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ADAPTIVE HYBRID DIFFERENTIAL EVOLUTION PARTICLE SWARM OPTIMIZATION ALGORITHM FOR OPTIMIZATION DISTRIBUTED GENERATION IN DISTRIBUTION NETWORKS

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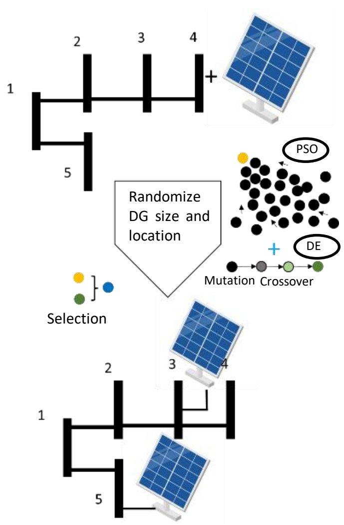
Graphical abstract



Abstract

The incorporation of Distributed Generation (DG) into the Radial Distribution System (RDS) aids in resolving power system issues such as power loss. However, finding the ideal location and size for DG is challenging yet crucial for maximizing these advantages. Inappropriate location and sizing of DG can negatively impact its benefits, highlighting the need for effective optimization methods**.** To address these challenges, metaheuristic methods like Particle Swarm Optimization (PSO), Differential Evolution (DE), and Firefly algorithms are particularly useful. This research aims to determine the best location and size of DG to minimize active power losses in the RDS. Despite the success of DE and PSO in previous works, a gap remains in achieving optimal convergence performance and computational efficiency. Building on the success of DE and PSO, this study presents a hybrid optimization approach, Adaptive Hybrid Differential Evolution and Particle Swarm Optimization (AHDEPSO), to reduce power loss in RDS. This approach combines the strengths of DE and PSO, enhancing exploration and exploitation capabilities while improving convergence performance. The effectiveness of this approach is demonstrated through testing on the IEEE 33 and IEEE 69 bus systems using MATLAB software, showing that AHDEPSO can achieve optimal computational time and best fitness function, being 38.3% faster than other algorithms. This hybrid approach offers a significant improvement over traditional methods, filling the research gap and providing a more efficient solution.

Keywords: Differential Evolution, Particle Swarm Optimization, Data Optimization, DG Optimization, Power Loss

Abstrak

Penyelidikan ini mencadangkan kaedah pengoptimuman (Adaptive Hybrid Differential Evolution and Particle Swarm Optimization, AHDEPSO) menggunakan teknik penyelesaian berdasarkan dua teknik terkenal, Evolusi Pembezaan (DE) dan Pengoptimuman Kawanan Partikel (PSO), untuk meminimumkan kehilangan kuasa dalam sistem pengedaran radial (RDS). Masalah sistem kuasa seperti kehilangan kuasa dalam RDS dapat diselesaikan dengan penyatuan Generasi Teragih (DG) dalam RDS. Lokasi dan saiz DG yang terbaik adalah halangan yang sangat mencabar untuk memaksimumkan faedahnya. Penempatan dan kapasiti DG yang tidak betul boleh menjejaskan kesan faedah DG. Teknik pengoptimuman seperti DE dan PSO sangat membantu menyelesaikan masalah tersebut. HDEPSO dapat mengoptimumkan lokasi dan saiz DG. Kelebihan DE dan PSO digabungkan untuk meningkatkan algoritma penerokaan dan eksploitasi serta prestasi penumpuan. Kebolehlaksanaan kerja ini diuji dan dilaksanakan pada RDS bas IEEE 33 dan IEEE 69 di dalam MATLAB serta menunjukkan AHDEPSO ini dapat mencapai solusi yang terbaik dengan 38.3% lebih cepat berbanding Teknik yang lain. Pendekatan hibrid ini menawarkan peningkatan yang ketara berbanding dengan kaedah tradisional, mengisi jurang penyelidikan dan menyediakan penyelesaian yang lebih cekap.

Kata kunci: Evolusi Pembezaan, Pengoptimuman Kawanan Partikel, Pengoptimuman *Data*, Pengoptimuman DG, kehilangan Kuasa

1.0 INTRODUCTION

Distribution systems are usually radial in form and straightforward to operate. Radial distribution systems (RDS) are supplied from a single location via the associated transmission network, like a substation that receives power from centralized generating plants to passively deliver unidirectional power flow to owner-end customers [1]. However, high R/X ratios in distribution lines cause substantial power losses, huge voltage fluctuations, and poor voltage stability. This causes the RDS to experience a sudden decrease in voltage under critical loading situations in several industrial zones because of the low value of the voltage stability index at the majority of RDS's nodes. Due to this problem, embedded generations in a distribution system known as scattered generations or distributed generations (DG) have been proposed to be installed in the distribution network [2, 3].

DG is defined as the small-scale energy generation that is located near the final user [4]. For instance, co-generators, solar panels, small-scale wind turbines, emergency generators and small-scale hydropower plants. It is anticipated that DG will take on a bigger role in future electrical power networks. According to studies, DG will make up a sizable portion of all future generations that join the workforce. They are expected to be increasing of the newly installed generations [5, 6]. However, the size and location of DG must be properly optimized to improve the system's performance.

Therefore, many researchers introduced effective optimization methods to optimize DG size and location. There are several ways to tackle the issue, including deterministic, heuristic, and metaheuristic approaches. Mathematical programming is a subset of deterministic optimization and comprises linear algebra-heavy methods that often compute the gradient and Hessian matrix of response variables [7]. The authors in [8] employed a deterministic optimization strategy called as mixed-integer conic programming (MICP), to determine the ideal type, size, and location for RES and ESS in RDS. In [9], the authors used a second-order conic programming problem to find the system's optimal DG size and location. However, due to the complexity of processes in the deterministic approach, the conventional optimization methods for addressing process synthesis and integrated design may fail to converge adequately due to the presence of local minima, discontinuities and numerical issues [10]. Some precise deterministic approaches may get the best answer under certain data formats if the nature and scale of the issue allow for easy formulations. For instance, nonlinear components are linearized using piecewise linear representations in a convex problem framework. However, the structure of the issues, in general, might be so complicated that it is difficult or impractical to utilize approaches that ensure global excellence. In addition, the structure is an uncharted territory of possible solutions in certain circumstances, necessitating a unique strategy for obtaining information from the solutions themselves [11].

Meanwhile, heuristic methods are being created in a variety of ways, ranging from simple empirical algorithms to complex algorithms such as evolutionary algorithms. Heuristic optimization may be used to solve continuous/integer problems repeatedly. It is typically used when no known method ensures obtaining the ideal answer at an efficient speed or when a "near-optimal" solution is enough for practical usage [7]. A Heuristic method based on the Genetic Algorithm (GA) was used in [12] to optimize the placement and size of DG. In addition, a heuristic is a method created to solve a problem more rapidly when classical approaches are ineffective or take too long to find a precise solution. A heuristic's goal is to generate a workable solution to the problem at hand in a fair amount of time. However, this answer might not be the best among all possible solutions to the problem, or it might only be a rough approximation [13], [14]. In this instance, using metaheuristics is a possible option.

