Optimal Integration of Multiple Renewable Energy Distributed Generations using Hybrid Optimization Technique

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Abstract- Recent times, the assimilation of renewable energy (RE) based distributed generation (DG) units in power distribution system (PDS) have become a major research area in electric power systems to improve the overall efficiency of PDS by reducing power losses and voltage drops. But, it is desired to integrate DG units at optimal place(s) and size(s) in order to achieve the anticipated objective(s). In this work, a hybrid optimization method using loss sensitivity factor (LSF) and a cuckoo search (CS) meta-heuristic algorithm is implemented for optimizing multiple renewable energy DG units in radial PDS to minimize total real power losses (TRPL). The proposed hybrid technique locates the optimal sites for DG placement using LSF and computes the optimal sizes via CSA. Besides, the computation of LSF significantly curtailed the search area for CSA to optimize DG sizes. The suggested hybrid optimization method is executed on standard symmetrical IEEE radial PDSs with 33 buses and 69 buses. The simulation study for the proposed technique is investigated for multiple Type I (solar photovoltaic system) and Type III (wind turbine) DG allocation. Furthermore, a numerical comparative analysis is performed between proposed and other optimization methods to assess effectiveness of proposed technique. The outcome of the comparative study highlighted that the proposed hybrid technique-based allocation of multiple RE-DGs achieved maximum power loss reduction and better voltage profile than other techniques. Furthermore, the outcome of this research work notified that Type III DG allocation has achieved more objective function minimization than Type I DG allocation.

Keywords Distributed generation, power distribution system, loss sensitivity factor, cuckoo search algorithm.

1. Introduction

Distributed generation (DG) is a unique way of generating electrical power at the distribution network or the point of use. Moreover, DG injects cleaner electricity into distribution networks since most DG technology employs renewable energy resources. The incorporation of renewable energy DGs in the radial distribution system (RDS) results in power loss reduction, reliability enhancement, fuel cost minimization, power quality enhancement and efficiency improvement. The growth of power demand in recent times and the difficulties related to planning and commissioning of new transmission systems plus the environmental concern have created an interest in renewable energy based DG integration in distribution systems [1]. The recent advancement in small generators, storage devices and power electronics devices also significantly increased the accommodation of DGs in RDS [2]. But, inappropriate siting of DGs in RDS ends up in undesirable outcomes such as high power losses, voltage deviation and energy costs. Therefore, DGs must be suitably allocated into RDS in order to get the anticipated benefit.

In the literature, the researchers suggested many optimization techniques for finding the optimal site(s) and size(s) of DG units [3]. Such optimization techniques were categorized into three types [4] such as analytical approaches, heuristic algorithms and a combination of analytical and heuristic algorithms.

In analytical methodologies, a mathematical expression is established to study the effect of DG placement on RDS. A few examples of such approaches are the efficient analytical (EA) method [5], iterative–analytical method [6] and analytical method [7]. Along with this, numerous indices (such as LSF) based methodologies were developed to locate candidate buses for integration of DSTATCOM [8]. Unfortunately, these methodologies have become ineffective whenever the complexity of the problem increases. Hence, these methods are not recommended for allocation of multiple DGs in RDS [9].

In order to overcome the setback of the analytical methods, the researchers have introduced the metaheuristic algorithms for solving complex multiple DG optimization problems since it solves the nonlinear optimization problems without getting into the complexion. Some of the familiar meta-heuristic optimization algorithms used for solving DG optimization problems are Particle swarm optimization (PSO) [10], Genetic algorithm (GA) [11], Ant lion optimizer (ALO) [12], Firefly algorithm (FA) [13], Grey wolf optimizer (GWO) [14], Bat algorithm (BA) [15], Krill herd algorithm (KHA) [16], Salp swarm algorithm (SSA) [17] and Backtracking search optimization algorithm (BSOA) [18].

The DG location and capacity were optimized via GA to reduce real power losses (RPL) and to enhance the magnitude of bus voltage. The performance of GA has been verified on 33 bus and 69 bus distribution power networks. The author(s) in Ref. [19] implemented GA based optimization approach for DS reconfiguration to reduce RPL of 13 bus and 15 bus DS. Solar energy storage system (ESS) was optimally sized and distributed using mixed-integer linear programming (MILP) technique in [20] to optimize the cost. PSO and DE algorithms-based optimization techniques were proposed to optimize multiple DG units in RDS. The DGs locations and capacities were optimized for RPL minimization and voltage improvement. The ideal bus location and sizes for DG units were optimized via BSOA for the objective of RPL reduction [18]. A multi-objective supervised FA-supported optimization method was proposed to optimize DG size and site in unbalanced RDS for an objective of RPL minimization. CSA-based optimization approach was presented in [21] to optimize site and size of single and multiple DG units for reducing RPL and improving voltage magnitude of IEEE 33 bus radial test system. A modified edition of PSO was implemented in [22] to optimize solar PV DG unit for power loss minimization.

The author(s) proposed an Adaptive Quantum inspired Evolutionary Algorithm (AQiEA) based technique to optimize DG into large radial PDSs with 85 bus and 118 bus for reducing TRPL [23]. The proposed technique optimized the DG units into radial PDS with voltage dependent load model. Similarly, AQiEA based optimization technique was implemented in [24] to integrate DG units into a RDS for an objective of TRPL minimization. The proposed methodology consider ZIP (impedance, current and power) load model for DG optimization problem. The optimal sites and sizes for DG and capacitor were optimized via AQiEA [25] to minimize power losses along RDS. The proposed methodology accounted load growth in radial PDS. In addition to above methodologies, hybrid optimization techniques such as TLBO-GWO [26], WIPSO–GSA [27], fuzzy-PSO [28] and analytical–PSO [29] were proposed by the researchers for solving DG optimization problem.

