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# Integration of Multiple Distributed Generation Sources in Radial Distribution System Using a Hybrid Evolutionary Programming-Firefly Algorithm

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**ABSTRACT**

*This paper presents an approach for the optimal integration of multiple distributed generation (DG) sources in a radial distribution system. The integration of DG sources poses various challenges such as can lead to higher power losses caused by reverse power flow, voltage exceeding secure limits, voltage stability, power quality, and economic operation. To address these challenges, a hybrid algorithm is proposed which combines the benefits of both Evolutionary Programming and Firefly Algorithm. The proposed hybrid Evolutionary - Firefly Algorithm is employed for the determination of the optimal size of the DG sources. The objective of the proposed algorithm is to minimize the total system power losses and improve the voltage profile. The algorithm considers various constraints including the DG capacity limits and voltage limits. A comprehensive case study is conducted on a radial distribution system to demonstrate the effectiveness of the proposed approach. The simulation results show that the hybrid algorithm can find the optimal size and location of DG sources while achieving the desired system performance. The integration of multiple DG sources leads to a significant reduction in power losses and improved voltage profile. Furthermore, the proposed approach provides a flexible framework for the optimal integration of DG sources in radial distribution systems, allowing for the accommodation of different types and capacities of DG sources. The proposed technique is tested on the IEEE Reliability Test systems, specifically the IEEE 69-bus. The combination of DG at bus 61 and bus 27 yields a loss reduction index of 94%.*

**Keywords:** Distributed generation, Evolutionary Programming, Firefly Algorithm, Hybrid Evolutionary - Firefly Algorithm, loss reduction index

## 1 INTRODUCTION

Distributed generation (DG) in power systems is gaining attention because the technology can benefit both utilities and utilities user. The use of DG technology is increasing and demand as it brings profits from both technical, economic, and environmental aspects. DG is used to meet the increasing demands of power in the time peak because its output power is easily controlled through the management of module units. Additionally, distributed generators can benefit utilities by providing voltage support, improving safety, and reducing power loss. Meanwhile, from the user's perspective, distributed generators can benefit by providing backup power during power outages and by providing financial benefits for additional power produced. There are numerous distributed generation technologies on the market today [1].

Basically, DG technology is divided into two types, that is, technology based on renewable energy sources and technology based on fossil energy sources. Generators distributed energy-based novelty is like photovoltaic, wind turbine and biomass while fossil-distributed generators are diesel engines, microturbines, and heat power combined generator. Use distributed generators play an important role and can be beneficial and aspects of reliability, stability, safety, and efficiency of the electrical power system Despite the benefits, connecting a distributed generator into an existing power system may result in changes to the network's technical characteristics that could cause problems. To ensure the connection of distributed generator units produces expected benefits, determination of location and optimal capacity for distributed generators is important. Optimal size of distributed generation and suitable location can provide technical and economic benefit to utilities by minimizing loss of power, increase stability, increase reliability, and reduce operating and maintenance costs [2]–[4].

DG is a concept that aims to decentralize electricity generation by installing small generators on or near customer sites or load centers. Conventionally, electric power is generated at centralized facilities and distributed to loads through transmission and distribution systems. The primary purpose of these distributed generation plants is to meet the increasing demand for electricity in specific regions and to enable certain activities to be self-sufficient in terms of power generation, resulting in cost reductions compared to conventional or centralized power generation stations. It has been observed that conventional or centralized power plants pose challenges in the electricity generation process due to their emission of environmentally hazardous gases, which contribute to ozone depletion in the environment. The size of DG is defined as the total power supplied by all the DG connected to the system to the total load of the system. The DG can be placed at any possible location in the distribution network. There are various feeder nodes in the distribution system, and the conceivable placement of the DG can be determined by the selected feeder node. The benefits of DG can only be realized by selecting the correct DG dimension and connecting it at the proper location in the system. DG has a substantial effect on the system's voltage profile [5].

Traditional optimization techniques, such as gradient methods, quadratic programming, linear programming, and dynamic programming have been used to solve optimization problems in power systems studies, particularly for DG allocation and sizing. However, due to the complexity of these problems, it may be difficult for these methods to identify optimal global solutions. In contrast, evolutionary computing techniques have proven to be highly effective in addressing a variety of search, classification, and optimization problems [6]. A hybrid evolutionary programming (HEP) optimization technique has been developed as a means of determining the optimal scale of DG [7].