In the context of heuristic algorithms, the word meta signifies "beyond" or "higher level," and metaheuristic algorithms often outperform more traditional heuristics. Each metaheuristic algorithm randomly chooses between local and global searches to provide a wide range of solutions. Metaheuristics can be divided into two categories which are population-based and trajectory-based. Despite the widespread usage of metaheuristics, there is no consensus in the literature about the definitions of heuristics and metaheuristics. Heuristics and metaheuristics are terms that some scholars interchangeably employ. The current tendency, however, is to refer to all stochastic algorithms including global search and randomization as metaheuristics. An effective approach to switching from local to global search is using randomization. Because of this, essentially all metaheuristic algorithms are always convenient for comprehensive optimization and nonlinear modeling [15]. Metaheuristics may be an effective method for producing acceptable solutions to complicated problems via hit-and-miss in an ideal amount of time. In [16], researchers developed a three-level optimization technique for planned network architecture, RES and ESS allocation, and ESS optimization in active distribution planning with renewable energy sources and energy storage systems. In this model, to tackle the presented optimization issue, a modified Pareto-based particle swarm optimization is used. While researchers in [17] employ PSO to optimize DG position and size to decrease power loss. In DG optimization, a paper [18] suggested an enhanced Harris Hawks Optimizer (HHO) employing Particle Swarm Optimization (PSO). The suggested method's goal was to decrease power loss while increasing the voltage stability index. Then, in [19], the Genetic Algorithm (GA) is used to boost system performance by optimizing DG location and size. This is done to maximize the effectiveness of the system. A brand-new strategy known as multi-objective opposition-based chaotic differential evolution (MOCDE) is designed to forestall the occurrence of premature convergence [20]. This approach seeks to solve the multi-objective issue by reducing the amount of money that is lost each year as much as possible. This loss takes into consideration the expenses involved with the installation, operation, and upkeep of the buses, as well as the power loss and voltage fluctuation that occurs across the buses.

In the literature review, many researchers used mathematical methods to find the optimal solution for DG planning. When it comes to a more complex problem, it can be seen clearly that the metaheuristic method is more often used than classical and heuristic methods and PSO is the widely used algorithm. The PSO algorithm was introduced by Eberhart and Kennedy (1995). PSO is an efficient optimization method by finding the entire high-dimensional problem space [21]. It is straightforward to build, requires just a small number of parameters to be set, is efficient for global search, is unaffected by the scaling of design variables, and is simple to parallelize for simultaneous processing [21]. In addition, the calculation in PSO is simple and is the main reason it is used in many research [22]. Paper [16-18, 23] used the PSO optimization method to find the optimal result for DG planning and produce an ideal solution for the problems. However, PSO is susceptible to local optimums in high-proportion spaces and has a poor convergence rate throughout the iterative phase [24].

There is a method that has important merits for a complex problem which is differential evolution (DE) where it can use the same setting for a different problem. The DE is an effective global optimization technique and a straightforward stochastic direct search approach with strong convergence features [25]. DE can be used to solve a wide range of optimization problems, including continuous [26], discrete [27], constrained [28], and unconstrained. Although DE is good at exploration and diversification [22], DE has a weakness when it faces a noisy situation [29]. Noise in fitness evaluations can arise from a variety of sources, including sensor measurement mistakes and randomized simulations. The noise in the objective function generates two forms of undesired behavior: 1) a candidate solution may be underestimated and hence removed, 2) a candidate solution may be overestimated and thus saved, and thus permitted to lead to wrong search directions. Alternatively, a noisy fitness landscape may be defined as having misleading optima that mislead the algorithm search [30]. Under these situations, optimization algorithms are readily misled by noise and consequently discover suboptimal solutions. Consequently, DE can produce an ideal solution, but it takes a longer time to converge. Therefore, many researchers improved existing optimization methods to obtain a good result for their problem. In another word, the improvised method is normally suitable only for a particular problem.

In this research, an integrated approach called Adaptive Hybrid Differential Evolution and Particle Swarm Optimization (AHDEPSO) is proposed to optimize the location and size of DG in distribution networks. AHDEPSO is selected over other methods due to its ability to overcome the limitations of both PSO and DE. This strategy hybridizes DE with the PSO component, updating particle velocity and location to compensate for the deficiencies of PSO and DE. This hybridization combo aids in exploration and increases convergence speed. In this hybridization, the PSO portion acts to improve exploration and enhance algorithm speed. Furthermore, an adaptive scaling factor method is introduced to ensure the algorithm can reach the optimal solution faster, as it is affected by the updated global best from the DE vector. This comprehensive approach leverages the strengths of both algorithms, making AHDEPSO a robust choice for complex optimization problems in power distribution networks.

2.0 METHODOLOGY

In this research, the main objective is to minimize power loss. The optimum power loss benefits have been analyzed by optimal placements and sizes of DG units RDSs. DG optimal sizes can be installed at the proper location in the IEEE Bus system as Figure 1 and Figure 2. This research only considered active power DG to be optimized to reduce active power loss in the system. In addition, three and five units of DGs are applied in the IEEE-33 bus and IEEE-69 bus systems, respectively.

The system is simulated using MATLAB with IEEE-33 bus and IEEE-69 bus systems. Through this test system, the optimal size and location of DGs are optimized by using the proposed AHDEPSO algorithm to minimize the system power loss. To achieve the objective, the problem is first formulated followed by the modeling of the proposed AHDEPSO algorithm. The AHDEPSO is then integrated with the optimization problem. The proposed methods are compared with several methods which are DE, PSO and FA to observe the effectiveness of the method in terms of mean, standard deviation, worst of the fitness value and the convergence rate of the algorithm.

2.1 Distribution System Configuration

In this research, the IEEE 33-Bus and IEEE 69-Bus test systems are employed to validate the proposed optimization approach. These test systems are well-known benchmarks in power system studies, providing a reliable platform for evaluating the performance of optimization algorithms.

The IEEE 33-Bus system consists of 33 buses and 32 branches, while the IEEE 69-Bus system includes 69 buses and 68 branches. These systems simulate real-world scenarios of power distribution networks, with specific data for buses and branches, including load demand, generation capacity, and network configuration. Figure 1 and Figure 2 shows the configuration of the IEEE 33-Bus and IEEE 69-Bus test systems.