As discussed above, different techniques including analytical, meta-heuristic algorithms and hybrid techniques were implemented by the researchers for optimizing DG units into RDS. These methodologies have given significant results. However, these methodologies often suffer from a slow convergence rate and also get stuck in local optima solutions when complexity of problem increased. Hence, considering the above problem statement, a hybrid optimization method using LSF and CSA is suggested in this work to optimally integrate multiple DG into radial PDS. CSA has distinctive and efficient random walks than other optimization algorithms. This has been effectively utilized for obtaining global optimal solution for various optimization problems. This distinct feature has made CSA superior over other algorithms. But, CSA also suffer from slow convergence rate. Therefore to increase the convergence rate, LSF approach has been integrated along with CSA. The inclusion of LSF effectively reduces the search area for CSA and increases the rate of convergence. The distinct advantage of LSF and CSA are integrated together to achieve global optimal solution at better convergence rate. The contributions of the work presented in this paper are listed below:

- A hybrid technique has been developed using LSF and CSA algorithm for optimizing Type I and III multiple DG placements in RDS.
- LSF for all buses of test system has been computed to locate optimal buses for DG placement.
- The optimal DG sizes of Type I (solar PV) and Type III (WT) has been computed using CSA to cut down TRPL of radial PDS.
- The impact of optimized multiple DG placement on the performance of radial PDS has been examined.
- The outcome of the proposed hybrid optimization method has been related to other optimization techniques to evaluate its effectiveness.

The remaining parts of the research work are presented as different sections as follows: Section 2 emphasizes the DG optimization problem formulation & constraints and DG modelling. Section 3 elaborates on the application of the proposed hybrid technique for multiple DG optimization problems. Section 4 details about the research findings of the proposed hybrid optimization method. Section 5 concludes the research outcome.

2. Problem Definition

The objective of a multi DG allocation problem is to locate the optimal buses and to compute the optimal sizes for multiple RE-DGs that minimize TRPL without violating constraints of RDS. Therefore, the objective function for the multi-DG optimization problem can be formulated as below:

2.1. Objective Function (OF)

The DG sizes are optimized to minimize TRPL of RDS. TRPL minimization is succeeded by minimizing the power loss index (PLI) of RDS [21]. PLI is a ratio between the RPL of RDS with DG placement to the RPL of RDS without DG placement.

$$PLI = \frac{P_{DG,Tloss}}{P_{Tloss}} \tag{1}$$

where, $P_{DG,Tloss}$ is the RPL of RDS after the accommodation of DGs and P_{Tloss} is the RPL without DGs. Therefore, objective function (OF) is expressed as follows:

$$OF = \min(PLI) \tag{2}$$

2.2. Constraints

The fitness value of objective function (OF) is minimized by satisfying numerous constraints related to radial PDS. The constraints accounted for DG optimization in this work are defined below.

2.2.1. DG Power Balance Constraint

The total incoming power to a DN should be equal to the total outgoing power including the DG power rating [30].

$$P_S + \sum_{m=1}^{N_{DG}} P_{DG}(m) = \sum_{m=1}^{L} P_{loss}(m) + \sum_{q=1}^{n} P(q) \tag{3}$$

where, P_s is the substation real power capacity; P_{DG} is a real power capacity of a DG; P_{loss} is the real power loss along a line; P is the real power demand. N_{DG} is a no. of DGs; L and n represents distribution lines and buses in RDS respectively.

2.2.2. Voltage Constraint

The voltage magnitude of buses need to be kept inside a quantified minimum (V_{mini}) and maximum (V_{max}) limit for ensuring safe and stable operation.

$$V_{mini} \leq |V_i| \leq V_{max} \tag{4}$$

2.2.3. DG Power Rating

Total sizes of DGs accommodated in DN must not exceed substation capacity to avert power flow reversal [27].

$$P_{TDG}^{mini} \leq P_{TDG} \leq P_{TDG}^{max} \tag{5}$$

$$Q_{TDG}^{mini} \leq Q_{TDG} \leq Q_{TDG}^{max} \tag{6}$$

where,

$$P_{TDG}^{max} = 0.75 \times \left(\sum_{q=1}^{n} P(q) + \sum_{m=1}^{L} P_{loss}(m) \right) \tag{7}$$

$$Q_{TDG}^{max} = 0.75 \times \left(\sum_{q=1}^{n} Q(q) + \sum_{m=1}^{L} Q_{loss}(m) \right) \tag{8}$$

where, P_{TDG}^{mini} and P_{TDG}^{max} are the allowable total minimum and maximum real power injection capacity of DGs. Likewise, Q_{TDG}^{mini} and Q_{TDG}^{max} are the total minimum and maximum reactve power injection capacity of DGs.

2.3. DG Modelling

Distributed generation (DG) is a distinctive approach employed for power generation near the load centre. DG technology deploys different energy resources including hydro, fuel cells, solar PV system, WT etc., for generating power locally. But, DG resources are typically grouped into four classes [18] as presented in Table 1.

Table 1. DG Types

Type	**Characteristics**
Type I	Produce real power only
Type II	Produce reactive power only
Type III	Produce real power and reactive power
Type IV	Produce real power but consumes reactive power

The proposed hybrid method optimizes sizes and sites for Type I and Type III DGs. DG units are mathematically modeled as per IEEE 1547 standards [27].

2.3.1. Type I DG:

A typical Type I DG unit (solar PV system) is characterized as a unity power factor model since it injects only real power into the radial PDS. Equation (9) mathematically describes the output power of a solar PV system.

$$P_{pv} = \begin{Bmatrix} P_{pvr} \times \left(\frac{G}{G_r} \right), & 0 \leq G \leq G_r \\ P_{pvr,} & G_r \leq G \end{Bmatrix} \tag{9}$$

where P_{pvr} is the rated output power of solar PV units, ‘G’ is the solar radiation received at the selected optimal location in $W/m^{2,}$ and G_r is the rated solar radiation at the earth's surface in W/m^2.

2.3.2. Type III DG:

Type III DG is modelled as PQ model. The real power (P_{wt}) and reactive power (Q_{wt}) injection of Type III DG unit is mathematically expressed in the following Eq. (10) and Eq. (11) respectively.

$$P_{wt} = \begin{cases} 0, & 0 \le v \le v_{cin} \\ P_{wr} \times \left(\dfrac{v - v_{cin}}{v_r - v_{cin}} \right), & v_{cin} \le v \le v_r \\ P_{wr}, & v_r \le v \le v_{cout} \end{cases} \quad (10)$$

$$Q_{wt} = P_{wt} \times \tan(\cos^{-1}(p.f._{DG})) \quad (11)$$

where P_{wr} is the rated output power of Type III DG at the rated speed, and v and v_r are the actual and rated Wind Speeds (WS) at the selected optimal location. v_{cin} and v_{cout} are the cut-in and cut-out WS; $p.f._{DG}$ is the power factor of DG unit and is assumed as 0.866 p.f.