In this study, a comparative analysis is conducted to evaluate the performance of a multi-DG installation with different combinations of DG types and determine the optimal sizing of DG using the hybrid Evolutionary Programming-Firefly Algorithm. The proposed technique is tested on the IEEE Reliability Test systems, specifically the IEEE 69-bus. The program is implemented using the MATLAB programming software.

## 2 DG ALLOCATION

Recently, Distributed Generators (DGs) have been rapidly expanding their presence in distribution networks all over the globe. The advantages of incorporating DG into an already established utility system include:

i. Reduced environmental consequences.

ii. Enhanced global energy effectiveness.

iii. Transmission and distribution congestion has been alleviated.

iv. Voltage support

v. Utilization of renewable resources, including wind, solar, hydro, biomass, geothermal, and ocean energy.

vi. Line loss decrease.

Additionally, it has been shown that inappropriate distribution or the size of DG can have a negative impact on the system. Researchers have utilized cutting-edge methodologies such as the BEE Colony Algorithm, Mixed Integer Non-Linear Programming, Exhaustive Load Flow (ELF) Method, Particle Swarm Optimization, Fuzzy-Genetic Algorithm, Hereford Ranch Algorithm, Ant colony search, Differential Evolution Approach, and Heuristic Curve-Fitted Technique in this loss-reduction strategy based on DG allocation. According to the literature, this promising method of Loss Minimization is gaining widespread attention due to its critical benefit of minimizing network loss while also providing electrical energy supply to meet demand crises and attempting to investigate new techniques to maximize benefit [8].

## 3 METHODOLOGY

The purpose of this study is to determine the optimal size, location, and type of DG by minimizing total losses as well as the cost of system losses from the distribution utility's perspective, rather than simply reducing system loss. The optimal sizing of DG is obtained using proposed HEPFA. To evaluate total losses, a load flow program is simulated in the base case. The resulting load flow values are recorded and used to compare the results obtained using the proposal method. In each instance, the fitness value was calculated based on the objective function specified. The optimal installation bus size is optimized by minimizing the objective function based on different cases. The proposed methods were evaluated utilizing the IEEE 69-bus Reliability Test system, and the MATLAB programming tools were utilized during the development of the program. The schematic diagram for the test system is shown in Figure 1.

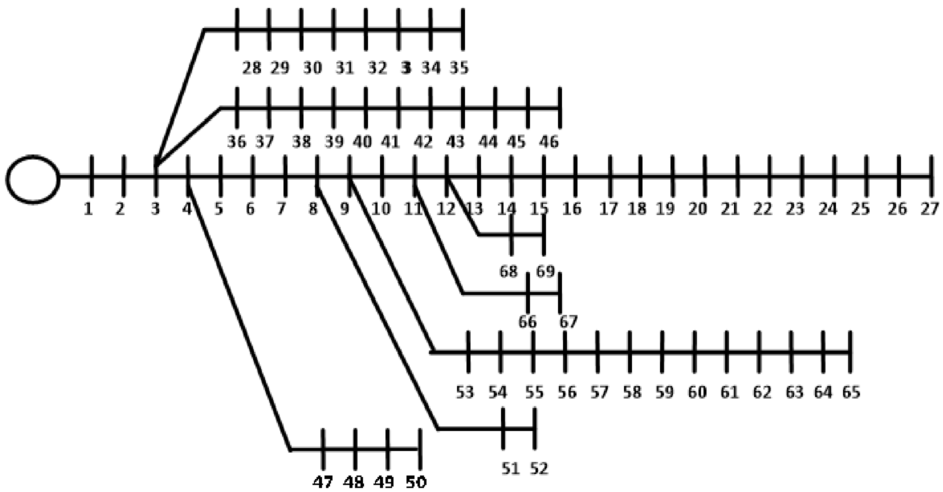


Figure 1: IEEE 69-Bus Distribution System

### 3.1 Problem Formulation

The details of problem formulation are discussed in this section. Equation (1) computes the CL and equation (2) computes the loss factor in terms of load factor (Lf).

$$\mathrm{CL} = (\mathrm{Tloss}) * (\mathrm{Kp} + \mathrm{Ke} * \mathrm{Lsf} * 8760) \tag{1}$$

$$\mathrm{Lsf} = \mathrm{k} * \mathrm{Lf} + (1 - \mathrm{k}) + \mathrm{Lf} \tag{2}$$

Where K=0.2, Lf=0.47, Ke=0.00961538, Kp=57.6923.