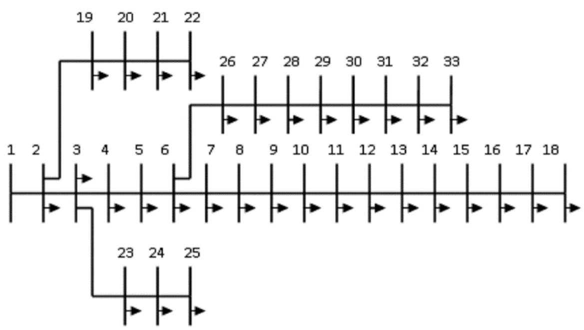


Figure 1 IEEE 33 bus radial system [31]

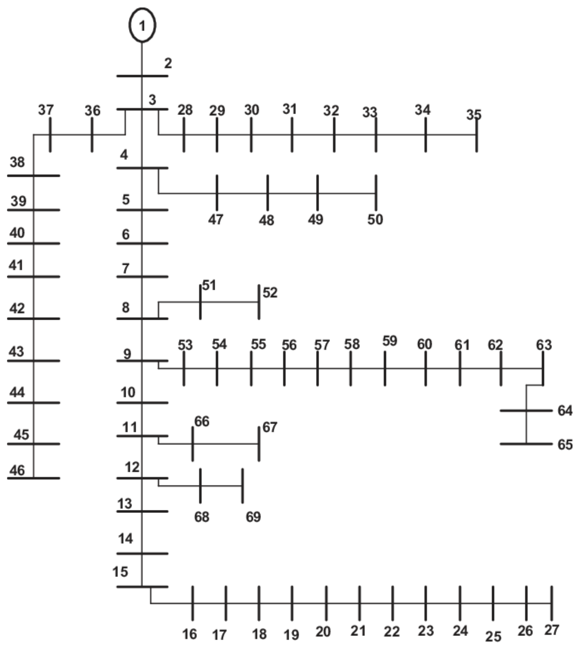


Figure 2 IEEE 69 bus radial system [32]

Table 1 and Table 2 present the detailed bus data for both test systems. This data includes parameters such as bus numbers, load demands, generation capacities, and other relevant details necessary for performing accurate simulations and analysis.

Table 1 Bus data and line data of IEEE 33 bus [33]

No of Branch	Bus	To Bus	R (Ω)	X (Ω)	Bus Load	
					P (kW)	Q (kW)
1	1	2	0.0922	0.0477	0	0
2	2	3	0.493	0.2511	100	60
3	3	4	0.366	0.1864	90	40
4	4	5	0.3811	0.1941	120	80
5	5	6	0.819	0.707	60	30
6	6	7	0.1872	0.6188	60	20
7	7	8	0.7114	1.2351	200	100
8	8	9	1.03	0.74	200	100
9	9	10	1.04	0.74	60	20
10	10	11	0.1966	0.065	60	20
11	11	12	0.3744	0.1238	45	30
12	12	13	1.468	1.155	60	35
13	13	14	0.5416	0.7129	60	35
14	14	15	0.591	0.526	120	80
15	15	16	0.7463	0.545	60	10
16	16	17	1.289	1.721	60	20
17	17	18	0.732	0.574	60	20
18	2	19	0.164	0.1565	90	40
19	19	20	1.5042	1.3554	90	40
20	20	21	0.4095	0.4784	90	40
21	21	22	0.7089	0.9373	90	40
22	3	23	0.4512	0.3083	90	40
23	23	24	0.898	0.7091	90	50
24	24	25	0.896	0.7011	420	200
25	6	26	0.203	0.1034	420	200
26	26	27	0.2842	0.1447	60	25
27	27	28	1.059	0.9337	60	25
28	28	29	0.8042	0.7006	60	20
29	29	30	0.5075	0.2585	120	70
30	30	31	0.9744	0.963	200	600
31	31	32	0.3105	0.3619	150	70
32	32	33	0.341	0.5302	210	100
33					60	40

Table 2 Bus data and line data of IEEE 69

No of Branch	Bus	To Bus	R (Ω)	X (Ω)	Bus Load	
					P (kW)	Q (kW)
1	1	2	0.0005	0.0012	0	0
2	2	3	0.0005	0.0012	0	0
3	3	4	0.0015	0.0036	0	0
4	4	5	0.0251	0.0294	0	0
5	5	6	0.366	0.1864	0	0
6	6	7	0.3811	0.1941	2.6	2.2
7	7	8	0.0922	0.047	40.4	30
8	8	9	0.0493	0.0251	75	54
9	9	10	0.819	0.2707	30	22
10	10	11	0.1872	0.0691	28	19
11	11	12	0.7114	0.2351	145	104

No of Branch	Bus	To Bus	R (Ω)	X (Ω)	Bus Load	
					P (kW)	Q (kW)
12	12	13	1.03	0.34	145	104
13	13	14	1.044	0.345	8	5
14	14	15	1.058	0.3496	8	5.5
15	15	16	0.1966	0.065	0	0
16	16	17	0.3744	0.1238	45.5	30
17	17	18	0.0047	0.0016	60	35
18	18	19	0.3276	0.1083	60	35
19	19	20	0.2106	0.069	0	0
20	20	21	0.3416	0.1129	1	0.6
21	21	22	0.014	0.0046	114	81
22	22	23	0.1591	0.0526	5	3.5
23	23	24	0.3463	0.1145	0	0
24	24	25	0.7488	0.2745	28	20
25	25	26	0.3089	0.1021	0	0
26	26	27	0.1732	0.0572	14	10
27	3	28	0.0044	0.0108	14	10
28	28	29	0.064	0.1565	26	18.6
29	29	30	0.3978	0.1315	26	18.6
30	30	31	0.0702	0.0232	0	0
31	31	32	0.351	0.116	0	0
32	32	33	0.839	0.2816	0	0
33	33	34	1.708	0.5646	14	10
34	34	35	1.474	0.4673	19.5	14
35	3	36	0.0044	0.0108	6	4
36	36	37	0.064	0.1565	26	18.55
37	37	38	0.1053	0.123	26	18.55
38	38	39	0.0304	0.0355	0	0
39	39	40	0.0018	0.0021	24	17
40	40	41	0.7283	0.8509	24	17
41	41	42	0.31	0.3623	1.2	1
42	42	43	0.041	0.0478	0	0
43	43	44	0.0092	0.0116	6	4.3
44	44	45	0.1089	0.1373	0	0
45	45	46	0.0009	0.0012	39.22	26.3
46	4	47	0.0034	0.0084	39.22	26.3
47	47	48	0.0851	0.2083	0	0
48	48	49	0.2898	0.7091	79	56.4
49	49	50	0.0822	0.2011	384.7	274.5
50	8	51	0.0928	0.0473	384.7	274.5
51	51	52	0.3319	0.1114	40.5	28.3
52	9	53	0.174	0.0886	3.6	2.7
53	53	54	0.203	0.1034	4.35	3.5
54	54	55	0.2842	0.1447	26.4	19

No of Branch	Bus	To Bus	R (Ω)	X (Ω)	Bus Load	
					P (kW)	Q (kW)
55	55	56	0.2813	0.1433	24	17.2
56	56	57	1.59	0.5337	0	0
57	57	58	0.7837	0.263	0	0
58	58	59	0.3042	0.1006	0	0
59	59	60	0.3861	0.1172	100	72
60	60	61	0.5075	0.2585	0	0
61	61	62	0.0974	0.0496	1244	888
62	62	63	0.145	0.0738	32	23
63	63	64	0.7105	0.3619	0	0
64	64	65	1.041	0.5302	227	162
65	11	66	0.2012	0.0611	59	42
66	66	67	0.0047	0.0014	18	13
67	12	68	0.7394	0.2444	18	13
68	68	69	0.0047	0.0016	28	20
69					28	20

2.2 Problem Formulation

The variable to be optimized is the location and size of DG.