3. Hybrid Optimization Technique using LSF and CSA

The suggested hybrid approach locates the optimal buses for DG placement via LSF and computes optimal sizes using CSA. This section details about the mathematical modelling and implementation of proposed methodology for optimizing multiple DG units.

3.1. Loss Sensitivity Factor

The optimal choice of buses for DG accommodation in RDS is significant to attain desired objectives. However, inappropriate provision of DGs in PDS will lead to undesirable results [26]. In this work, a LSF based approach is adopted to locate optimal buses for DG placement. The computation of LSF not only identifies the suitable locations but also significantly minimizes the search space for CSA which in turn improves convergence rate. LSF for a two-bus RDS shown below (Fig.1) is calculated using Eq. (12).

$$LSF_{i,i+1} = \frac{2Q_{i+1,eff} R_k}{|V_{i+1}|^2} \quad (12)$$

where, R_k denotes p.u line resistance and X_k corresponds to p.u line reactance.

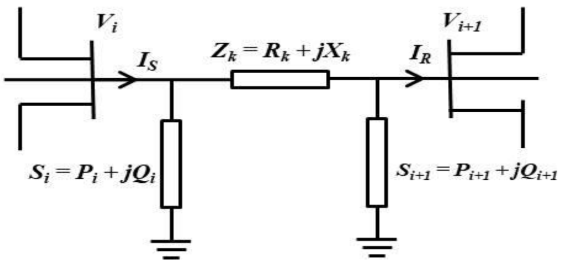

Fig. 1. Two bus radial PDS

3.2. Optimal bus selection using LSF

The algorithm for the selection of optimal buses for DG placement based on LSF is illustrated as a flowchart in Fig.2. The LSF for radial PDS is computed using the power flow assessment result. LSF and V_{norm} for IEEE 33 bus and 69 bus radial PDS displayed in Fig.3 and Fig.4, respectively. According to LSF and V_{norm}, 21 number of buses were identified as suitable locations for DG placement for both radial PDSs. Computation LSF has noticeably reduced the search space by 36.36% and 69.56% for 33 bus and 69 bus radial PDS respectively. Furtherrmore, the decision to pick the optimal bus location has been made in accordance with respective normalized voltage of the buses. For 33 bus radial PDS (fig.3), bus numbers 30, 13 and 10 are found as optimal locations for DG integration. Likewise, for 69 bus radial PDS (fig.4) buses 61, 17 and 65 are located as optimal points for DG allocation.

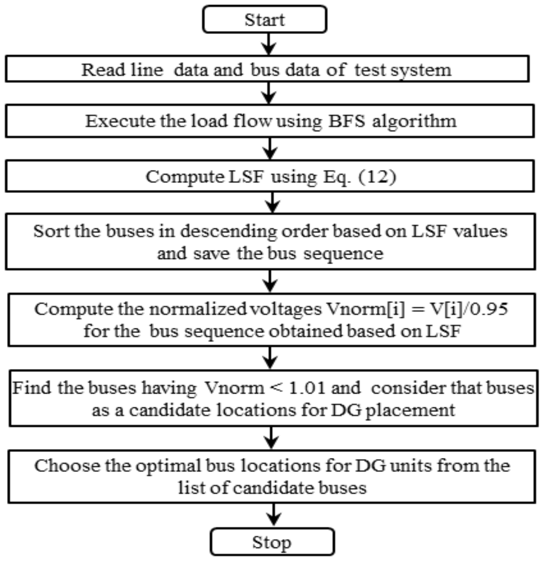

Fig. 2. Algorithm for optimal bus identification for DG placement

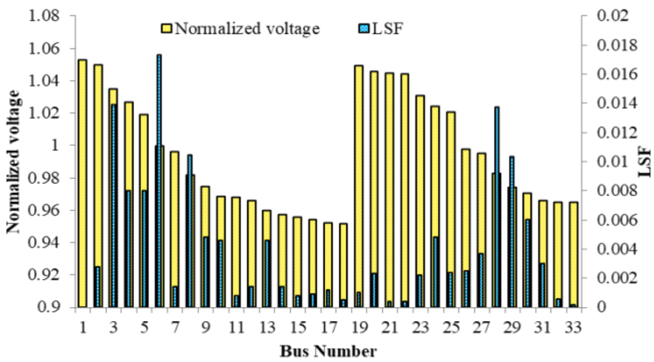

Fig. 3. LSF and normalized voltage for IEEE 33 bus radial PDS

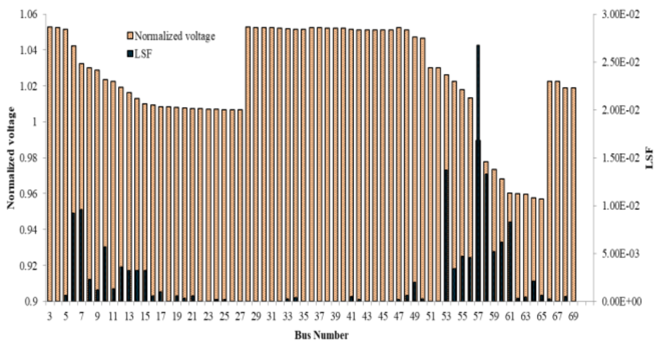

Fig. 4. LSF and normalized voltage for IEEE 69 bus radial PDS

3.3. Power flow/load flow in radial PDS

The power flow assessment (PFA) is important for transmission and distribution networks to compute line flows, line losses and bus voltages. The popular PFA approaches applied in transmission power networks are not appropriate for RDS since it do not provide effective solution because of its radial structure, high R/X ratio, more number of buses & lines and asymmetrical loads [21]. Moreover, it demands more memory and convergence requirements. Therefore, to overcome the above said problems in power flow assessment, backward/forward sweep (BFS) algorithm based power flow calculation technique is implemented for radial PDS [31]. PFA using BFS technique is executed in two phases.

First phase is known as **backward sweep** in which magnitude of branch current is calculated. The calculation begins from far end node of the PDS and proceeds in a backward direction to the head node by keeping bus voltage constant.

Second phase is known as **forward sweep** where magnitude of bus voltage is computed. The computation is initiated from head bus and moves forward to far-end node by keeping current constant. The algorithmic representation of BFS power flow assessment technique is presented as flowchart in Fig.5.

