Power Loss Minimization in Radial Distribution Systems with Simultaneous Placement and Sizing of Different Types of Distribution Generation Units Using Improved Artificial Bee Colony Algorithm

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Abstract: Power loss is considered as one of the important indicators used to quantify the performance of distribution networks. Minimisation of power losses with integration of distributed generation (DG) units in distribution systems has gained significant momentum due to the associated techno – economic incentives. In this paper, a novel Improved Artificial Bee Colony Algorithm (IABC) is developed to robustly detect the optimal site and size of DG units for minimisation of total power losses without violating the equality and inequality constraints. The proposed algorithm is simulated in MATLAB environment, and the effectiveness of the algorithm is validated on IEEE – 34 bus and IEEE – 69 bus radial distribution systems. The performance of the proposed technique has been validated by comparing the results obtained from other compete algorithms. Comparisons show that the proposed technique is more efficient in terms of simulation results of power loss and convergence property than the other reported algorithms, suggesting that the solution obtained is a global optimum.

Keywords : Distributed Generation, Artificial Bee Colony Algorithm, Power Loss Minimization, Optimal Location, Radial Distribution System

Abbreviations

DG	Distributed Generation
ABC	Artificial Bee Colony
DE	Differential Evolution
IABC	Improved Artificial Bee Colony
GA	Genetic Algorithm
PSO	Particle Swarm Optimization
IA	Improved Analytical
BFOA	Bacteria Foraging Optimization Algorithm
ACO	Ant Colony Optimization
IWD	Intelligent Water Drop
OKH	Oppositional Krill Herd
CABC	Chaotic Artificial Bee Colony
IWO	Invasive Weed Optimization
BBO	Biogeography-based optimization
IMDE	Intersect Mutation Differential Evolution
GWO	Grey Wolf Optimizer
HGWO	Hybrid Grey Wolf Optimizer
IWO	Invasive Weed Optimization
CTLBO	Comprehensive Teaching Learning-Based Optimization

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1. Introduction

In recent years, the penetration of intermittent renewable energy sources such as wind and solar into the India's energy profile has increased significantly. The Government of India (GoI) has set ambitious renewable electricity targets for the short to medium term. By 2022 the country aims to have 175 GW of installed renewable electricity capacity [1, 2]. Energy sources utilized in this manner are known as distributed generation (DG) units. Distributed generation (DG) refers to relatively small generation systems that are designed, installed, and operated in distribution networks or distributed at the customer side to meet special customers' needs and support the operation of distribution networks based on economic, efficient, convenient, and reliable generation [3]. From the perspective of utilities, integration of DG units can bring multiple technical benefits to distribution networks such as loss reduction, voltage profile improvement, voltage stability, network upgrade deferral and reliability while supplying energy sales as a primary task [4].

The distribution system is well-known for its high R/X ratio and significant voltage drops that could cause substantial power losses along the feeders [5]. It is added that the distribution system incurs a power loss which is normally higher than the transmission system. For instance, a study by Wong *et al*. [6] and Nourai *et al*. [7] has showed that an American Electric Power's distribution system incurred a loss in the range of 7–9% when compared to the transmission loss of 2.5–8.5%. This figure would be much higher in radial distribution systems (RDSs) with a high R/X ratio. Consequently, distribiution loss reduction has been one of the greatest challenges to power distribution utilities worldwide, both in matured and growing power systems. Loss reduction at the distribution system level is one of the major benefits due to its impact on the utilities' revenue. In addition, as a key consideration for DG planning, the loss reduction can lead to positive impacts on system capacity release, voltage profiles and voltage stability [8]. Renewable energy based DG units are developing fast all over the world in recent years due to its promising potential to minimize power losses and harmful carbon emissions. However, the challenges in DG applications for loss reduction are proper location, appropriate sizes, and operating strategies. Even if the location is fixed due to some other reasons, improper size would increase the losses in the system beyond the losses for case without DG. Hence, optimal location and size of DG in the RDS is most important to harness the maximum benefits from the DG when connected with the RDS. Further, optimal location and sizing depend on the type of DG as well [9].

Most of the techniques currently available in the literature to determine the optimal location and size of DG units for loss reduction are based on the assumption that DGs can only deliver real power. This assumption is unrealistic because there are many types of DGs that provide and/or consume both active and reactive powers. The most significant work dealing with all types of DGs has been presented in [10]. The study adopted an Improved Analytical (IA) method, a modification of the method proposed in [11], to obtain the optimal location and size of a single DG unit. Although robust, this method also provides similar results as those of the original analytical method. Moreover, the IA method optimizes the DG size and location separately. Optimal location can only be obtained after determining the optimal size.

The contribution of this paper is to find the globally optimal site and size of different types of DG units simultaneously, for minimization of losses in the RDS, using an Improved Artificial Bee Colony (IABC) optimizer. In the proposed IABC approach, the exploration ability of Artificial Bee Colony (ABC) algorithm and the exploitation ability of Differential Evolution (DE) algorithm are integrated to enhance the performance of both algorithms in searching of optimal minimum objective function. The effectiveness of the proposed algorithm is validated on IEEE 33 - and 69 - bus RDS with two different test cases. The results show that in terms of optimality of the solution, IABC has outstanding performance in attaining the simultaneous optimal location and sizing of different types of DG units in the distribution network for power losses reduction, thereby suggesting that the solution is a globally optimal one.

2. Literature Review

Most of the DG allocation and sizing studies were performed with the objective of real power loss minimization. In all such studies, optimal location and sizing of DG units has been investigated by minimizing active power loss in the distribution lines through DG allocation. In this section, the existing research works on DG allocation and sizing problem for power loss minimization are reviewed from the viewpoint of used optimisation algorithms. Many algorithms have been proposed by various researchers to determine the location and sizesof DGs for minimizing power losses in the distributed network.

A summary of prominent research studies that have been conducted in the past to determine the optimal location and sizing of DG units for loss minimization in radial distribution networks is presented in Table 1.