2.2.1 *Objective Function*

The objective of this research is to minimize power loss.

a) Power Loss:

Equation (1) is used to determine real power loss. The system's total active power loss is calculated by adding all of the power losses between branch x and y bus [34].

$$P_{loss(x,y)} = \sum \frac{P_x^2 + Q_x^2}{|V_x|^2} \times R_x \quad (1)$$

Where:
P_x and Q_x active and reactive power at x bus respectively.
R_i is the resistance between bus x and y.
V_x is the bus x^{th} voltage.

2.2.2 *Constraint*

The optimization process must meet several constrain such as:

a) Voltage constraint

Following the DG output adjustment, the voltage value for all buses in the distribution network must operate within the allowed limit, which is ±5% of the rated value [35].

$$0.95p.u \leq Vm \leq 1.05\, p.u \tag{2}$$

b) Generator operation constraint:

$$Pmin \leq P_{DGi} \leq Pmax; \quad 0 \leq P_{DGi} \leq 2MW \tag{3}$$

All DG units must operate between minimum DG output, $Pmin$ and maximum DG output, $Pmax$. Therefore, DG sizing results must not exceed this limit during initialization or updating in optimization.

c) Power balance constraint:

$$\sum_{i=1}^{k} P_{DG} + P_{Grid} = P_{Load} + P_{Loss} \tag{4}$$

Where P_{DG} is the real power generated by DG, P_{Grid} is real power injected from the grid to the system, P_{Load} is demand real power and P_{Loss} is the real power loss in the system.

The total power generated in the network which is from DG units and the grid must be equal to the summation of total load and the total power loss.

d) Reverse Power Flow

$$P_{DG} < P_{Load} \tag{5}$$

It is essential that the power produced by DG does not go above the local load to avoid reverse power flow (RPF), which refers to the flow of electricity in the opposite direction of what is typical.

2.3 Adaptive Hybrid Differential Evolution Particle Swarm Optimization

A hybrid metaheuristic strategy is employed in this research to handle the power loss issue in a distribution system. The suggested technique intends to hybridize PSO part with DE called AHDEPSO, to increase the speed of convergence and the optimal fitness value. DE takes longer time to converge although it has high capability in local search. Meanwhile, PSO converges than other algorithms and tends to be trapped in local optima and gives premature convergence.

AHDEPSO starts with an initialization and the evaluation of the population. Next, a normal DE method and advances to the production of the trial vector. If the experimental course outperforms the associated target course in terms of fitness, it is added to the DE contestant occupant. Simultaneously, the location and velocity update equations are then used by the PSO component to build a new PSO contestant occupant from the contestant occupant. From this, AHDEPSO will have two contestant occupants then will be evaluated to find the fitness function. This two-fitness function will give AHDEPSO more diversity to find the global best from DE and PSO vector. The population for the following production will be chosen from the best target contestant from the DE and PSO contestant occupant. The process is iterated in the goal of finding better answers or achieving optimum values. The velocity and position update techniques work together to let the PSO algorithm traverse the search space more efficiently and converge quicker. The velocity update approach directs particles to the best solution identified thus far by any particle in the swarm, whereas the position update method directs particles to a wide range of viable solutions and keeps them from being stuck in local optima. Finally, the large scaling factor is set in the initial stage to increase the exploration. The scaling factor is then self-updated based on latest global best due to the DE vector. The scaling factor shrinks down so that the search will focus on that location to get the best solution. The suggested AHDEPSO algorithm's primary structure is shown in Algorithm 1 in Figure 3.

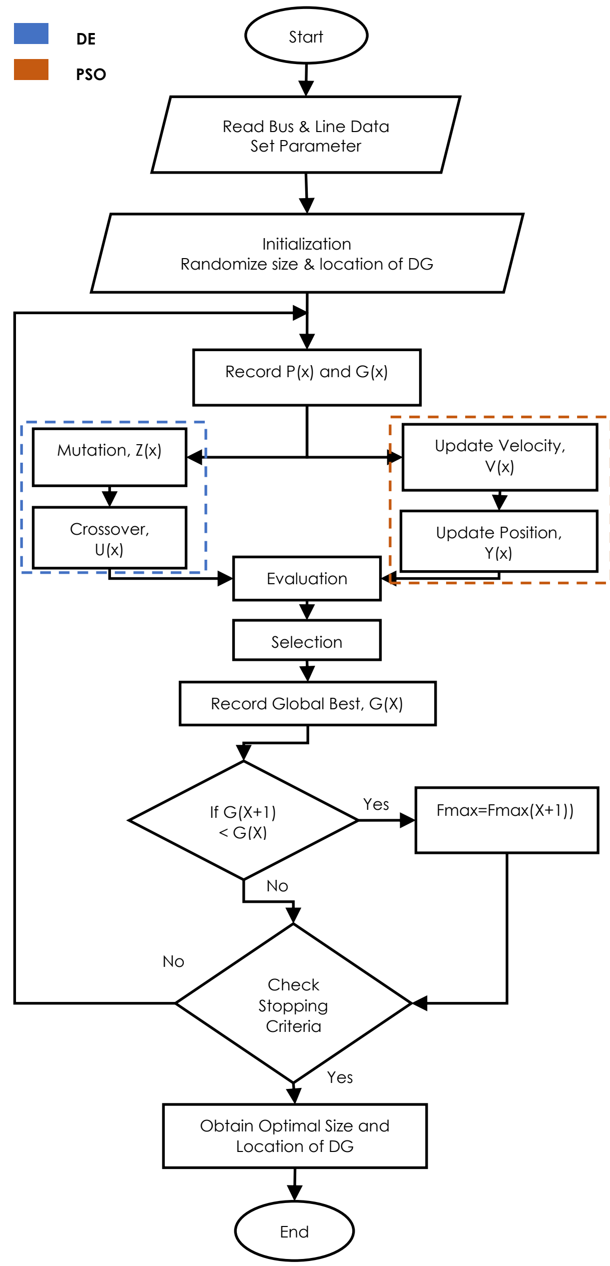


Figure 3 Adaptive Hybrid Differential Evolution Particle Swarm Optimization algorithm

The following are the primary stages of the suggested algorithm:

The algorithm will read the bus and line data for the IEEE-33 and IEEE-69 bus system to be used as the system. Then the parameter is set up before the initialization.

2.3.1 Initialization

The size and location of the DG is randomized for the algorithm creates an initial set of population (NP) that includes the position and size of the DG. Then, each set of NPs is used in the objective function (OF) to find the power loss, a solution Xg is produced (t). The power flow method used in the given algorithm is the Newton-Raphson (NR) method. As a result, the OF and solution vector may be written as in Equations (6), (7), (8) and (9).

$$OF = \text{Minimize } P_{loss(x,y)} \quad (6)$$

$$\text{Minimize } P_{loss(x,y)} = \sum \frac{P_x^2 + Q_x^2}{|V_x|^2} \times R_x \quad (7)$$

$$NP(t) = [X_1(t), X_2(t), \dots X_{NP}(t)] \quad (8)$$

$$X_g(t) = [X_{g,1}(t)\ , X_{g,2}(t), \dots\ X_{g,D}(t)] \quad (9)$$

From the initial solution, personal best, P_p and global best, P_G will be determined.