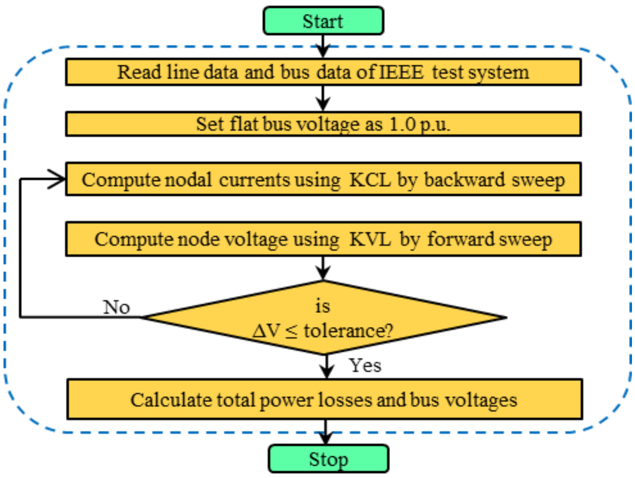

Fig. 5. Flowchart for BFS power flow assessment technique

3.4. Cuckoo Search Algorithm: An Overview

Xin-She Yang and Suash Deb established a nature-inspired optimization algorithm known as Cuckoo search algorithm (CSA) in the year 2009 [32] to solve complex and non-linear problems in diverse domains. The aggressive brooding parasitism between the cuckoo and other species (host) of birds for laying an egg in the nets has been mimicked in the CS algorithm.

The egg laid by the Cuckoo will be quite similar to that of the host species in regard to size and color. This characteristic creates an arms race system between the Cuckoo and Host bird. Chances for the Host bird to find and abandon Cuckoo's egg from the nets can be represented with a probability of p_a.

If n is considered as the number of eggs, then xi is a vector that represents the position of an egg for an optimization problem. The similarity between Cuckoo's (x_i) and Host egg (x_j) can be found in their difference (x_j-x_i). For a given optimization problem, the egg position at iteration t can be updated [33] by

$$x_i^{t+1} = x_i^t + \alpha s \otimes H(p_a - \in) \otimes (x_j^t - x_k^t) \tag{13}$$

where, H is a Heaviside step function used to represent the probability of discovery along with the aid of a random number ϵ and s indicates step size and is scaled by a factor α.

Naturally, animals and species look for food in a random manner. Here, Cuckoo also searches for the Host bird nest randomly for laying an egg. Lévy flights pattern of search mechanism is adopted in CS. This is due to the fact that the Host bird might fly away by abandoning the nets once they get to know the eggs were contaminated or swapped by the Cuckoo. CS will function more efficiently in exploration with Lévy flights [33]. The step size variation by Lévy flights can be mathematically expressed as [34]:

$$x_i^{t+1} = x_i^t + \alpha L(s,\lambda) \tag{14}$$

where,

$$L(s,\lambda) \approx \frac{\lambda\Gamma(\lambda)\sin(\pi\lambda/2)}{\pi}\frac{1}{s^{1+\lambda}} \text{ and } (s >> 0) \tag{15}$$

CS follows three idealized rules for any optimization problem [35].

- Every Cuckoo lays an egg inside a randomly selected nest.
- High quality eggs in the nests will have higher probability of chances to get into next generation.
- Number of Host bird nets is fixed and probability of chances for host bird to discover the Cuckoo's egg is $p_a \in (0, 1)$.

3.5. Implementation of hybrid optimization technique

Step 1: Get the line data and load data of RDS.
Step 2: Execute power flow using BFS method and compute TRPL of RDS without DG placement. Now, set TRPL as a initial standard fitness value.
Step 3: Initialize the necessary parameters for CSA. Set maximum iteration count as 50, p_a as 0.25 and number of Host nets as 30.
Step 4: Randomly initialize the solutions (nest) as follows:

$$nest(i,:) = L_b + (U_b - L_b) * rand(size(L_b)) \tag{16}$$

where, (L_b and U_b) is a lower and upper boundary for DGs position and size. Set the current solution as the best fitness value for OF.
Step 5: Run power flow with DG units and find the TRPL to compute the initial fitness value.
Step 6: Begin iterative process.
Step 7: Find the new solution by initiating Lévy Flights Random Walk (LFRW).
Step 8: Now for the updated value (DG sizes) obtained via LFRW, implement PFA and determine TRPL.

Step 9: Relate the obtained fitness value with the initially set value in order to discover the best solution thus far.
Step 10: Now discover a new nest and again initiate a random process.
Step 11: Run PFA again to compute TRPL of RDS with updated solution (DG sizes). Consider this TRPL as the second fitness value.
Step 12: Now discover the best objective function (OF) value (TRPL) computed thus far.
Step 13: Check the iteration count and increase it by 1 if maximum iteration count is not reached. Otherwise go to step 10.
Step 14: Run the program till the maximum iteration count and print the best solution that gives the least OF value.

Fig. 6 illustrates the flowchart for the propsed hybrid optimization method.

4. Test Results and Discussion

The simulation outcome for the proposed hybrid method is obtained for optimal allocation of multiple Type I and Type III DG units on IEEE 33 bus and 69 bus radial PDS. For simulation study, IEEE 33 bus and 69 bus radial PDS are referred as test system-1 and test system-2, respectively. The necessary programs are executed in MATLAB software version 2020a. The control parameter of CSA is listed in Table 2. The simulation is executed for 50 independent run considering following assumptions:

- Symmetrical test systems is considered
- Type I and III DGs are modelled as constant P and PQ model, respectively.
- The reactive power injection of Type I DG is neglected.
- The stochastic nature of solar irradiance for Type I DG and wind velocity for Type III DG is neglected.

Table 2. Control parameter of CSA

Parameter		Values
Number of host nets		30
p_a		0.25
Number of iterations		50
Number of DGs		3
DG capacity (Min.)	Type - I	60 kW
	Type -III	60 kVA
DG capacity (Max.)	Type - I	3000 kW
	Type - III	3500 kVA

4.1. *Test System-1: IEEE 33 bus radial PDS*

4.1.1. *Test System-1 without DGs*

Initially, power flow assessment (PFA) for the IEEE 33-bus radial PDS without accommodating DG units has been executed to compute TRPL and bus voltages. The required data needed for PFA of test system-1 illustrated in Fig.7 is taken from [36]. The PFA outcome for test system-1 without DG placement is presented in Table 3.

