tr>
<tr>
<td>29</td>
<td>29</td>
<td>30</td>
<td>5</td>
<td>30</td>
<td>15</td>
<td>40</td>
</tr>
<tr>
<td>30</td>
<td>30</td>
<td>31</td>
<td>1</td>
<td>30</td>
<td>4</td>
<td>30</td>
</tr>
<tr>
<td>31</td>
<td>31</td>
<td>32</td>
<td>5</td>
<td>30</td>
<td>15</td>
<td>40</td>
</tr>
<tr>
<td>32</td>
<td>32</td>
<td>33</td>
<td>1</td>
<td>30</td>
<td>4</td>
<td>30</td>
</tr>
<tr>
<td>33</td>
<td>33</td>
<td>34</td>
<td>5</td>
<td>30</td>
<td>15</td>
<td>40</td>
</tr>
<tr>
<td>34</td>
<td>34</td>
<td>35</td>
<td>1</td>
<td>30</td>
<td>4</td>
<td>30</td>
</tr>
<tr>
<td>35</td>
<td>35</td>
<td>36</td>
<td>5</td>
<td>30</td>
<td>15</td>
<td>40</td>
</tr>
<tr>
<td>36</td>
<td>36</td>
<td>37</td>
<td>1</td>
<td>30</td>
<td>4</td>
<td>30</td>
</tr>
<tr>
<td>37</td>
<td>37</td>
<td>38</td>
<td>5</td>
<td>30</td>
<td>15</td>
<td>40</td>
</tr>
<tr>
<td>38</td>
<td>38</td>
<td>39</td>
<td>1</td>
<td>30</td>
<td>4</td>
<td>30</td>
</tr>
<tr>
<td>39</td>
<td>39</td>
<td>40</td>
<td>5</td>
<td>30</td>
<td>15</td>
<td>40</td>
</tr>
</tbody>
</table>

Table II: IEEE 33 Bus Radial System Bus Data

F: Results and analysis

Simulations were run on the 33Bus Radial distribution Test System. The real and reactive power losses obtained through load flow, PSO and HGAPSO are as shown in the tables III, IV, V, and VI.

![Figure 2: Table III](image)

Table III: Case A: 1.5 MW DFIG on Bus 18

METHOD | P LOSS | Q LOSS | LOSS REDUCTION % |
---|---|---|---|
LOAD FLOW | 221.4346 | 150.1784 | REAL |
PSO | 70.9526 | 57.2155 | 67.95 | 61.90 |
PSO-GA | 69.5578 | 56.2116 | 68.59 | 62.57 |