2.3.2 Update Personal and Global Best

After the initialization, the personal and global best will be recorded. P(X), Represents the best position and cost that a particle has achieved so far. While, G(X), Represents the best position and cost achieved by any particle in the swarm.

2.3.3 Mutation

Equations (10) and (11) produce a mutant vector Zg(t) from the vector Xg(t), j = 1,2,3, NP.

$$Z_g(t) = [z_{g,1}(t)\ , z_{g,2}(t), \dots\ z_{g,D}(t)] \quad (10)$$

$$z_{g,j}(t) = [X_{g,v1}(t) + F\ (X_{g,v2}(t) - X_{g,v3}(t))] \quad (11)$$

In differential iteration, F is a scaling factor in the range [0 1] to govern exploration and exploitation. The vector indices v1, v2, and v3 were picked at random.

2.3.4 Crossover

To increase the variety of the population vectors, the crossover mechanism is implemented. Equation (12) and (13) may be used to construct a trial vector Ug(t).

$$U_g(t) = u_{g,1}(t), u_{g,2}(t) \dots, u_{g,D}(t) \quad (12)$$

$$u_{g,j}(t) = \begin{cases} z_{g,j}(t)\ if random[0,1] \le CR \\ X_{g,h}(t), otherwise \end{cases} \quad (13)$$

2.3.5 Updating the Vlocity and Position of the Particle

To improve the exploitation capability of DE, the velocity and position update method inspired from PSO is integrated with DE. Equation (14) is be used to create the velocity vector.

$$V_G(t) = w(V_G(t-1) + C_1 r_1(P_G(t) - U_G(t)) + C_2 r_2(P_p(t) - U_G(t)) \quad (14)$$

where V_G is the velocity of vector G, P_G is the global best position of all vectors and P_p is the personal best position of vector g. $C1$ and $C2$ are the weights for the personal and global best positions, respectively; r_1 and r_2 are random values ranging from 0 to 1, and w is the inertial weight. Equation (15) will be used to update each trial vector.

$$Y_G(t) = U_G(t) + V_G(t) \quad (15)$$

Where Y_G is the position of vector g.

2.3.6 Evaluation

The new population set is produced after it go through the PSO and DE part which is $U_g(t)$ and $Y_G(t)$ respectively. These vectors will be evaluated in the OF as stated in Equation (6). The solution obtained then is used in the selection process.

2.3.6 Selection

Power loss will be used as a selection factor for the following generation's population. The size and location of DG produced are included in the power flow analysis to obtain the fitness value (power loss). The minimum power loss is chosen as the best fitness function in this algorithm. Equation (16) is used to pick the vector for the following generation

$$X_G(t+1) \begin{cases} U_G(t), & if\ f(U_G(t)) < f(Y_G(t))\ and\ f(U_G(t)) < f(X_G(t)) \\ Y_G(t), & if\ f(Y_G(t)) < f(U_G(t))\ and\ f(Y_G(t)) < f(X_G(t)) \end{cases} \quad (16)$$

From Equation (16), the global best will be replaced with DE population when objective function from DE vector is lower than global best before and PSO objective function, $f(Y_G(t))$. While the PSO population will replace global best when PSO fitness function is lower from global best before and DE fitness function.

2.3.7 Adaptive Scaling Factor

After the new global best is updated, the algorithm will update the new scaling factor, F_{max}. Initially, F is randomized from 0 to 1. The scaling factor is then adaptively updating the new value itself when the global best is updated. The limit scaling factor will change to [0 F_{max}]. This F_{max} is produced by randomized value in the iteration before. These shrunk values of scaling factor will help the algorithm to exploit more at that solution area.

$$F_{max+1} = \begin{cases} F_{max-1}, if\ X_G(t+1) = U_G(t) \\ F_{max}, otherwise \end{cases} \quad (17)$$

Where F_{max-1} is the value of scaling factor randomized in the iteration before and F_{max+1} is the new values of max limit scaling factor that will be used for the next iteration to randomize it.

3.0 RESULTS AND DISCUSSION

The effectiveness of the HDEPSO algorithm is evaluated on the IEEE 33 and IEEE 69 bus to obtain the minimum power loss in the system. AHDEPSO performance is compared with former PSO, former DE, Firefly, Fixed HDEPSO and Range HDEPSO algorithms to observe the capability of exploration and exploitation of each algorithm. To investigate the impact of scaling factor on the optimal solution, fixed scaling factor and randomized scaling factor are applied in AHDESPO, named fixed HDEPSO and range HDEPSO

This research measures performance by obtaining the power loss by each algorithm. The mean, standard deviation and worst of the fitness value are calculated to analysis the algorithm performance. The time to converge and the convergence rate were also recorded to analysis the algorithm convergence behaviors. PSO convergence time was set as reference for the convergence rate. Table 3 shows the parameter values for the algorithms [36-38]and 30 trials are executed for each.

Table 3 Parameter settings for the optimization algorithms

Algorithms	Parameter	Value
AHDEPSO	Inertia Weight	1
	Damping Ratio	0.99
	Fmax	1
	Fmin	0
	C	0.8
PSO	Inertia Weight	1
	Damping Ratio	0.99
DE	F	0.7
	C	0.8
FA	gamma	1
	beta	2
	alpha	0.2
	alpha_damp	0.98

The population size and number of iterations for all algorithms were set to 20 and 200, respectively.

3.1 Analysis of Proposed Optimization Method on IEEE-33 Bus

Table 4 shows the results of AHDEPSO, fixed HDEPSO, range DEPSO DE, PSO, DE, and FA for optimizing 3 DG units in IEEE 33-bus system. The result included best, worst, mean, and standard deviation (SD) values of the fitness value across 30 trials. The best, worst, and average values produced by AHDEPSO outperform those obtained by other techniques. The mean value, often known as the average, represents the center tendency of the algorithm's results while the standard deviation is a measure of the dispersion or spread of the algorithm's results. It indicates the amount by which solutions depart from the mean value. A smaller standard deviation implies that the answers are densely grouped around the mean value, while a larger standard deviation suggests that the solutions are more dispersed.

Table 4 Statistical results of the fitness functions for IEEE 33 bus

Data	PSO	DE	FA	Fixed HDEPSO	Range HDEPSO	AHDEPSO
Best (MW)	0.08501	0.0832	0.0827	0.0824	0.0823	0.0823
Worst (MW)	0.1053	0.085	0.1058	0.083	0.0828	0.0859
Mean (MW)	0.0935	0.0835	0.0929	0.0826	0.0826	0.0845
SD	0.00526	5.75E-04	0.00862	1.90E-04	1.50E-04	7.10E-15
Convergence Time (s)	15.64 (35th)	13.22 (37th)	4.43 (4th)	35.23 (149th)	40.77 (168th)	14.34 (40th)
Convergence Rate %	-	15%	71.68%	-125.25%	-160.68 %	8.31 %

The value of SD for PSO and Firefly are the greatest which is led to wide dispersed of the solutions found by the algorithms and indicate that PSO and FA have high in exploration. The former DE has lower SD than Fixed HDEPSO and Range HDEPSO. This shows that DE has lower exploration in this case. In this case, AHDEPSO shows the lowest SD from another algorithm. It is because with the implementation of PSO update velocity and position method encourages the algorithm to optimize faster.