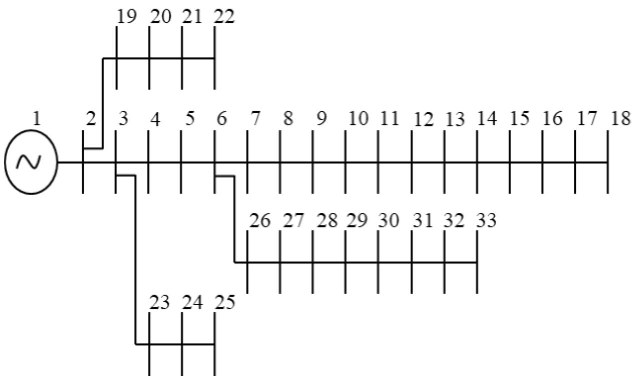

Fig. 7. Test system – 1: IEEE 33 bus radial PDS

Table 3. PFA results for test system-1 without DG

Parameter	Values
Total active power demand (AP_T)	3.72 MW
Total reactive power demand (RP_T)	2.3 MVAr
TPRL	210.98 kW
V_{mini}	0.9038p.u
V_{max}	0.9970p.u

The test system-1 with no DG placement recorded 210.98 kW of TRPL with 0.9038p.u magnitude of minimum bus voltage (V_{mini}) and 0.9970p.u magnitude of maximum bus voltage (V_{max}) at bus 18 and 2, respectively. Fig.8 illustrates the voltage magnitude of test system-1 with no DG placement.

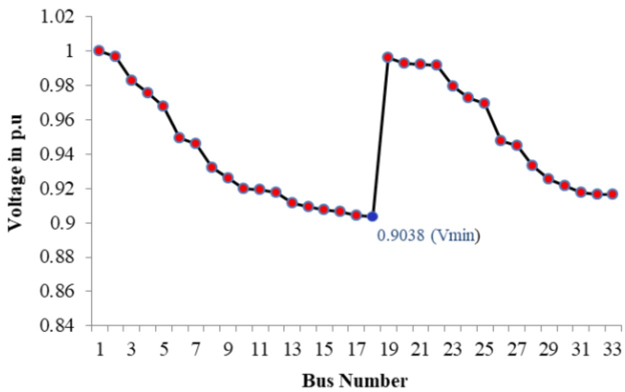

Fig. 8. Voltage profile of 33 bus radial PDS before DG placement

4.1.2. *With Multiple DGs*

Table 4 presents the outcome of test system-1 with optimized Type I and Type III DGs placement. The TRPL of test system -1 is reduced to 70.98 kW and the V_{mini} is improved to 0.9793p.u with optimized Type I DG placements at buses 30, 13 and 10. The test system experienced 0.0755p.u enhancement in V_{mini} after the inclusions of Type I DG units. Likewise, optimal inclusion of Type III DG units has decreased TRPL to 16.89 kW and enhanced V_{mini} to 0.9863p.u. However, V_{mini} is recorded at bus no. 25 after DG placements. Fig.9 showcase the improvement in bus voltage profile of test system-1 after the multiple DG allocations. Similarly, Fig.10 illustrates the variation in the voltage magnitude of weaker buses after the DG placements. Refering to Fig.9 and Fig.10, the test system has seen a substantial improvement in the bus voltage magnitude particularly, at the weaker buses after the integration of multiple DGs. However, the optimized Type III DG placements has given better results over Type I DGs since Type III DGs provides both real and reactive power support to radial PDS. The CSA took 26 iterations for Type I DGs placement and 21 iterations in the case of Type III DGs placement to converge optimal solution. The convergence curve of CSA for test system-1 is illustrated in Fig.11.