Table 1. Summary of various optimization methods for DG allocation and sizing for loss minimization

Author(s)	Objective	Optimization Method	IEEE Test System	Year
Wang and Nehrir [12]	Power loss minimization in the system	Analytical Approach	6 and 30 bus	2004
Keane and O'Malley [13]	Minimizing the system losses	Linear Programming Approach	Irish Distribution Network	2005
Acharya *et al.* [11]	Power loss minimization	Analytical Method	16, 33 and 69 bus	2006
Borges and Falcao [14]	Minimization of power loss	GA	Experimental Test System	2006
Harrison *et al.* [15]	Power loss minimization	Hybrid GA – OPF	69 bus	2008
Injeti *et al.* [16]	Power Loss Reduction	Particle Swarm Optimization (PSO)	33 and 69 bus	2011
Hung *et al.* [17]	Loss Minimization	Improved Analytical	16, 33 and 69 bus	2013
Imran and Kowsalya [18]	Minimization of losses	Bacterial Foraging Optimization Algorithm (BFOA)	33 and 69 bus	2014
Moradi *et al.* [19]	Minimization of power loss in distribution system	ICA - GA	33 and 69 bus	2014
Prabha *et al.* [20]	Total line loss minimization	Intelligent Water Drop (IWD)	10, 33 and 69 bus	2015
Kefayat *et al.* [21]	Minimization of loss and total emissions	Hybrid Ant Colony Optimization (ACO) and Artificial Bee Colony (ABC)	33 and 69 bus	2015
Sultana and Roy [22]	Line loss minimization	Oppositional Krill Herd (OKH) Algorithm	33, 69 and 118-bus	2015
Mohandas *et al.* [23]	Power loss minimization in the system	Chaotic Artificial Bee Colony (CABC) algorithm	33 and 69 bus	2015
Prabha *et al.* [24]	Total line loss minimization	Invasive Weed Optimization (IWO)	33 and 69 bus	2016

Author(s)	Objective	Optimization Method	IEEE Test System	Year
Kansal *et al.* [25]	Power loss reduction	Hybrid Analytical and Heuristic Approach	33 and 69 bus	2016
Khodabakhshian and Mohammad [26]	Power loss minimization	IMDE	33 and 69 bus	2016
Sanjay *et al.* [27]	Minimization of power loss	Hybrid Grey Wolf Optimizer (HGWO)	33, 69 and Indian 85 bus	2017
Mohan and Albert [28]	Line loss minimization	GA - PSO	33, 69 and Portuguese 94 bus	2017
Quadri *et al.* [29]	Network loss reduction	Comprehensive Teaching Learning-Based Optimization (CTLBO)	33, 69 and 118 bus	2018
Duong et al. [30]	Power loss reduction	Biogeography-based optimization (BBO)	33 and 69 bus	2019
M'hamdi *et al.* [31]	Power loss minimization	GWO, WOA and PSO	33 and 69 bus	2020
Suresh and Edward [32]	Loss Reduction	Hybrid GOA - CS	33 and 69 bus	2020

Based on the above review, it is clear that considerable research has been conducted to resolve the DG allocation problem. However, most of the studies are based on the assumption that DGs can only deliver real power. In addition, most of the studies didn't provide the optimal solution for simultaneously allocating a mix of different DG types. In recent years, researchers have been interested to solve the optimal placement of different types of DGs simultaneously in the RDS for more loss reduction and better voltage profile. In simultaneous placement of different types of DGs, there is a need for combined or hybrid techniques for global optima with fast convergence. To bridge this gap, this paper contributes to develop an efficient hybrid algorithm IABC using ABC and DE for solving the simultaneous placement of different types of multiple DG units to reduce the losses in the RDS.

DG can be classified into four major types based on their terminal characteristics in terms of real and reactive power delivering capability as follows [10]:

a. *Type 1: DG capable of injecting P (i.e. real power) only.*
b. *Type 2: DG capable of injecting Q (i.e. reactive power) only.*
c. *Type 3: DG capable of injecting both P and Q.*
d. *Type 4: DG capable of injecting P but consuming Q.*

Photovoltaic , micro-turbines, fuel cells, which are integrated to the main grid with the help of converters/inverters are good examples of Type1. Type 2 could be synchronous compensators such as gas turbines. DG units that are based on synchronous machine (cogeneration, gas turbine, etc.) fall in Type 3. Type 4 is mainly induction generators that are used in wind farms [17].

In this paper, an Improved Artificial Bee Colony (IABC) algorithm which is a hybrid algorithm that integrates ABC (Artificial Bee Colony) and DE (Differential Evolution) is proposed for solving the simultaneous placement of differentatypes of multiple DG units for minimizing the losses in RDS with three scenarios.

- **Scenario I:** Placement of Type III DGs alone.
- **Scenario II:** Placement of Type I and II DGs simultaneously.
- **Scenario III:** Placement of Type II and III DGs simultaneously.

In all the three scenarios, both real and reactive power is injected into the system by different type of multiple DGs. The schematic diagram with load and different types of DGs is shown in Figure 1.

3. Problem Formulation

The total real power loss in power system is represented by Eq. (1), popularly known as "exact loss formula" [11]:

$$P_{Loss}=\sum_{i=1}^{N}\sum_{j=1}^{N}\left[\alpha_{ij}\left(P_iP_j+Q_iQ_j\right)+\beta_{ij}\left(Q_iP_j-P_iQ_j\right)\right] \tag{1}$$

Where

$$\alpha_{ij}=\frac{r_{ij}}{V_iV_j}cos\left(\delta_i-\delta_j\right),\quad \beta_{ij}=\frac{r_{ij}}{V_iV_j}sin\left(\delta_i-\delta_j\right);$$

$V_i\angle\delta_i$ the complex voltage at the ith bus;

$r_{ij}+x_{ij}=Z_{ij}$ the ijth element of $[Z_{bus}]$ impedance matrix;

P_i and P_j the active power injections at the ith and jth buses, respectively;

Q_i and Q_j the reactive power injections at the ith and jth buses, respectively;

N the number of buses

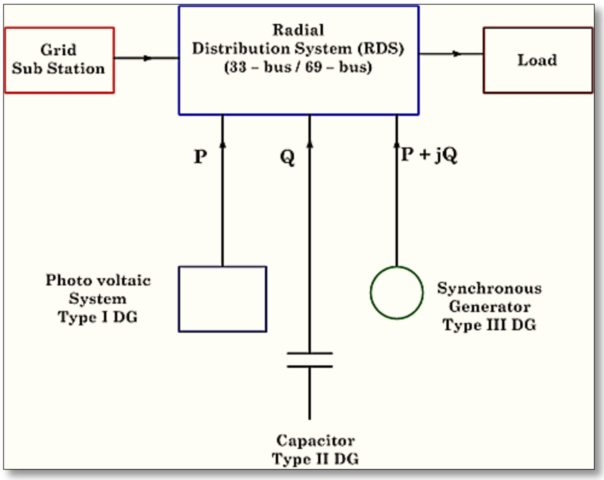

Figure 1. Schematic diagram of RDS with load and different types of DGs

In the current study, the main objective of simultaneously placing and sizing DG units in RDS is to minimize power losses while satisfying all operating constraints. Thus, the objective function is formulated as:

Minimize f = min (P_{Loss})

Subject to the following equality and inequality constraints

(a) Power balance constraint

Sum of all incoming and outgoing real and reactive power at each bus must be zero. Mathematically, expressed as:

$$P_{Gi}-P_{Di}-V_i\sum_{j=1}^{N}V_jY_{ij}cos\left(\delta_i-\delta_j-\theta_j\right)=0 \tag{2}$$

$$Q_{Gi}-Q_{Di}-V_i\sum_{j=1}^{N}V_jY_{ij}sin\left(\delta_i-\delta_j-\theta_j\right)=0 \tag{3}$$