Total loss (TLoss) is the total real power losses in megawatts, Kp is the yearly demand cost of power loss in dollars per kilowatt, Ke is the CL in dollars per kilowatt hour, and Lsf stands for loss factor. VPI indicates the difference in voltage profile between a bus. It functions as a metric to evaluate the efficacy of voltage enhancements in the system while DG is optimally positioned. The VPI index is defined by equation (3) and it should preferably be less than 0.05 given that the minimum voltage is limited to the range $0.95 \leq V_m \leq 1.05$.

$$\mathrm{VPI} = \frac{V_{i\,nominal} - V_{DG}}{V_{i\,nominal}} \tag{3}$$

Modifications must be made to the selected networks to enable DG installation. In the following stages, voltage deviation is considered for objective function evaluation to determine the impact of DG utilization on the network. According to the assumptions, the slack bus remains constant and is excluded from the calculation of voltage deviation. The voltage deviation is calculated as shown in (4). $Vdev$ is the total voltage deviation of network buses.

$$Vdev = \frac{\sum_{i=2}^{Bus\ iNo} 1 - Vi}{Bus\ iNo - 1} \tag{4}$$

To display the top ten places for DG installation, the voltage profile has been sorted in ascending order. Calculating power losses typically lead to calculating the difference between injected power and consumed power at various system nodes or branches. The loss reduction index (LRI) is calculated using (5).

$$\text{Loss Reduction Index (LRI)} = \frac{\text{Tloss}_{\text{without DG}} - \text{Tloss}_{with\ DG}}{\text{Tloss}_{\text{without DC}}} \tag{5}$$

### 3.2 Proposed HEPFA Optimization Technique

The HEPFA technique was created to minimize total losses and meet the voltage limitation set in the system. It employs several of the Firefly Algorithm's (FA) features in conjunction with the traditional EP method. Lawrence J. Fogel is credited with being the one who initially thought up the stochastic optimization approach known as the EP [9]. The initialization procedure in EP is what's responsible for generating random numbers at the initial stage. To produce new individuals, often referred to as offspring, the mutation process is applied to each individual value that is based on the population. The process of producing children whose behavior influences the search for the optimum ideal value requires mutation, which is a key step in the process. After that, the offspring population is combined with the parent population while the process of combination is taking place, this results in an increase in the total number of individuals.

The results of previous studies imply that combining a variety of optimization strategies can result in increased efficiency as well as resilience. To lessen the load of computational work and cut down on the amount of time lost due to inaccurate location, the convergence criterion in this investigation has been set to 200 iterations. The rand function in MATLAB, which produces random values that are uniformly distributed between 0 and 1, is used to create a random variable to initialize DG size. These random numbers fall somewhere between 0 and 1. These arbitrary numbers stand in for the variable xi, which oversees directing the optimization procedure. After population has been generated, the objective function is calculated to determine the level of fitness it possesses before it is analyzed. During the firefly attraction operation, the initial location of each solution is compared with the initial location of its neighboring solution, and the firefly attractiveness is assessed as a result. The process of mutation involves the random modification of individual values, with only a remote possibility of the offspring being passed on. New values are calculated by combining data from parents or the original data with mutations by using the formula in equation (6). The combined dataset is then sorted, with the lowest power losses determined.

$$\text{Ai} + \text{mj} = \text{Aij} + \text{N}(0, \beta(\text{Aj max} - \text{Aj min})(\frac{\text{fi}}{\text{fmax}}) \tag{6}$$

$Ai + mj$ = Mutated clones

$A_{ij}$ = Clones

N = Gaussian random number

β = Mutation scale, 0 < β > 1

$A_j$ max = Highest random number

$A_j$ min = Lowest random number

$f_i$ = Fitness for $i^{th}$ random number

$f_{max}$ = Maximum fitness

The HEPFA case study is described in Table 1. Various scenarios with and without DG installation are assessed. The table outlines the categories and quantities of DG utilized in each case. Case 0 will run the power flow program for the base case to compare the performance with DG installation. The location will be determined based on the lowest voltage value recorded during simulation for the base case. For case 1, only one unit of DG type 3 is considered. Only ten buses will be selected to the location based on the simulation's lowest recorded voltage profile value for the base case. Case 2 will optimize the 2 units of DG, with the first unit being DG type 3 installed on bus 61 and the second unit being DG type 1. DG1 will be set as DG type 3 and DG2 will be set as DG type 2 for case 3. Case 4 will optimize DG type 3.

Figure 2 illustrates the flowchart for the proposed HEPFA technique. The mutation process in this case utilizes the Gaussian mutation method. The analysis includes evaluating DG sizing, active power losses (Ploss), reactive power losses (Qloss), cost of energy losses (CL), minimum voltage (Vmin), maximum voltage (Vmax), Voltage profile index (VPI), and the number of iterations.