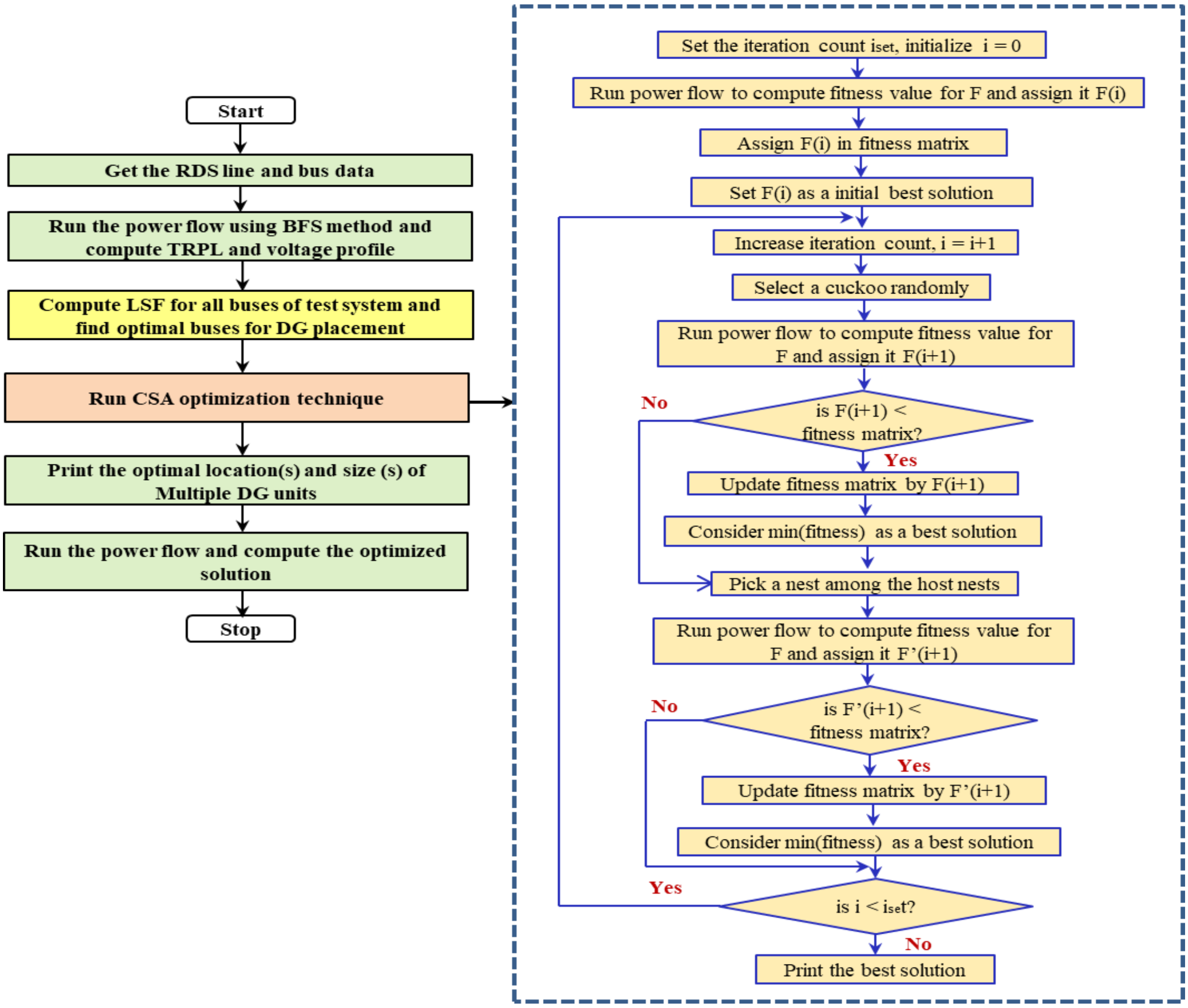

Fig. 6. Flowchart for LSF-CSA hybrid technique

Table 4. Optimized outcome for 33 bus radial PDS after DG inclusion

Parameter	Multiple Type I DGs	Multiple Type III DGs
Optimal bus locations	30, 13, 10	30, 13, 10
Optimal sizes of DGs (kW/kVA)	1304.1 468.2 633.1	1402.1 586.8 695.3
$P_{DGTloss}$ in kW	70.98	16.89
V_{mini} in p.u.	0.9793	0.9863

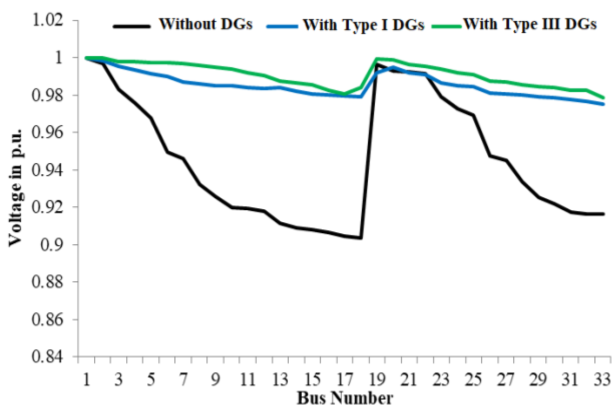

Fig. 9. Voltage profile of test system-1 with and without multiple DG

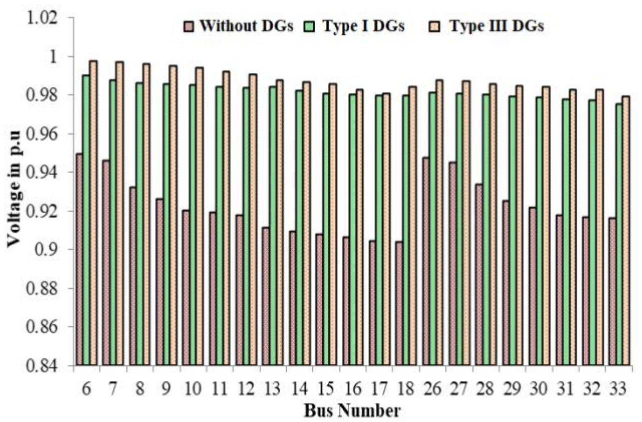

Fig. 10. Voltage profile of weaker buses of 33 bus radial PDS without and with DGs

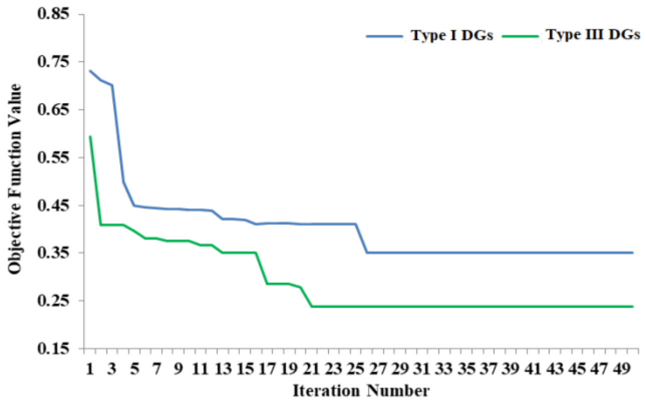

Fig. 11. Convergence curve of CSA for test system -1

4.1.3. Comparative Analysis

The outcome of proposed hybrid optimization approach is related to different optimization approaches including GA, PSO, BSOA and CSA available in the literature for comparison study. Table 5 and Table 6 presents the numerical comparison of different optimization techniques. The proposed technique achieved 66.35% of TRPL reduction for optimized Type I DG allocation and 91.99% for optimized Type III DG allocation. And, the V_{mini} of the test system has been enhanced to 0.9793p.u for Type I DG placement and 0.9863p.u for Type III DG placement. But, the literature outlined that GA, PSO, BSOA and CSA optimization methods achieved 49.61%, 50.06%, 57.38% and 64.21% TRPL reduction with corresponding V_{mini} 0.9809p.u, 0.9806p.u, 0.9705p.u and 0.9712p.u for multi Type I DG placement. Similarly, CSA and BSOA have reportedly achieved TRPL reduction of 90.60% and 82.06% with corresponding V_{mini} 0.9891p.u and 0.9802p.u for multi Type III DGs placement. The comparative report presented in Table 5 and Table 6 epitomized that the proposed method significantly minimized the TRPL with considerable voltage profile enhancement. Furthermore, a statistical report for the aforementioned comparative study is shown graphically in Fig.12. The report highlighted that the proposed hybrid DG optimization technique outperformed GA, PSO, CSA and BSOA techniques by providing a maximum percentage of TRPL reduction.