(b) Voltage limits

In order to maintain the quality of supply, the voltage profile of the network should be maintained to an acceptable range. The voltage limits at all the buses of the RDS can be expressed as follows:

$$V_{i\,min} \leq V_i \leq V_{i\,max} \tag{4}$$

(c) Line power flow

All the branch apparent power flows should be maintained within their thermal capacities to maintain the line security.

$$S_{ij} \leq S_{ij\,max} \tag{5}$$

(d) DG capacity limits

The minimum and maximum pre-specified limits of the realiand reactive power capacity of DG units at candidate buses can be expressed as follows:

$$P_{DGi}^{min} \leq P_{DGi} \leq P_{DGi}^{max} \tag{6}$$

$$Q_{DGi}^{min} \leq Q_{DGi} \leq Q_{DGi}^{max} \tag{7}$$

Where,

$$Q_{DGi} = P_{DGi} \tan\left[\cos^{-1}\left(pf_{DGi}\right)\right] \tag{8}$$

$$i \in \{1,2,......,N_{DG}\}$$

(e) DG power factor limit

The minimum and maximum pre-specified limits of the power factors of DG units at candidate buses can be expressed as follows:

$$pf_{DGi}^{min} \leq pf_{DGi} \leq pf_{DGi}^{max} \tag{9}$$

Where,

$$i \in \{1,2,......,N_{DG}\}$$

4. Proposed Methodology

The problem of optimal locating and sizing of different types of multiple DG units simultaneously in RDS is solved by IABC algorithm. The proposed IABC algorithm is a hybrid metaheuristic algorithm combining the features of Artificial Bee Colony (ABC) algorithm and Differential Evolution (DE) algorithm. First, a brief description of ABC algorithm is presented, and then the proposed algorithm is explained in the following sections.

A. Overview of Artificial Bee Colony (ABC) Algorithm

The ABC algorithm is an optimization algorithm based on the intelligent foraging behavior of honey bee swarm, proposed by Derviş Karaboğa in 2005 [33]. In ABC algorithm, the colony of artificial bees contains three groups of bees known as employed bees, onlookers, and scouts. A bee going to the food source visited by itself is called an employed bee. For every food source, there is only one employed bee. The number of employed bees is equal to the number of food sources around the hive. A bee waiting on the dance area for making decision to choose a food source is called an onlooker. A bee carrying out random search is called a scout. The onlookers observe the dance of the employed bees within the hive to select a food source, whereas scouts search randomly for new food sources. The employed bees comprise the first half of the colony, whereas the second half consists of the onlookers. In the context of ABC algorithm, the number of food sources (that is the employed or onlooker bees) is considered equivalent to the number of solutions in the population. Furthermore, the position of a food source signifies the position of a promising solution to the optimization problem, whereas the quality of nectar of a food source represents the fitness cost (quality) of the associated solution. To apply ABC algorithm, the considered optimization problem is first converted to the problem of finding the best parameter vector that minimizes an objective function. Then, the artificial bees randomly discover a population of initial solution vectors and then iteratively improve them by employing the strategies, moving toward better solutions by means of a neighbor search mechanism while abandoning poor solutions.

The search cycle of ABC algorithm consists of three steps: (i) sending the employed bees to a food sources and then measuring the nectar quality, (ii) selecting the food sources by the onlookers after sharing the information of employed bees and determining the nectar amount of the foods, and (iii) determining the scout bees and then sending them onto possible food sources.

In ABC optimization algorithm, the position of a food source represents a possible solution of the optimization problem, and the nectar amount of a food source corresponds to the quality (fitness) of the associated solution. The number of the employed bees or the onlooker bees is equal to the number of solutions in the population. Initially, the algorithm generates a randomly distributed initial population of N solutions, where N denotes the size of population. For each solution (food source), $x_i(i=1,2,......,N)$ is a D-dimensional parameter vector. After initialization, the population of the positions (solutions) is subjected to repeated cycles of the search processes of the employed bees, onlooker bees, and scout bees. The algorithm is implemented as explained below:

Let $X_i = \{x_{i,1}, x_{i,2}, ..., x_{i,n}\}$ represent *ith* solution in the swarm, where n is the dimension of the solution vector. Each employed bee X_i generates a new candidate solution V_i in the neighbourhood of the present position as given by the equation below:

$$\mathbf{V_{i,k} = X_{i,k} + \varphi_{i,k} (X_{i,k} - X_{j,k})} \tag{10}$$

Where, X_j is a randomly selected candidate solution $(i \neq j)$, k is a random dimension index selected from the set $\{1,2,........,N\}$, and $\varphi_{i,k}$ is a random number within [-1,1]. Once the new candidate solution V_i is generated, a greedy selection is used. If the fitness value of V_i is better than that of its parent X_i, then update X_i with V_i; otherwise, keep X_i unchanged. After all employed bees complete the search process, they share the information of their food sources with the onlooker bees through waggle dances. An onlooker bee evaluates the nectar information taken from all employed bees and chooses a food source with a probability related to its nectar amount. This probabilistic selection is really a roulette wheel selection mechanism that is described by the following equation:

$$P_i = \frac{fit_i}{\sum_j fit_j} \tag{11}$$

where, fit_i is the fitness value of the *ith* solution in the swarm. As seen, the better the solution i, the higher the probability of the *ith* food source selected. If a position cannot be improved over a predefined number (called limit) of cycles, then the food source is abandoned. If the abandoned source is X_i, then the scout bee discovers a new food source to be replaced with *ith* food source as expressed by the equation below:

$$X_{i,k} = l_{b,j} + rand(0,1)\left(u_{b,j} - l_{b,j}\right) \tag{12}$$

Where *rand (0, 1)* is a random number within [0, 1] based on a normal distribution, l_b and u_b are lower and upper boundaries of the *ith* dimension, respectively.

The implementation of the algorithm is illustrated with the following steps:
1. Initialize population with random solutions.
2. Evaluate fitness of the population.
3. Check for convergence.
4. Select sites for neighbourhood search.

5. Recruit bees for selected sites and evaluate their fatnesses.
6. Select the fittest bee from each patch.
7. Assign remaining bees to search randomly and evaluate their fatnesses.
8. End.

The main advantage of ABC lies in that it conducts local search in each iteration. ABC can produce a more optimal solution and thus is more effective than the other methods in several optimization problems. However, the main drawback of ABC is that in the searching process of ABC, only one vector is updated at each time for both employed bee phase and onlooker bee phase. Although this update strategy has a good exploitation, it will result in ABC easily falling into local optima when solving complex multimodal problems. The convergence rate of the algorithm also decreased.

B. Improved Artificial Bee Colony (ABC) Algorithm

To overcome the limitation of conventional ABC algorithm, mutation process of Differential Evolution (DE) is incorporated in the conventional ABC algorithm for enhancing the speed of the searching process.