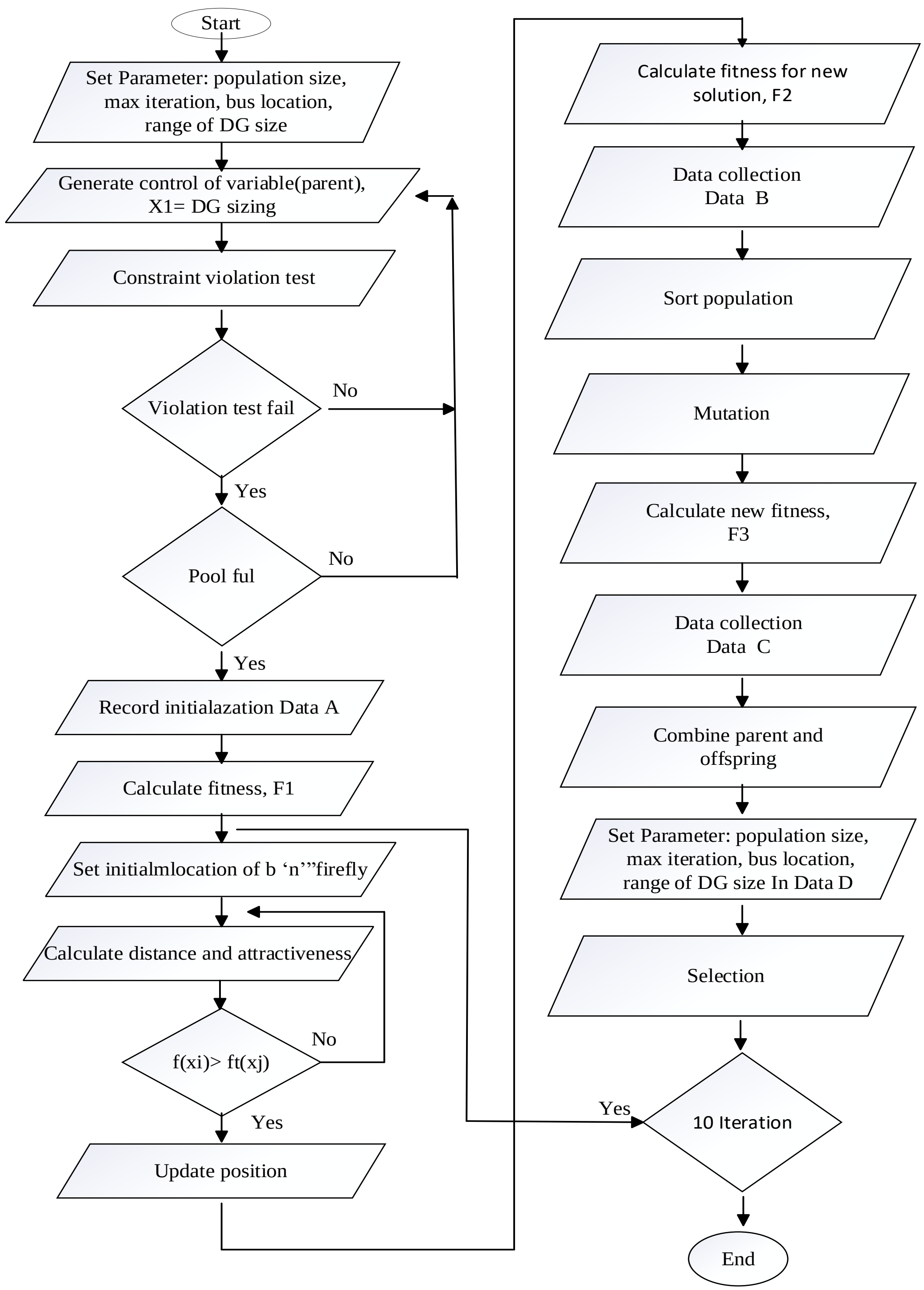


Figure 2: The Flowchart for implementation of proposed HEPFA

Table 1 : The case study associated with the proposal hybrid-HEPFA technique.

| Case | Without DG | DG1 (DG UNIT #1) | | | DG2 (DG UNIT #2) | | |
|---|---|---|---|---|---|---|---|
| | | Type | | | Type | | |
| | | 1 | 2 | 3 | 1 | 2 | 3 |
| 0 | √ | - | - | - | - | - | - |
| 1 | - | - | - | √ | - | - | - |
| 2 | - | - | - | √ | - | - | √ |
| 3 | - | - | - | √ | √ | - | - |
| 4 | - | - | - | √ | - | √ | - |

## 4 RESULTS AND DISCUSSION

This section presents the results obtained using the proposed technique. The data was run without DG and then with DG. The proposed techniques were validated using the EEE 69-bus Reliability Test system, and the program was written in the MATLAB programming language.