Table 5. Test results comparison of different technique for multiple Type I DG placement

Parameters	**Optimization Techniques**				
	PSO [10]	**GA [11]**	**BSOA [18]**	**CSA [21]**	**Proposed**
Optimal bus location	13 32 8	11 29 30	14 18 32	24 13 30	30 13 10
Optimal DG size (kW)	981.6 829.7 1176.8	1500 422.8 1071.4	652.1 198.4 1067.2	1201.9 776.1 1302.6	1304.1 468.2 633.1
P_{Tloss} (kW)	210.98				
V_{mini} without DGs (p.u.)	0.9038				
$P_{DG,Tloss}$ (kW)	105.35	106.30	89.90	75.16	70.98
Power loss reduction (%)	50.06	49.61	57.38	64.21	66.35
V_{mini} with DGs (p.u.)	0.9806	0.9809	0.9705	0.9712	0.9793

Table 6. Test results comparison of different techniques for multiple Type III DG placement

Parameters	**Optimization Techniques**		
	BSOA [18]	**CSA [21]**	**Proposed**
P_{Tloss} (kW)	210.98		
V_{mini} without DGs (p.u.)	0.9038		
Optimal bus location	14 18 32	13 30 24	30 13 10
Optimal DG size (kVA)	784.8 150.7 1279.8	620.2 1441.3 1367.6	1402.1 586.8 695.3
$P_{DG,Tloss}$ (kW)	37.85	19.7443	16.89
Power loss reduction (%)	82.06	90.60	91.99
V_{mini} with DGs (p.u.)	0.9802	0.9891	0.9863

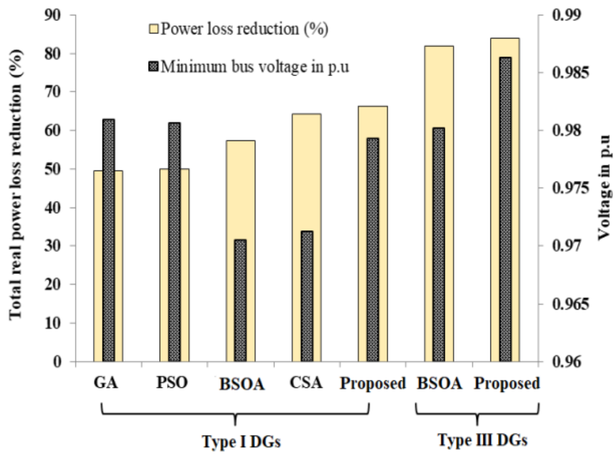

Fig. 12. Statistical comparison of different optimization algorithms for IEEE 33 bus RDS

4.2. Test System-2: IEEE 69 bus radial PDS

4.2.1. Test System-2 without DGs

The essential data for PFA of test system – 2 shown in Fig.13 is gathered from [36]. The PFA result for 69 bus radial PDS without accommodating DG units is presented in Table 7. Fig.14 presents the voltage magnitude of test system-2 with no DG placement.

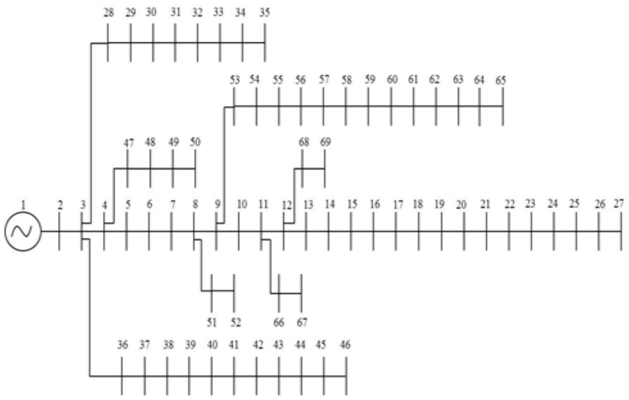

Fig. 13. Test system-2: IEEE 69 bus RDS

Table 7. PFA results of 69 bus radial PDS with no DG placement

Parameter	Values
Total active power demand (AP_T)	3.802 MW
Total reactive power demand (RP_T)	2.694 MVAr
P_{Tloss}	225 kW
V_{mini}	0.9092p.u.
V_{max}	0.9999p.u.

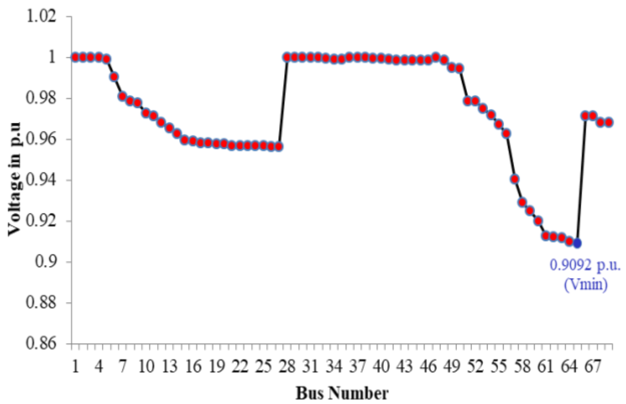

Fig. 14. Voltage profile of 69 bus radial PDS with no DG placement

4.2.2. Test System-2 with DGs

Based on LSF, the bus numbers 61, 17 and 65 are found to be the multiple optimal positions for DG placement in test system-2. The optimal DG sizes at the optimal buses are computed via CSA. The simulation test results after optimized multiple DG placements are presented in Table 8. The addition of multiple Type I DGs has reduced the TRPL of test system-2 to 74.56 kW from 225 kW. Besides power loss reduction, the V_{mini} has been enhanced to 0.9856p.u. To be precise, the V_{mini} of the test system-2 is enhanced by 0.0764p.u from the base case. In the same way, the optimal inclusion of multiple Type III DGs decreased TRPL to 10.60 kW and increased V_{mini} to 0.9912p.u. Fig.15 illustrates a variation in bus voltage profiles of test system -2 after the inclusion of optimized DG units. Additionally, Fig. 16 exemplifies the voltage profile variation at potentially weaker buses before and after multiple DG placements. The optimized DG integrations have resulted promising improvements in the voltage magnitude of weaker buses. The optimal solution for the test system-2 is converged at 28th iteration for Type I DG placements and 22nd iteration for Type III DG placements. The convergence characteristic of CSA for test system-2 is shown in Fig.17.