B.1 Efficient search operation based on DE

DE algorithm introduced by Storn and Price, 1997 [34] is a branch of evolutionary programming used to solve optimization problems. Among the evolutionary methods, DE is a simple population-based search method used for global optimization of real-valued functions. This heuristic search technique is useful to optimize the nonlinear and non-differentiable continuous space problems. This method exhibits faster convergence and is easier to implement, and it has few control parameters. DE is similar to GA as it uses the evolutionary operators such as selection, recombination, and mutation as in GA. However, DE differs from GA in a mutation scheme that makes DE self-adaptive and in the selection process. In DE, all the solutions have the same chance of being selected as parents. DE employs a greedy selection process: the better one of new solution and its parent wins the competition providing significant advantage of converging performance over GAs.

The standard mutation operator of DE needs three randomly selected different individuals from the current population for each individual to form a simplex-like triangle. It prevents premature local convergence and ensures global convergence in the final stage as all individuals in general evolve to one optimal point.

Among the several variants of DE algorithm based on the mutation strategy, the frequently used method of mutation strategy is DE/best/1. The differential mutation operation generates a mutated individual given by:

$$V_i = X_{best} + F\left(X_{r1} - X_{r2}\right) \tag{13}$$

where $r_1, r_2 \in \{1, 2, ..., N\}$ are randomly chosen integers, which are different from each other and also different from the running index *i*, and *F* is the mutation constant ranging between 0 and 2 that controls the amplification of the difference between two individuals.

In DE/best/1, the solutions explored in the history are used to direct the movement of the current population. Based on the variant DE algorithm and the property of ABC, the solution search equation is devised as follows:

$$ABC/best/1: v_{i,j} = x_{best,j} + F(x_{r1,j} - x_{r2,j}) \tag{14}$$

where x_{best} is the best individual vector with the best fitness in the current population; and *j* is randomly chosen indexes.

The mutation process shown in Eq. 14 is incorporated into the employed bee phase of ABC and the Improved Artificial Bee Colony (IABC) algorithm is developed. Hence, the updated variables are increased and the information about the best solution of the current population is utilized to enrich the searching behavior and to avoid being trapped into a local optimum.

The parameters of the IABC algorithm are the colony size (NP=50), the number of food sources (SN=NP/2), the limit for scout, L = SN×D, D is the dimension of the problem and a Maximum Cycle Number (MCN=500).

The flowchart for IABC algorithm for solving the problem of optimal placement and sizing of DG units is shown in Figure 2.

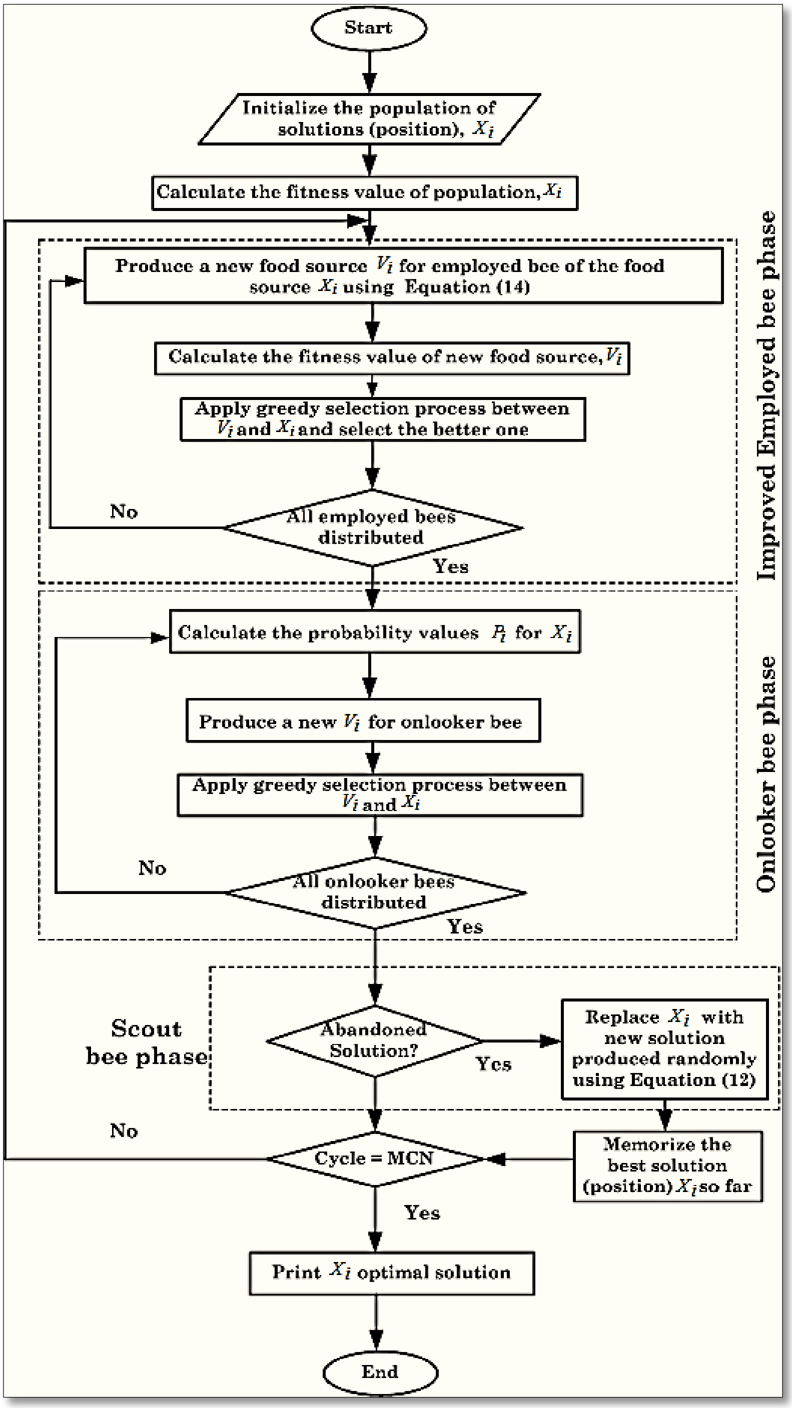

Figure 2. Flowchart of Improved Artificial Bee Colony Optimization Algorithm

5. Results and Discussions

To verify the effectiveness of the proposed IABC algorithm, the IEEE 33-bus and 69-bus RDS are considered in the different scenario for different test cases. Also, the results are compared with the results obtained from other methods. The proposed IABC algorithm is implemented in MATLAB and is executed on an Intel core^{TM} i3 PC with 2.66-GHz speed and 4GB RAM.

For all the three scenarios that are mentioned in literature review, the following two test cases are considered.

- **Test case -1**: Two numbers of DGs in each type.
- **Test case -2**: Three numbers of DGs in each type.