### 4.1 Result of Case 0 (without DG)

The base case results for total losses of the 69-bus system, the result from the simulation shown the value and graph to find the suitable location. Observations from simulations conducted led to the decision to implement the DG at the lowest voltage profile value. The voltage profile for the base case is shown in ascending order in Table 2. According to the voltage profile results listed n ascending order, the deal location s bus 65, which has a voltage profile of 0.9299, 64 of 0.9305, 63 of 0.9324, 62 of 0.9327, 61 of 0.9330, 60 of 0.9403, 59 of 0.9452, 58 of 0.9494, 57 of 0.9602, and 27 of 0.9760.

Table 2 : Voltage profile for the base case in ascending

| No | Bus No | Vm | No | Bus No | Vm | No | Bus No | Vm |
|---|---|---|---|---|---|---|---|---|
| 1 | 65 | 0.929996 | 24 | 56 | 0.982184 | 47 | 48 | 0.998816 |
| 2 | 64 | 0.930557 | 25 | 13 | 0.984778 | 48 | 41 | 0.99895 |
| 3 | 63 | 0.932415 | 26 | 55 | 0.986455 | 49 | 35 | 0.999053 |
| 4 | 62 | 0.932794 | 27 | 69 | 0.98732 | 50 | 34 | 0.99912 |
| 5 | 61 | 0.933077 | 28 | 68 | 0.987321 | 51 | 33 | 0.999456 |
| 6 | 60 | 0.940309 | 29 | 12 | 0.987644 | 52 | 40 | 0.999648 |
| 7 | 59 | 0.945221 | 30 | 67 | 0.990686 | 53 | 39 | 0.99965 |
| 8 | 58 | 0.949404 | 31 | 66 | 0.990687 | 54 | 38 | 0.999696 |
| 9 | 57 | 0.960216 | 32 | 11 | 0.990742 | 55 | 32 | 0.999712 |
| 10 | 27 | 0.976028 | 33 | 54 | 0.990828 | 56 | 31 | 0.999819 |
| 11 | 26 | 0.976047 | 34 | 10 | 0.991822 | 57 | 30 | 0.99984 |
| 12 | 25 | 0.976115 | 35 | 53 | 0.993998 | 58 | 37 | 0.999854 |
| 13 | 24 | 0.976281 | 36 | 50 | 0.994427 | 59 | 29 | 0.999961 |
| 14 | 23 | 0.976434 | 37 | 49 | 0.994972 | 60 | 1 | 1 |
| 15 | 22 | 0.976504 | 38 | 9 | 0.996722 | 61 | 7 | 1 |
| 16 | 21 | 0.976511 | 39 | 52 | 0.997788 | 62 | 2 | 1.00002 |
| 17 | 20 | 0.976984 | 40 | 51 | 0.997798 | 63 | 36 | 1.000026 |
| 18 | 19 | 0.977276 | 41 | 8 | 0.997833 | 64 | 28 | 1.000033 |
| 19 | 18 | 0.977732 | 42 | 46 | 0.998512 | 65 | 3 | 1.00004 |
| 20 | 17 | 0.977741 | 43 | 45 | 0.998513 | 66 | 47 | 1.000061 |
| 21 | 16 | 0.978604 | 44 | 44 | 0.998611 | 67 | 4 | 1.00011 |
| 22 | 15 | 0.979126 | 45 | 43 | 0.998619 | 68 | 6 | 1.000185 |
| 23 | 14 | 0.981938 | 46 | 42 | 0.998658 | 69 | 5 | 1.000628 |

### 4.2 Result of Case 1 (DG1 Type 3)

Table 3 exhibits the results of the proposed HEPFA technique incorporating 2 DG units, both of which are DG type 3. The first combination from DG at bus 61 and bus 27 demonstrates a 94% LRI index, which is the highest. The second simulation reveals that the percentage, 89%, corresponds to a slightly lower proportion of LRI than 94%. DG is located at bus 61 and 46. The third simulation demonstrates that 90% s achieved when DG s installed on buses 61 and 50. The data demonstrate varying levels of achievement, with the first percentage being the highest, followed by the third percentage, and finally the second percentage.