FA algorithm exploits better than others where it gives the fitness value, 0.0827 MW lower than PSO and DE. PSO give the largest fitness value, 0.08501 MW followed by DE, 0.0832 MW. Even though DE gives 15% converge faster than PSO, the exploitation in DE is not the best as the fitness value is not the lowest. While the Fixed HDEPSO gives the second lowest value of fitness value and Range HDEPSO and AHDEPSO provides the lowest value of fitness function. The result shows that Fixed HDEPSO is good in exploitation followed by Range HDEPSO and AHDEPSO is the best in exploitation. This exploitation is affected by the scaling factor which motivates the algorithm to exploit better to find the fitness value.

In terms of speed, FA shows its ability to converge fastest than others. However, the FA gives the premature convergence as it converges at 4th iteration with 4.43 seconds and indirectly it cannot be considered as stable algorithm to optimize this problem.

Meanwhile, DE is the most stable algorithm in terms of speed as DE converges fastest than HDEPSO variant. Fixed HDEPSO and Range HDEPSO obtained the slowest speed which -125.25% and -160.68%, respectively and this shows both algorithm is the low in achieving convergence. The proposed algorithm only improved the convergence rate by 8.31%. However, the stability of DE and AHDEPSO can be compared with the solution quality to indicate which is the most stable. In addition, the fitness value gained by AHDEPSO is better than DE, this can be concluded that the solution quality of AHDEPSO is better than DE and AHDEPSO is more stable than DE. The impact of the scaling factor also can be seen clearly as only randomized scaling factor is not guarantee the HDEPSO to be a stable algorithm and increase the speed of convergence. By capping the scaling factor, it helps AHDEPSO to increase the convergence speed as well as to make the algorithm stable.

The value of the fitness function at the best solution found by the algorithm can be used as an indicator of accuracy. A smaller value indicates that the solution is closer to the true optimal solution and therefore more accurate. PSO show the least accuracy as gained the highest value of fitness value. FA shows a better accuracy than DE, but FA gives the premature convergence as it converges too early. The fixed HDEPSO algorithm obtained the second-best fitness value while Range HDEPSO and AHDEPSO produced the same best fitness value. However, AHDEPSO shows a better accuracy than Range HDEPSO as the convergence rate is better than Range HDESPO.

Based on the Table 5, the optimal locations and sizes of DG for the IEEE-33 bus system were evaluated using various algorithms, including PSO, DE, FF, Fixed HDEPSO, Range HDEPSO, and AHDEPSO. PSO suggests placing DGs at buses 7, 14, and 29, each with a size of 2 MW, indicating a straightforward distribution strategy with larger capacities at fewer locations. In contrast, DE proposes a more varied approach with DGs at buses 16, 24, and 31, with sizes of 0.82 MW, 1.32 MW, and 0.95 MW, respectively, aiming for a balanced power loss reduction across the network. Similarly, FF distributes DGs at buses 27, 23, and 21, with sizes of 0.97 MW, 1.05 MW, and 1.11 MW, indicating a different optimization approach for power flow and loss reduction.

Table 5 Optimal Location and Size of DG for IEEE-33 Bus

Algorithm / Optimal Solution	PSO	DE	FF	Fixed HDEPSO	Range HDEPSO	AHDEPSO
DG Location (Bus No.)	7	16	27	14	24	24
	14	24	23	29	29	29
	29	31	21	24	14	14
DG Size (MW)	2	0.82	0.97	0.79	1.21	1.22
	2	1.32	1.05	1.27	1.27	1.21
	2	0.95	1.11	1.11	0.82	0.83

Fixed HDEPSO suggests placing DGs at buses 14, 29, and 24, with sizes of 0.79 MW, 1.27 MW, and 1.11 MW, combining elements of DE and PSO for effective power loss reduction. Range HDEPSO also combines elements of DE and PSO but suggests slightly different DG sizes and locations, with DGs at buses 24, 29, and 14, and sizes of 1.21 MW, 1.27 MW, and 0.82 MW. The hybrid nature of these algorithms aims to balance the power loss reduction and the efficient power distribution across the network.

AHDEPSO, being the most advanced hybrid algorithm, suggests DGs at the same locations as Range HDEPSO but with sizes of 1.22 MW, 1.21 MW, and 0.83 MW, indicating a fine-tuned optimization solution for minimal power loss. Overall, the hybrid algorithms, especially AHDEPSO, offer a refined approach for optimizing DG placement and sizing, effectively balancing power distribution and loss reduction. The adaptive nature of AHDEPSO highlights its potential superiority in achieving the most efficient reduction of power loss due to its refined approach in DG placement and sizing.

As seen from Figure 4, there are various optimization algorithms that tend to minimize the objective function related to power loss in the distribution network over 200 iterations. Among these algorithms are DE, PSO, AHDEPSO as well as Firefly, Fixed HDEPSO, and Range HDEPSO. Being the most efficient amongst all tested algorithms, AHDEPSO exhibits steady-state behaviour of objective function values resulting in a minimum power loss of 0.0823 MW. Although it reaches its final value by the fourth iteration, Firefly does not improve beyond that and has a larger power loss than AHDEPSO. In comparison with DE and PSO which quickly converge too but cannot achieve the efficiency of AHDEPSO, with final power losses of 0.0832 MW and 0.08501 MW respectively.

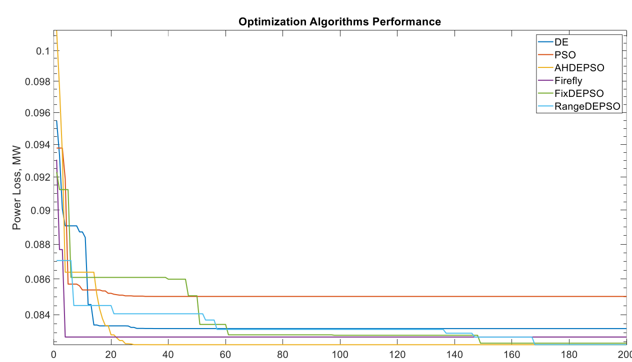


Figure 4 Iteration of the six algorithms for IEEE 33 bus

While Fixed HDEPSO and Range HDEPSO do show some improvements at reducing power loss, they cannot match the performance of AHDEPSO. The convergence patterns for these methods indicate some progress over time; however, this progress is insufficient when compared to low-power losses demonstrated by AHDEPSO algorithm. Moreover, AHDEPSO has very low standard deviation in terms of performance implying robustness and stability during optimization process.

The performance of the AHDEPSO algorithm was evaluated against other optimization techniques, including DE, PSO, Firefly, Fixed HDEPSO, and Range HDEPSO, to assess how well they maintain bus voltage levels in a distribution network. Figure 5 illustrates the voltage profiles across various bus numbers for each algorithm.