A. IEEE – 33 Bus Radial Distribution System

The single line diagram of IEEE 33-bus distribution system is shown in Figure 3 [20]. The system voltage is 12.66 kV and total system active and reactive loads are 3715 kW and 2300 kVAr, respectively. This test system consists of 33 buses and 32 branches. For 33-bus system without installation of DG real, reactive power losses are 210.954 kW and 143.0324 kVAR respectively.

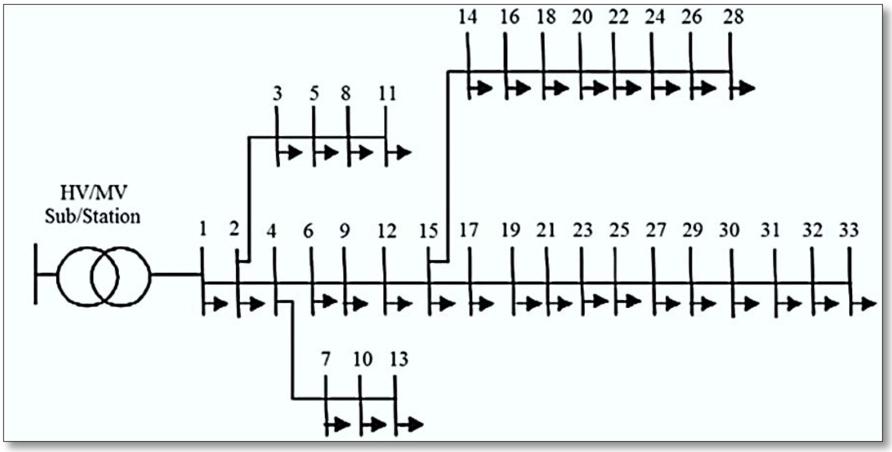

Figure 3 Single line diagram of IEEE 33-bus radial distribution system

In the scenario I, only Type III DGs are used for supplying real and reactive power to the system. At first, for the scenario I with both test cases, ABC and IABC algorithms are implemented. The results obtained in one trail among many trails are compared and given in Table 2. From this table, it is observed that the number of iteration and computational time required to attain the global optimum using IABC algorithm is lesser than the number of iteration and computational time using ABC algorithm.

Table 2. Performance of ABC and IABC with 33-bus RDS for scenario I

Test Case	Method	Optimal Location and Size of DGs			Total DG Capacity (MVA)	Power Loss (kW)	Percentage Loss Reduction	Number of Iterations	Time (sec)
		Bus No	Size (MVA)	Power factor					
1	ABC	13	0.933	0.91	2.489	28.50	86.49[1]	287	66.30
		30	1.546	0.731					
	IABC	**13**	**0.934**	**0.91**	**2.491**	**27.89**	**86.78**	**55**	**9.35**
		30	**1.547**	**0.73**					
2	ABC	14	0.841	0.898	3.482	11.79	94.41	464	109.70
		24	1.181	0.891					
		30	1.458	0.721					
	Proposed IABC	**13**	**0.876**	**0.90**	**3.506**	**11.74**	**94.43**	**75**	**12.75**
		24	**1.189**	**0.90**					
		30	**1.441**	**0.71**					

The convergence characteristics for both the algorithms are compared and shown in Figure 4. From this figure, it is clear that the IABC approach takes less number of cycles compared to ABC algorithm that required more than 250 cycles to reach the objective function (i.e. minimization of power loss). Hence, the proposed algorithm reduces the computational time significantly. To verify the superiority of the IABC algorithm, it has been implemented for above mentioned three scenarios with two test cases.

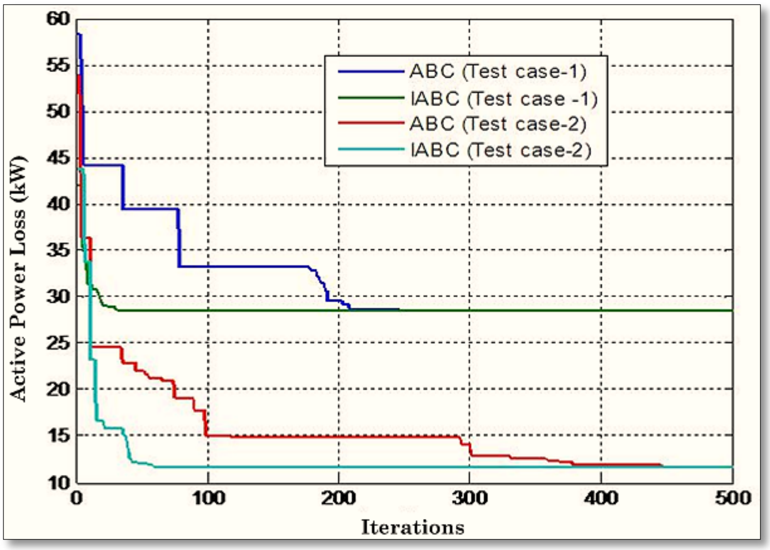

Figure 4. Convergence of ABC and IABC for 33 – bus RDS for scenario I

A.1 Comparison of Performance of IABC and other Methods for Scenario - I

Simulation results of 33-bus RDS for the scenario – I are compared with other methods and presented in Table 3. It is observed from Table 3, that for the scenario - I, the loss reduction percentage given by test case-2 is higher than the loss reduction percentage

[1]The percentage loss reductions is calculated as:

$$\frac{(\text{Active Power Losses}-(\text{kW}))_{\text{without DG}}-(\text{Active Power Losses}-(\text{kW}))_{\text{withDG}}}{(\text{Active Power Losses}-(\text{kW}))_{\text{without DG}}}\times 100\%=\frac{210.954-28.50}{210.954}\times 100\%=86.49\%$$

given by test case-1.When compared to IA, CLS-MINLP, A-PSO methods, the proposed algorithm gives the lowest real power losses 28.45 kW for the test case-1.The optimal power factors of two number of Type III DGs attained by the proposed technique (0.91, 0.73) and APSO (0.91, 0.72) are also more or less same. In the test case-2, the real power loss obtained from the proposed technique is obtained as 11.15 kW which is lower than the results (23.05kW, 21.05 kW, 15.91 kW and 12.74 kW) obtained by the methods IA, BFOA, HACO - ABC and IWO respectively. At the same time, the optimal power factors of Type III DGs obtained by the proposed technique (0.90, 0.90, and 0.71) are almost same as that of PSO and BBO

Table 3. Comparison of Performance of IABC and other methods with 33-bus RDS for scenario - I