Table 3 : A summary of the simulation results for ten suggested locations using HEPFA technique.

| Bus location | 65 | 64 | 63 | 62 | 61 | 60 | 59 | 58 | 57 | 27 |
|---|---|---|---|---|---|---|---|---|---|---|
| P DG (MW) | 1.5419 | 1.7496 | 1.9089 | 1.9458 | 1.9712 | 2.0232 | 2.0668 | 2.0993 | 2.1985 | 0.6558 |
| Q DG (MVAR) | 0.8104 | 0.9196 | 1.0033 | 1.0227 | 1.0360 | 1.0633 | 1.0863 | 1.1033 | 1.1555 | 0.3447 |
| *P loss (MW)* | 0.0641 | 0.0436 | 0.0311 | 0.0282 | 0.0263 | 0.0375 | 0.0462 | 0.0542 | 0.0754 | 0.1930 |
| Q loss (MVAR) | 0.0350 | 0.0248 | 0.0183 | 0.0167 | 0.0157 | 0.0214 | 0.0239 | 0.0265 | 0.0336 | 0.0859 |
| Cost of energy losses | 5.1580 | 3.5064 | 2.5032 | 2.2693 | 2.1142 | 3.0189 | 3.7166 | 4.3619 | 6.0685 | 15.537 5 |
| Vmin (p.u) | 0.9690 | 0.9707 | 0.9720 | 0.9723 | 0.9725 | 0.9728 | 0.9731 | 0.9733 | 0.9728 | 0.9146 |
| Vmax (p.u) | 1.0030 | 1.0018 | 1.0010 | 1.0009 | 1.0008 | 1.0011 | 1.0013 | 1.0014 | 1.0017 | 1.0007 |
| VPI | 0.0310 | 0.0293 | 0.0280 | 0.0277 | 0.0275 | 0.0272 | 0.0269 | 0.0267 | 0.0272 | 0.0854 |
| Percentag e (LRI) | 74% | 82% | 87% | 88% | 89% | 85% | 81% | 78% | 69% | 22% |

### 4.3 Result of Case 2 (DG1 Type 3 and DG2 type 3)

The proposed HEPFA technique was implemented which integrates two DG units. Both DG units are type 3 DG units. Table 4 tabulates the results of the proposed HEPFA technique incorporating 2 DG units, both of which are DG type 3. The first combination from DG at bus 61 and bus 27 demonstrates a 94% LRI index, which is the highest. The second simulation reveals that the percentage, 89%, corresponds to a slightly lower proportion of LRI than 94%. DG is located at bus 61 and 46. The third simulation demonstrates that 90% s achieved when DG s installed on buses 61 and 50. The data demonstrate varying levels of achievement, with the first percentage being the highest, followed by the third percentage, and finally the second percentage.

Table 4 : A simulation results of the hybrid HEPFA for case 2 (DG1 Type 3 and DG2 type 3)

| Bus location | Bus 27 | Bus 46 | Bus 50 |
|---|---|---|---|
| P DG1 (MW) at bus 61 | 1.8960 | 1.9867 | 1.970 |
| Q DG1 (MVAR) at bus 61 | 0.9965 | 1.0442 | 1.035 |
| P DG2 (MW) | 0.4190 | 1.9713 | 0.835 |
| Q DG2 (MVAR) | 0.2202 | 1.0361 | 0.439 |
| P loss (MW) | 0.0135 | 0.0263 | 0.024 |
| Q loss (MVAR) | 0.0107 | 0.0157 | 0.010 |
| Cost of energy losses | 1.0894 | 2.1142 | 1.934 |
| Vmin (p.u) | 0.9918 | 0.9725 | 0.973 |
| Vmax (p.u) | 1.0008 | 1.0008 | 1.001 |
| VPI | 0.0082 | 0.0275 | 0.027 |
| Percentage | 94% | 89% | 90% |

### 4.4 Result of Case 3 (DG1 Type 3 and DG2 type 1)

Table 5 presents the results of the proposed HEPFA technique for Case 3 incorporating two units of DG as DG1 type 3 and DG2 type 1. integration DG at 61 and 27 has the greatest LRI percentage, at 92%. The second percentage, 90%, represents the results of DG installation at bus 61 and bus 50. Lastly, the LRI for DG installation at bus 61 and 46 s only 88%.