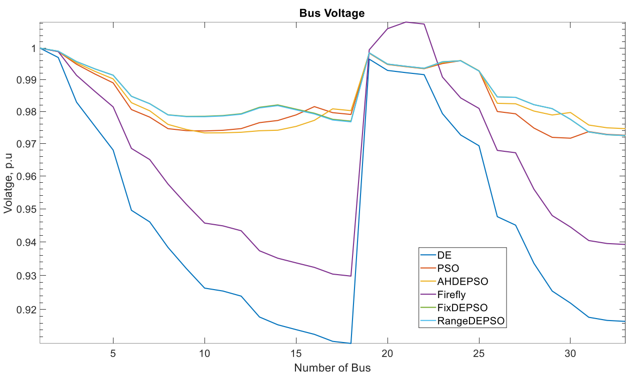


Figure 5 Bus Voltage for the six algorithms for IEEE-33 bus

This algorithm AHDEPSO is the first to hold a higher voltage level at most buses which indicates its stability unlike DE and PSO that have wide voltage drops, especially around bus numbers 10 and 25. The reduced voltage drops and the smoother curve under AHDEPSO's case shows that it performs better in terms of power losses reduction and voltage stabilization.

Crucially, AHDEPSO's algorithm makes certain that the voltages are kept within acceptable range from 0.95 p.u to 1.05 p.u as per operational requirements. Conversely, other algorithms show voltage levels approaching or falling below this lower limit indicating possible difficulties in maintaining reasonable voltages during changing load conditions.

AHDEPSO achieves superior results due to its hybrid nature which combines the exploratory potential of DE with the exploitative power of PSO hence yielding a more robust optimization process altogether. This study therefore supports AHDEPSO as an appropriate selection for DG optimization in distribution networks with improved overall system reliability and voltage regulation also confirmed by the survey findings.

3.2 Analysis of Proposed Optimization Method on IEEE-69 Bus

Table 5 shows the results of AHDEPSO, HDEPSO, PSO, DE, and FA to optimize 5 DG units in IEEE 69-bus system. The AHDEPSO algorithm also outperforms other algorithms where minimum fitness value is produced compared to others.

For a large and more complicated system, AHDEPSO has the capability of computing 38.3% faster than other algorithms and at the same time produces the lowest fitness value. The SD for AHDEPSO is the lowest (0.00036), indicating the highest precision and least variability in the solutions found by the algorithm. This shows that AHDEPSO has the lowest exploration level due to its highly clustered solutions. The low SD is attributed to the implementation of the PSO update velocity and position method, which leads this algorithm to the optimal solution faster. The PSO algorithm has the second-lowest SD (0.00060), which suggests it also has a low exploration level. This is followed by DE (0.00080), HDEPSO (0.00120), and FF (0.00270). The relatively higher SD for DE indicates a higher exploration level compared to HDEPSO and FF, with FF having the highest exploration level among the algorithms.

Table 5 Statistical results of the fitness functions for IEEE 69 bus

Data	PSO	DE	FF	HDEPSO	AHDEPSO
Best (MW)	0.0768	0.0720	0.0808	0.0733	0.0699
Worst (MW)	0.0805	0.0780	0.1058	0.0820	0.0701
Mean (MW)	0.0795	0.0755	0.0929	0.0786	0.0715
SD	0.0006	0.0008	0.0027	0.0012	0.00036
Convergence Time (s)	18.08 (45^{th})	30.32 (162^{nd})	14.95 (6^{th})	18.94 (119^{th})	11.16 (70^{rd})
Convergence Rate %	-	-67.7%	17%	-4%	38.3%

The results shown in Table 5 indicate that HDEPSO exploits better than others, giving a fitness value (0.0733 MW) lower than PSO (0.0768 MW), DE (0.0720 MW), and FF (0.0808 MW). FF gives the largest fitness value (0.0929 MW), followed by PSO (0.0795 MW). Even though DE provides a fitness value better than PSO and FF, its exploitation is not the best as the fitness value is not the lowest. HDEPSO gives the second-lowest fitness value, with AHDEPSO providing the lowest fitness function value (0.0699 MW). This shows that AHDEPSO is the best in exploitation, followed by HDEPSO. This exploitation is influenced by the scaling factor, which helps the algorithm exploit better to find the optimal fitness value.

In terms of speed, AHDEPSO converges the fastest among the algorithms, with a convergence time of 11.16 seconds at the 70th iteration and a convergence rate of 38.3%. FF follows, converging in 14.95 seconds at the 6th iteration. However, FF suffers from premature convergence, making it less stable for optimizing this problem. DE is the least stable algorithm in terms of speed, with a convergence time of 30.32 seconds at the 162nd iteration. HDEPSO obtained the third-fastest convergence speed (18.94 seconds at the 119th iteration) and is the second most stable due to FF's premature convergence. The proposed AHDEPSO algorithm improved the convergence rate by 38.3%.

In terms of solution quality, AHDEPSO provides the most stable solution, achieving the best fitness value. In a larger system, the impact of adapting the scaling factor becomes more apparent in maintaining the balance between exploration and exploitation. Even though AHDEPSO has a low exploration level due to its low SD, this algorithm has the highest accuracy, consistently maintaining the best fitness value. The PSO update velocity and position method helps AHDEPSO quickly reach the optimal solution area, enhancing early exploration. Furthermore, the shrinking scaling factor helps consistently achieve the best fitness value.

FF gives the lowest accuracy compared to DE, PSO, and HDEPSO. The DE algorithm offers a more accurate solution than PSO but cannot match the solution quality of HDEPSO and AHDEPSO, as DE's fitness value is lower. Additionally, AHDEPSO provides the lowest fitness function value compared to other algorithms. Although FF converges first in calculating the objective function, there are no changes in value from the 4th iteration onward. DE and PSO tend to converge early but still cannot provide the lowest fitness value like AHDEPSO.

Different algorithms such as DE, HDEPSO, PSO, FF and AHDEPSO were used to determine the optimal locations as well as sizes for DGs in IEEE-69 bus system as per Table 6.

Table 6 Optimal Location and Size of DG for IEEE-69 Bus

Algorithm / Optimal Solution	PSO	DE	FF	HDEPSO	AHDEPSO
DG Location (Bus No.)	51	37	47	53	61
	60	68	35	47	61
	50	50	41	68	10
	61	66	56	50	2
	50	64	51	61	18
DG Size (MW)	0.93	0.51	0.73	0.50	0.50
	0.50	1.29	1.87	1.99	1.65
	1.45	0.71	1.15	0.63	0.50
	1.27	0.52	1.88	1.00	1.34
	0.72	0.50	0.84	1.52	0.50

For PSO however, it proposes positioning of DGs at buses 51, 50, 60, 61 and 50 with their sizes being 0.93 MW, 1.45 MW ,0.5MW ,1.27MW and 0.72 MW respectively. This approach suggests a combination of low to very high capacities that are spread around multiple locations to optimize power loss reduction.

On the other hand, though DE's technique coordinates this action by offering small and medium sized DG facilities in various points across the network, such as in buses 37,64 ,68 ,66, and 50 whose respective powers are 0.5 MW,0.5Mw,0.71 Mw,1.29 Mw, and 0.52Mw.