Test Case	**Optimization Method**	**Type III DGs**			**Total DG Capacity (MVA)**	**Power Loss (kW)**	**Percentage Loss Reduction**
		Bus No	**Size (MVA)**	**Power factor**			
1	IA [17]	6	2.117	0.845	3.176	44.83	78.76
		30	1.058	0.85			
	HGWO [26]	13	0.927	0.883	2.866	29.30	86.09
		30	1.936	0.80			
	PSO [16]	13	1.038	0.912	2.547	28.97	86.27
		30	1.509	0.729			
	Proposed IABC	**13**	**0.935**	**0.90**	**2.491**	**28.45**	**86.52**
		30	**1.557**	**0.73**			
2	IA [17]	6	1.058	0.85	2.86	23.05	89.08
		14	0.74	0.85			
		30	1.059	0.85			
	BFOA [18]	14	0.786	0.88	3.134	21.05	90.02
		25	1.002	0.64			
		30	1.348	0.62			
	HACO-ABC [21]	12	1.014	0.85	3.337	15.91	92.46
		25	0.960	0.85			
		30	1.363	0.85			
	IWO [24]	13	0.880	0.87	3.498	12.74	93.95
		24	1.186	0.88			
		30	1.432	0.80			
	BBO [29]	13	0.883	0.90	3.52	11.94	94.35
		24	1.189	0.90			
		30	1.448	0.71			
	PSO [16]	13	0.872	0.90	3.499	11.77	94.43
		24	1.185	0.89			
		30	1.438	0.71			
	Proposed IABC	**13**	**0.875**	**0.90**	**3.507**	**11.15**	**94.52**
		24	**1.188**	**0.90**			
		30	**1.442**	**0.71**			

A.2 Comparison of Performance of IABC and other Methods for Scenario – II

Comparison of performance of IABC and other methods for scenario II are given in Table 4. From the Table 4, it is observed that the loss reduction percentage obtained in scenario II is same as that of scenario I for both test cases. The proposed technique offers lowest real power losses (28.10 kW) when compared to other methods such as IMDE (32.08kW) and GA-PSO (28.55kW) for test case-1. Similarly, when considering test case-2, proposed method gives the better result of power loss reduction (11.65 kW) than the results (11.80kW and 11.75kW) obtained by the methods PSO and GA-PSO respectively for the same optimal locations (14, 24 and 30).

Table 4 Comparison of Performance of IABC and other methods with 33-bus RDS for scenario – II

Test Case	Method	Type I DGs		Type II DGs		Power Loss (kW)	Percentage Loss Reduction
		Bus No.	Size (MW)	Bus No.	Size (MVAR)		
1	IMDE [26]	10	1.079	16	0.253	32.079	84.78
		31	0.895	30	0.933		
	GA – PSO [28]	13	0.829	12	0.435	28.56	86.46
		30	1.113	30	1.035		
	Proposed IABC	**13**	**0.845**	**12**	**0.445**	**28.10**	**86.63**
		30	**1.136**	**30**	**1.043**		
2	PSO [16]	14	0.752	13	0.364	11.81	94.41
		24	1.074	24	0.515		
		30	1.027	30	1.007		
	GA – PSO [28]	14	0.754	13	0.365	11.75	94.42
		24	1.076	24	0.517		
		30	1.029	30	1.009		
	Proposed IABC	**14**	**0.753**	**13**	**0.371**	**11.55**	**95.12**
		24	**1.075**	**24**	**0.516**		
		30	**1.027**	**30**	**1.010**		

A.3 Comparison of Performance of IABC and other Methods for Scenario – III

In scenario III, Type II and III DGs are installed simultaneously in the system for attaining minimum objective function. The real power is supplied only by Type III DGs and reactive power is supplied by both Type II and Type III DGs. The simulation results obtained for 33-bus RDS with scenario III are compared with other methods and shown in Table 5. It reveals that the loss reduction percentage obtained by using scenario III is higher than the loss reduction obtained by implementing scenario I and II for both test cases. In scenario III, proposed approach yields lowest power losses (24.50kW and 10.28 kW) for test cases-1 and 2 respectively among all three scenarios for both test cases-1 and 2. For the test case-2, proposed method gives lowest active power loss (10.28 kW), when compared to the power losses (17.01 kW and 14.00 kW) obtained by the methods GA-PSO and ICA-GA respectively.

Table 5. Comparison of Performance of IABC and other methods with 33-bus RDS for scenario III

Test Case	Method	Type II DGs		Type III DGs			Power Loss (kW)	Percentage Loss Reduction
		Bus No.	Size (MVAR)	Bus No.	Size (MVA)	Power factor		
1	CTLBO [29]	25	0.521	14	1.526	0.72	26.89	87.25
		12	0.356	24	1.012	0.81		
	IABC	**24**	**0.468**	**30**	**1.454**	**0.79**	**24.50**	**88.30**
		6	**0.280**	**13**	**0.903**	**0.90**		
2	GA – PSO [28]	12	0.151	14	0.765	0.88	17.01	91.94
		30	0.451	25	0.787	0.85		
		32	0.150	30	0.927	0.90		
	ICA – GA [19]	8	0.152	13	0.877	0.905	14.10	93.35
		18	0.152	24	1.187	0.90		
		30	0.299	30	1.269	0.81		
	IABC	**22**	**0.103**	**14**	**0.826**	**0.836**	**10.28**	**95.12**
		26	**0.278**	**24**	**1.173**	**0.90**		
		32	**0.193**	**30**	**1.256**	**0.90**		

The comparison of convergence characteristics for 33 – bus RDS with Test Case – 2 for all the three scenarios is shown in Figure 5. The figure reveals that the losses provided by the scenario III are lowest among all the scenarios I, II &III.

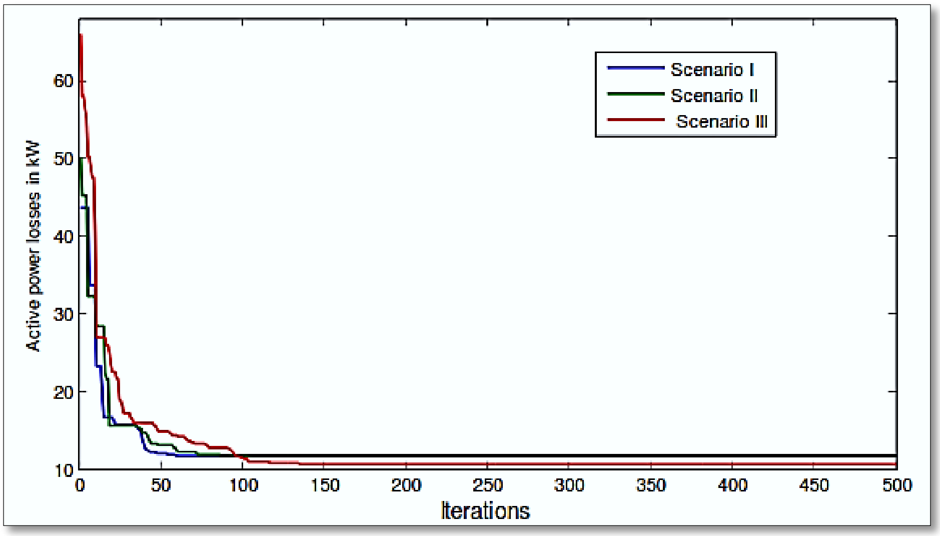

Figure 5. Comparison of Convergence Characteristics for 33 – bus RDS for all three Scenarios

B. IEEE – 69 Bus Radial Distribution System

The IEEE 69-bus distribution system with 12.66-kV base voltage (Baran and Wu, 1989) is shown in Figure 6 is employed in this paper. It consists of one slack bus and 68 load buses. The total real and reactive power demand is 3802.190 kW and 2694.600 kVAr, respectively. This test system consists of 69 buses and 68 branches. For 69-bus system without installation of DG real, reactive power losses are 225.023 kW and 102.1763 kVAR respectively.