Table 5 : A simulation result of the hybrid HEPFA case 3 (DG1 Type 3 and DG2 Type 1)

| | Bus 27 | Bus 46 | Bus 50 |
|---|---|---|---|
| P DG1 (MW) at bus 61 | 1.9182 | 1.8023 | 1.9563 |
| Q DG1 (MVAR) at bus 61 | 1.0082 | 0.9473 | 1.0282 |
| P DG2 (MW) | 0.3775 | 0.3293 | 0.6122 |
| Q DG2 (MVAR) | 0.0000 | 0.0000 | 0.0000 |
| P loss (MW) | 0.0180 | 0.0279 | 0.0248 |
| Q loss (MVAR) | 0.0126 | 0.0170 | 0.0121 |
| Cost of energy losses | 1.451 | 2.2458 | 1.9953 |

| | | | |
|---|---|---|---|
| Vmin (p.u) | 0.9891 | 0.9712 | 0.9724 |
| Vmax (p.u) | 1.0008 | 1.0013 | 1.0002 |
| VPI | 0.0109 | 0.0288 | 0.0276 |
| Percentage | 92% | 88% | 90% |

### 4.5 Result of Case 4 (DG1 Type 3 and DG2 type 2)

In Table 6 are the results of the proposed HEPFA technique that integrates 2 DG, with DG1 being of type 3 and DG2 being of type 2. It is evident from these tables that the system's loss reduction rate has increased significantly. The LRI percentage for the combination of buses 61 and 27 is the greatest, at 91%. 89% is the reduction index for the combination of DG installations at bus 61 and bus 50. The LRI percentage for the DG implementation on buses 61 and 46 is 86%.

Table 6 : The Data simulation of the hybrid HEPFA (P loss MW) with DG type 3 & DG type 1 (Case 4)

| | Bus 27 | Bus 46 | Bus 50 |
|---|---|---|---|
| P DG1 (MW) at bus 61 | 1.9498 | 1.6151 | 1.9745 |
| Q DG1 (MVAR) at bus 61 | 1.0248 | 0.8489 | 1.0378 |
| P DG2 (MW) | 0.0000 | 0.0000 | 0.0000 |
| Q DG2 (MVAR) | 0.2851 | 0.6261 | 0.3943 |
| P loss (MW) | 0.0214 | 0.0345 | 0.0255 |
| Q loss (MVAR) | 0.0137 | 0.0220 | 0.0139 |
| Cost of energy losses | 1.7240 | 2.7789 | 2.0544 |
| Vmin (p.u) | 0.9775 | 0.9698 | 0.9725 |
| Vmax (p.u) | 1.0008 | 1.0052 | 1.0009 |
| VPI | 0.0225 | 0.0302 | 0.0275 |
| Percentage | 91% | 86% | 89% |

### 4.6 Comparative Study

A comparative study was conducted between the case studies by analyzing the performance of each case. Table 7 lists the optimal output for two DG units with different combinations of DG type, and Figure 4.21 compares the $P_{loss}$ n MW for various cases based on optimal output. The results indicate that Case 2 provides the best performance, with the lowest $P_{loss}$ and the maximum LRI (94%) when compared to other cases.

Table 7 : Best optimal output for each case of DG sizing.

| | Case 0 | Case 1 | Case 2 | Case 3 | Case 4 |
|---|---|---|---|---|---|
| P DG1 (MW) at bus 61 | - | 1.9712 | 1.8960 | 1.9182 | 1.9498 |
| Q DG1 (MVAR) at bus 61 | - | 1.0360 | 0.9965 | 1.0082 | 1.0248 |
| P DG2 (MW) at bus 27 | - | - | 0.4190 | 0.3775 | - |
| Q DG2 (MVAR) at bus 27 | - | - | 0.2202 | - | 0.2851 |
| P loss (MW) | 0.225 | 0.0263 | 0.0135 | 0.0180 | 0.0214 |
| Q loss (MVAR) | 0.102 | 0.0157 | 0.0107 | 0.0126 | 0.0137 |
| Cost of energy losses | | 2.1142 | 1.0894 | 1.4518 | 1.7240 |
| Vmin (p.u) | 0 | 0.9725 | 0.9918 | 0.9891 | 0.9775 |
| Vmax (p.u) | 1.0 | 1.0008 | 1.0008 | 1.0008 | 1.0008 |
| VPI | - | 0.0275 | 0.0082 | 0.0109 | 0.0225 |
| Percentage | - | 89% | 94% | 92% | 91% |