FF on its part has placed DG at Buses numbered 47,35,41,56,51 with respective areas of capacities being:0.73 kW;1.87 kw;1.15kw ;1.88 kw and 0.84kw Consequently this will mean a different optimization strategy which would emphasize larger capacities at fewer places where better load flow control and reducing losses can be attained or achieved. These DGs can be located at buses 53, 47, 68, 50 and 61 with sizes of 0.50 MW, 1.99 MW, 0.63 MW, 1.00 MW and 1.52 MW respectively as suggested by HDEPSO. It combines DE and PSO in this strategy with different sizes of DGs for effective power loss reduction.

In line with this finding, AHDEPSO suggests that there should be a DG at bus number 61, capable of producing 50kW of electricity to serve it; along with those that must be installed at points 61,2,10 and 18 which have got capacities of 1.65 MW, 0.5 MW,1.34 MW and 0.5 MW respectively. This shows the best optimization solution for minimizing power loss because DE's advantages are combined with PSOs'. Its adaptability is evident from the fact that it uses higher order polynomial expressions since placing DGs in DE are not constant.

As a result, hybrid algorithms particularly AHDEPSO has been refined to provide an approach towards optimal sizing of distribution system components (DG placement). The adaptive nature of AHDEPSO means it can achieve the least possible power losses thereby being the best among all other techniques studied herein.

Figure 6 displays the performance of different optimization algorithms in minimizing power loss for the IEEE 69 bus distribution network over 200 iterations. The algorithms compared are DE, PSO, AHDEPSO, FF, and HDEPSO.

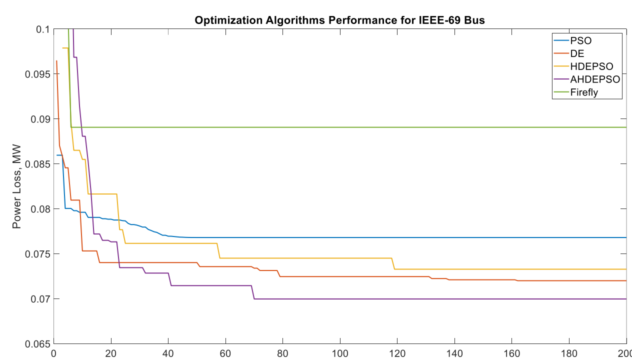


Figure 6 Iteration of the all algorithms for IEEE-69 bus

Among these algorithms, AHDEPSO demonstrates the most efficient performance, achieving a minimum power loss of 0.0699 MW. It converges quickly and steadily, reaching its optimal value in early iterations. This rapid and effective convergence highlights AHDEPSO's capability to find the best solution efficiently.

FF algorithm, although converging rapidly within a few iterations, does not improve further and results in a higher power loss of 0.0808 MW compared to AHDEPSO. DE and PSO also converge relatively quickly but do not reach the same efficiency level as AHDEPSO, with final power losses of 0.0720 MW and 0.0768 MW, respectively.

HDEPSO shows notable improvements in reducing power loss and achieves a power loss of 0.0733 MW. This algorithm demonstrating better performance than PSO and FF but not surpassing AHDEPSO.

The convergence patterns of these algorithms indicate varying degrees of efficiency and stability. AHDEPSO not only achieves the lowest power loss but also exhibits a very low standard deviation, indicating robustness and consistent performance during the optimization process.

Overall, the AHDEPSO algorithm stands out as the most effective and reliable method for minimizing power loss in the IEEE 69 bus distribution network, demonstrating superior optimization capabilities compared to the other algorithms tested.

Other optimizers like Firefly, PSO, DE and HDEPSO were used to compare their performance against that of AHDEPSO for maintaining bus voltages in a distribution network. The voltage of the buses is displayed in Figure 7 across several different bus numbers per each algorithm.

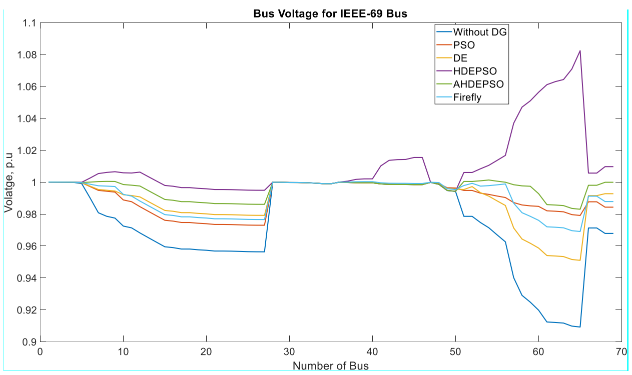


Figure 7 Bus Voltage for the six algorithms for IEEE-69 bus

This algorithm AHDEPSO is the first to hold a higher voltage level at most buses, which indicates its stability, unlike DE and PSO that have wide voltage drops, especially around bus numbers 10 and 25. The reduced voltage drops and the smoother curve under AHDEPSO's case show that it performs better in terms of power losses reduction and voltage stabilization.

Essentially, this algorithm by AHDEPSO ensures that voltages are maintained within the range between 0.95 p.u to 1.05 p.u according to operating limits. Conversely, other algorithms show voltage levels approaching or falling below this lower limit, indicating possible improper size and location of DG optimized by those algorithms.

AHDEPSO achieves superior results due to its hybrid nature, which combines the exploratory potential of DE with the exploitative power of PSO, hence yielding a more robust optimization process altogether. This study, therefore, supports AHDEPSO as an appropriate selection for DG optimization in distribution networks with improved overall system reliability and voltage regulation, as also confirmed by the survey findings.

4.0 CONCLUSION

This research will demonstrate how the Adaptive Hybrid Differential Evolution Particle Swarm Optimization (AHDEPSO) algorithm outperforms PSO, DE, and Firefly in optimizing DG. The combination of a DE and PSO results in this hybrid approach which makes it possible to enhance both exploration and exploitation abilities hence leading to a better convergence thus, better optimization. Key findings showed that AHDEPSO minimized power losses well having a power loss of 0.0823 MW compared to PSO's 0.08501MW and DE's 0.0832 MW. This decline indicates a tangible increase in the overall performance efficiency of the distribution network.

Moreover, AHDEPSO algorithm keeps bus voltages within its optimal range; 0.95 p.u.<V<1.05 p.u., hence ensuring stability and lowering voltage drops more effectively as opposed to other algorithms. In addition, this confirms its effectiveness under smoother voltage profile observed mainly at critical bus numbers with respect to AHDEPSO. Moreover, it has taken less time for AHDEPSO to reach convergence than many other algorithms because its convergence time is very much shorter by up to 38.3% than those of others.

Power loss reduction, voltage stabilization and convergence efficiency are areas where AHDEPSO outperforms other optimization tools like Firefly, PSO and DE in comparative analysis. The hybrid approach inherent in AHDEPSO combines the strengths of both DE and PSO making it a more effective solution for DG optimization in RDS. Significantly, the AHDEPSO algorithm is a substantial leap towards improving performance metrics across different parameters for DG optimization. It is highly dependable and efficient due to its ability to minimize power losses, sustain voltage stability and achieve fast convergence; thus, enhancing the operation of distribution networks. Therefore, this study advocates for the implementation of AHDEPSO as a reliable and robust tool for optimization with respect to power systems' reliability and efficiency increase

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Conflicts of Interest

The author(s) declare(s) that there is no conflict of interest regarding the publication of this paper.

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