B.1 Comparison of performance of IABC and other methods for Scenario – I

From the results of 69-bus RDS for the scenario - I, given in Table 6, it is observed that the loss reduction percentage given by proposed approach with Test case-2 is higher (98.10%) than the Test case-1 (96.80%). Considering Test case-1, the proposed method provides the percentage of loss reduction (96.80%) higher than that of percentage of loss reduction offered by other techniques like A-PSO and CLS-MINLP. Also, for test case-2, the percentage of power loss reduction (98.10%) given by proposed technique is higher than the percentage of power loss reduction (95.10%, 97.87% and 97.90%) provided by the other methods GA-PSO, A-PSO and PSO respectively. At the same time, proposed method yields same results as that of the results obtained using CLS-MINLP and ICA-GA methods.

Table 6. Comparison of Performance of IABC and other methods with 69-bus RDS for scenario - I

Test Case	**Method**	**Type III DGs**			**Total DG Capacity (MVA)**	**Power Loss (kW)**	**Percentage Loss Reduction**
		Bus No	**Size (MVA)**	**Power factor**			
1	HGWO [26]	17	0.633	0.824	2.765	7.31	95.10
		61	2.131	0.814			
	PSO [16]	17	0.63	0.82	2.75	7.31	95.10
		61	2.12	0.81			
	Proposed IABC	**17**	**0.630**	**0.82**	**2.762**	**7.20**	**96.80**
		61	**2.131**	**0.81**			
2	GA – PSO [28]	18	0.510	0.71	2.495	10.33	95.10
		61	1.627	0.77			
		64	0.358	0.81			
	HACO-ABC [21]	18	0.48	0.77	3.07	4.71	97.87
		61	2.06	0.83			
		66	0.53	0.82			
	PSO [16]	11	0.60	0.83	3.120	4.61	97.90
		18	0.46	0.81			
		61	2.06	0.81			
	IWO [24]	11	0.608	0.814	3.123	4.55	97.91
		17	0.458	0.828			
		61	2.056	0.814			
	ICA – GA [19]	11	0.608	0.814	3.121	4.46	97.92
		18	0.454	0.833			
		61	2.059	0.813			
	IABC	**11**	**0.647**	**0.82**	**3.120**	**4.27**	**98.10**
		21	**0.415**	**0.83**			
		66	**2.057**	**0.82**			

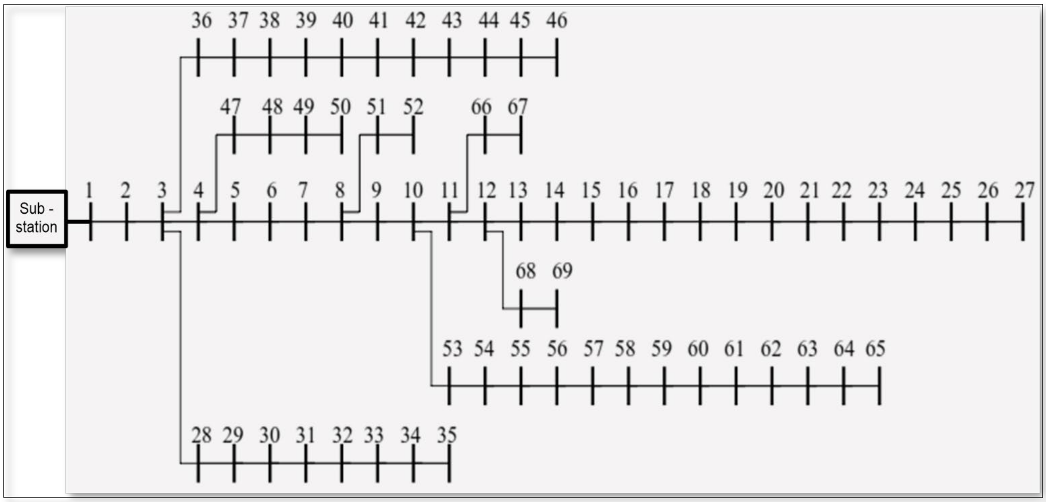

Figure 6. Single line diagram of IEEE 33-bus radial distribution system

B.2 Comparison of performance of IABC and other methods for Scenario – II

Table 7. Comparison of Performance of IABC and other methods with 69-bus RDS for scenario II

Test Case	Method	Type I DGs		Type II DGs		Power Loss (kW)	Percentage Loss Reduction
		Bus No.	Size (MW)	Bus No.	Size (MVAR)		
1	IMDE [26]	24	0.479	61	1.192	13.83	93.84
		62	1.738	63	1.234		
	PSO [16]	17	0.517	17	0.352	7.59	96.63
		61	1.725	61	1.234		
	GA – PSO [28]	17	0.517	17	0.352	7.21	96.79
		61	1.725	61	1.234		
	Proposed IABC	**17**	**0.517**	**17**	**0.353**	**7.20**	**96.80**
		61	**1.734**	**61**	**1.238**		
2	PSO [16]	11	0.633	18	0.326	5.15	97.70
		21	0.321	53	0.206		
		61	1.647	61	1.192		
	GA – PSO [28]	11	0.518	11	0.375	4.27	98.10
		20	0.358	21	0.230		
		61	1.670	61	1.194		
	Proposed IABC	**11**	**0.495**	**11**	**0.374**	**4.25**	**98.11**
		17	**0.379**	**21**	**0.230**		
		61	**1.673**	**61**	**1.196**		

Comparison of performance of IABC and other methods for scenario II are given in Table 7. From the Table 7, it is clear that the scenario II obtained the same real power loss as that obtained in scenario - I, irrespective of the approaching methods for both Test cases 1 and 2. For Test case-1, the proposed method presents lowest losses (7.20kW) than the losses (13.83kWand

7.59kW) given by IMDE and PSO respectively. However, the proposed technique offers the same result as that of the result given by the method A-PSO, due to same optimal locations (17& 61) for installing both Types I and II DGs. When considering test case-2, active power loss (4.25kW) obtained by the proposed method is lower than the losses (5.15kW and 4.27kW) provided by the approaches PSO and A-PSO respectively.