## 5 CONCLUSION

The proposed HEPFA technique successfully demonstrates its effectiveness in minimizing the total losses and CL value and ensuring voltage constraints are met in power systems. By incorporating the properties of the Firefly Algorithm into the classical EP technique, the HEPFA provides a more efficient and robust optimization approach. The utilization of random variable initialization for DG sizing enables the exploration of various parameter combinations. The fitness evaluation based on the objective function allows for the assessment of the quality of each solution. The Firefly Attraction operation facilitates the comparison of solution attractiveness based on their locations. Additionally, the mutation process, implemented using the Gaussian mutation method, introduces randomness and diversifies the search process. Through testing on the on the IEEE 69-bus test system, derived from a distribution network the HEPFA technique is validated. Comparing Case 0, Case 1, Case 2, Case 3 and Case 4 in the simulation, the result of Ploss in MW for various cases based on the optimal output indicated that case 2 has a total loss as low as 0.0267 MW. The combination of DG at bus 61 and bus 27 yields an LRI index of 94%. The second lowest Ploss in MW is 0.018 in case 3. Case 4 loss of 0.0214 placed Ploss in third position, followed by case 1, Ploss of 0.02563. The results obtained from the HEPFA technique offer valuable insights for decision-making in power systems. By minimizing power losses and improving voltage profiles, the HEPFA contributes to enhancing the overall system performance. It provides a means to optimize the sizing and placement of DG installations, thereby facilitating the integration of renewable energy sources into the power grid. The combination of the Firefly Algorithm with the EP technique demonstrates its potential in addressing optimization challenges encountered in power systems. The HEPFA presents a promising approach for achieving efficient and effective optimization, paving the way for future advancements in power system analysis and planning.

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## REFERENCES

[1] J. Y. Lee, R. Verayiah, K. H. Ong, A. K. Ramasamy, and M. B. Marsadek, "Distributed generation: A review on current energy status, grid-interconnected pq issues, and implementation constraints of dg in malaysia," *Energies*, vol. 13, no. 24, 2020, doi: 10.3390/en13246479.

[2] M. H. Hassan, E. H. Houssein, M. A. Mahdy, and S. Kamel, "An improved Manta ray foraging optimizer for cost-effective emission dispatch problems," *Engineering Applications of Artificial Intelligence*, vol. 100, no. September 2020, p. 104155, 2021, doi: 10.1016/j.engappai.2021.104155.

[3] C. H. Prasad, K. Subbaramaiah, and P. Sujatha, "Cost – benefit analysis for optimal DG placement in distribution systems by using elephant herding optimization algorithm," *Renewables: Wind, Water, and Solar*, 2019, doi: 10.1186/s40807-019-0056-9.

[4] A. Davoodi, A. R. Abbasi, and S. Nejatian, "Multi-objective techno-economic generation expansion planning to increase the penetration of distributed generation resources based on demand response algorithms," *International Journal of Electrical Power and Energy Systems*, vol. 138, no. November 2021, p. 107923, 2022, doi: 10.1016/j.ijepes.2021.107923.

[5] T. P. Nguyen, T. A. Nguyen, T. V. H. Phan, and D. N. Vo, "A comprehensive analysis for multi-objective distributed generations and capacitor banks placement in radial distribution networks using hybrid neural network algorithm," *Knowledge-Based Systems*, vol. 231, p. 107387, 2021, doi: 10.1016/j.knosys.2021.107387.

[6] M. P. H. A, M. Nazari-heris, and B. Mohammadi-ivatloo, "A hybrid genetic particle swarm optimization for distributed generation allocation in power distribution networks," *Energy*, vol. 209, p. 118218, 2020, doi: 10.1016/j.energy.2020.118218.

[7] L. F. Grisales-Noreña, O. D. Montoya, C. A. Ramos-Paja, Q. Hernandez-Escobedo, and A. J. Perea-Moreno, "Optimal location and sizing of distributed generators in dc networks using a hybrid method based on parallel pbil and pso," *Electronics (Switzerland)*, vol. 9, no. 11, pp. 1–27, 2020, doi: 10.3390/electronics9111808.

[8] A. S. Hassan, E. S. A. Othman, F. M. Bendary, and M. A. Ebrahim, "Optimal integration of distributed generation resources in active distribution networks for techno-economic benefits," *Energy Reports*, vol. 6, pp. 3462–3471, 2020, doi: 10.1016/j.egyr.2020.12.004.

[9] A. Slowik and H. Kwasnicka, "Evolutionary algorithms and their applications to engineering problems," *Neural Computing and Applications*, vol. 32, no. 16, pp. 12363–12379, 2020, doi: 10.1007/s00521-020-04832-8.