B.3 Comparison of performance of IABC and other methods for Scenario – III

In scenario III, to achieve the minimum objective function (i.e. minimization of real power loss), Type II and Type III DGs are placed simultaneously in the RDS. The simulation results of 69-bus RDS for scenario - III is presented in Table 8. From Table 8, it is observed that as reactive power is injected into the system using Type II and Type III DGs, the loss reduction is higher than the loss reduction in scenario II for both test cases 1 and 2.

Table 8. Comparison of Performance of IABC and other methods with 69-bus RDS for scenario - III

Test Case	Method	Type II DGs		Type III DGs			Power Loss (kW)	Percentage Loss Reduction
		Bus No.	Size (MVAR)	Bus No.	Size (MVA)	Power factor		
1	**Proposed IABC**	**11**	**0.353**	**17**	**0.579**	**0.90**	**5.43**	**97.58**
		49	**0.569**	**61**	**2.106**	**0.82**		
2	GA – PSO [28]	11	0.150	18	0.515	0.85	8.02	96.43
		49	0.150	61	1.345	0.88		
		61	0.60	64	0.367	0.83		
	Proposed IABC	**9**	**0.236**	**12**	**0.542**	**0.87**	**3.16**	**98.51**
		50	**0.508**	**21**	**0.371**	**0.84**		
		64	**0.205**	**61**	**1.947**	**0.87**		

The comparison of convergence characteristics for 69 – bus RDS for all the three scenarios for test case -2 is shown in Figure 7. The figure reveals that scenario III gives the highest loss reduction among all the three scenarios.

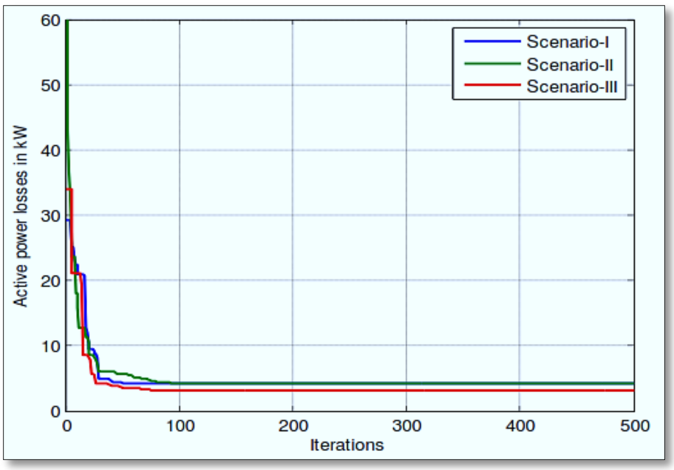

Figure 7. Comparison of Convergence Characteristics for 69 – bus RDS with Test Case – 2 for all the three Scenarios

The loss reduction given by proposed method for all the three scenarios i.e. scenario - I, II & III for both the test cases for 33-bus and 69-bus system is depicted in Figure 8 and Figure 9.

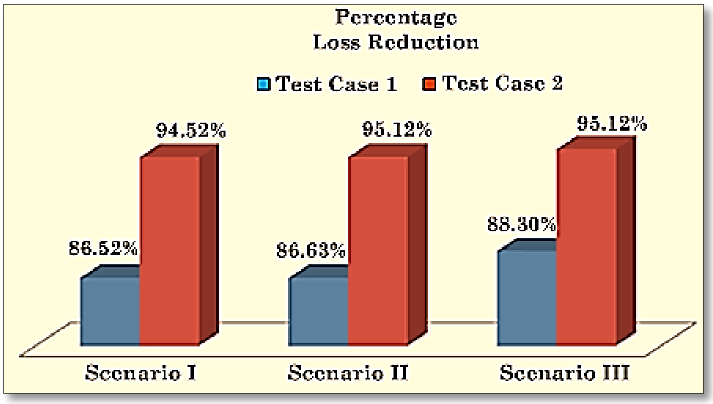

Figure 8. Comparison of Percentage Loss Reduction using IABC for 33 – bus RDS

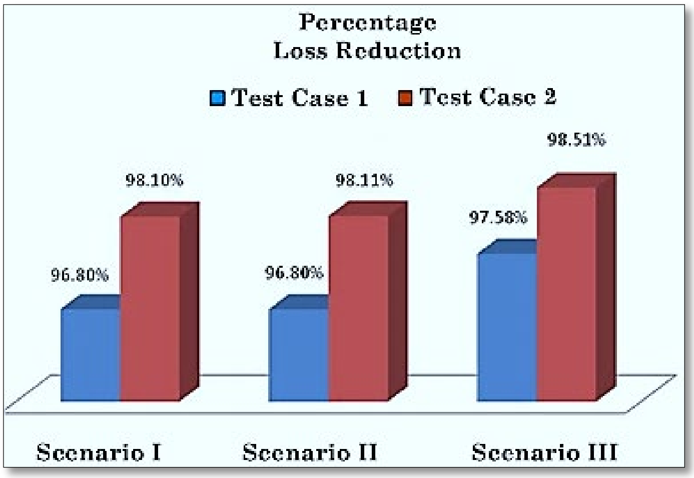

Figure 9. Comparison of Percentage Loss Reduction using IABC for 69 – bus RDS

Among the all scenarios, scenario III provides the highest loss reduction percentage for both test cases 1 and 2 because in scenario III, reactive power is injected into the system by Type II and Type III DGs simultaneously. Consequently, the reactive power supplied by Type III DG is significantly reduced with flat voltage profile and maximum loss reduction in the system. Also, the losses are minimized when the numbers of DGs are increased.

6. Conclusions

In this paper, a novel hybrid IABC algorithm (combining the features of ABC and DE algorithm) for optimal placement and sizing of different types (Type I, II & III DGs) of DGs with the objective for power loss minimization in the RDS is proposed. In order to demonstrate the efficacy and performance of the proposed technique, it is implemented and tested on 33-bus and 69- bus RDS. Results obtained from the proposed technique are compared with those of other compete methods. The empirical findings reveal that the proposed technique exhibits better results in terms of real power loss reduction, and convergence speed. The maximum loss reduction with better voltage profile is obtained using the proposed hybrid IABC technique by optimal siting and sizing of different types of multiple DG units simultaneously than optimal placement and sizing of DGs independently in the RDS. Especially, simultaneous placement of three numbers (Test case-2) of Type II & Type III DGs (Scenario-III) yield maximum loss reduction than simultaneous placement of two numbers (Test case-1) of Type III DGs (Scenario I) and Type I & II DGs (Scenario II). In view of this, the proposed IABC optimizer can provide planning better locations for distributed generation sources and better management of real and reactive power deployment. The author is in discussion with local power DISCOM to implement the proposed optimization algorithm in a real distribution system.

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