Table 8. Optimized test results of test system-2 after DG accommodation

Parameter	Multiple Type I DGs	Multiple Type III DGs
Optimal bus locations	61, 17, 65	61, 17, 65
Optimal sizes of DGs (kW/kVA)	1289.3 520.4 273.1	1583.8 498.6 259.5
$P_{DGTloss}$ in kW	69.56	10.60
V_{min} in p.u.	0.9856	0.9912

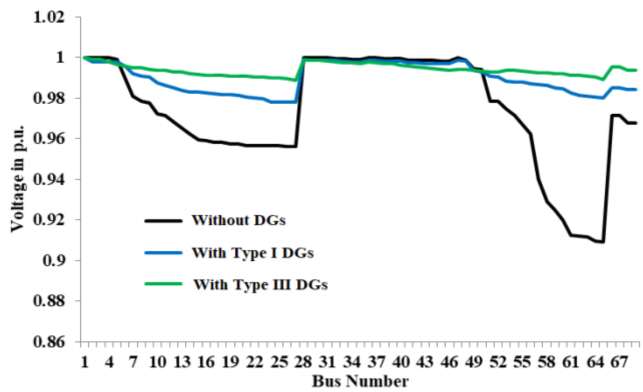

Fig. 15. Voltage profile of 69 bus radial PDS after multiple DG placements

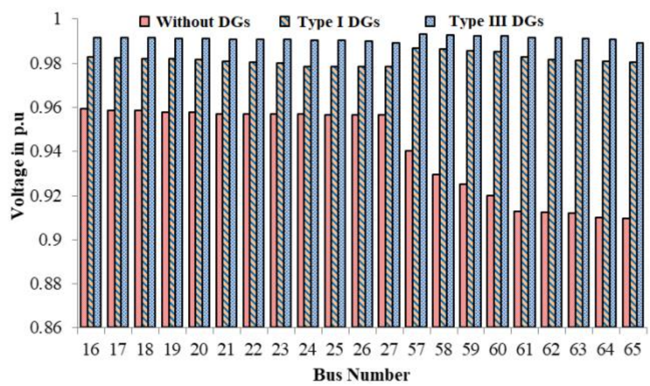

Fig. 16. Voltage profile of weaker buses of test system-2 after DG placement

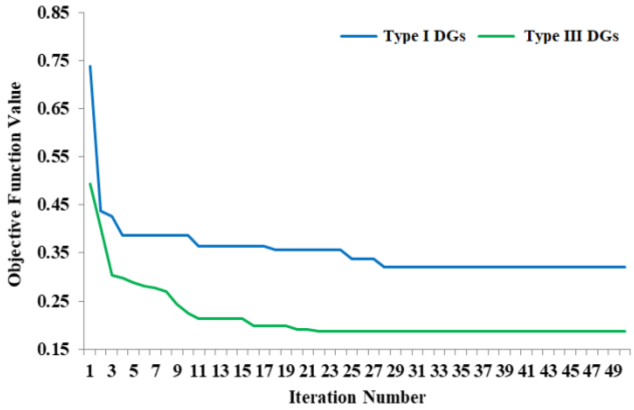

Fig. 17. Convergence characteristics curve of CSA for test system-2

2.1.1. Comparison Analysis

In order to realize the efficacy of the proposed hybrid method, the optimized test results of test system-2 are related to GA, PSO and BSOA optimization methods. Table 9 and Table 10 present the comparative study of different optimization methods. The proposed hybrid method has reduced TRPL by 69.08% and 95.29% for optimized multi Type I and Type III DG placements, respectively. Furthermore, the V_{mini} of the test system-2 has been increased from 0.9092p.u to 0.9856p.u and 0.9912p.u for Type I and Type III DG placements, respectively. Whereas, for the multi Type I DG allocations GA, PSO and BSOA optimization techniques reported TRPL reduction of 60.44%, 63.02% and 66.56%, respectively with corresponding V_{mini} 0.9936p.u, 0.9901p.u and 0.9808p.u. Likewise, for the optimized Type III DG integration BSOA reported 94.26% of TRPL reduction. The statistical report for the comparative study of different optimization techniques for test system-2 is graphically presented in Fig.18.

Table 9. Comparison of test results for multiple Type I DG allocations

Parameters	Optimization Techniques			
	PSO [10]	GA [11]	BSOA [18]	Proposed
Optimal bus locations	61 63 17	21 62 64	61 65 27	61 17 65
Optimal size of DG (kW)	1199.8 795.6 992.5	929.7 1075.2 992.5	1345.1 447.6 295.4	1289.3 520.4 273.1
P_{Tloss} (kW)	225			
V_{mini} without DGs (p.u.)	0.9092			
$P_{DG,Tloss}$ (kW)	83.20	89.00	75.23	69.56
Power loss reduction (%)	63.02	60.44	66.56	69.08
V_{mini} with DGs	0.9901	0.9936	0.9808	0.9856

(p.u.)				

Table 10. Comparison for test results for multiple Type III DG allocations

Parameters	Optimization Techniques	
	BSOA [18]	Proposed
Optimal bus locations	61 65 27	61 17 65
Optimal size of DG (kVA)	1542.7 379.3 436.5	1583.8 498.6 259.5
P_{Tloss} (kW)	225	
V_{mini} without DGs (p.u.)	0.9092	
$P_{DG,Tloss}$ (kW)	12.90	10.60
Power loss reduction (%)	94.26	95.29
V_{mini} with DGs (p.u.)	0.9896	0.9912

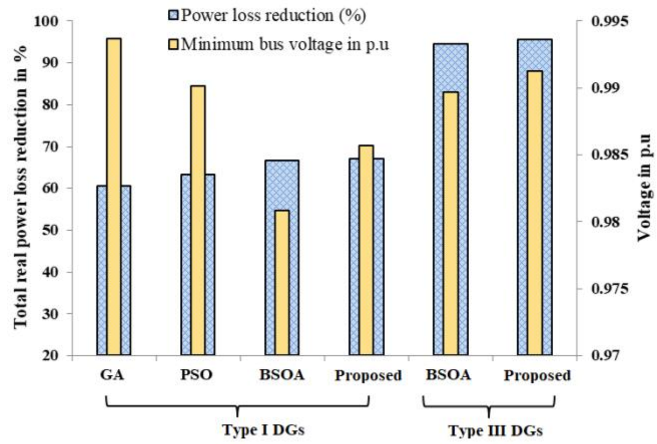

Fig.18. Statistical comparison of different optimization algorithms for IEEE 69 bus RDS

3. Conclusion

A hybrid optimization method using LSF and CSA has been implemented in this work for optimizing Type I and Type III multiple renewable energy DG units into IEEE 33 bus (test system-1) and IEEE 69 bus (test system-2) radial PDS. The DG sites and sizes are optimized to reduce TRPL. The proposed hybrid method has optimized Type I DGs into IEEE 33 bus radial PDS at the bus locations 30, 13 and 10 with capacities of 1304.1 kW, 468.2 kW and 633.1 kW respectively. Similarly, Type III DGs have been optimized with capacities 1402.1 kVA, 586.8 kVA and 695.3 kVA. The optimized allocation of multiple Type I and Type III DGs via the proposed methodology has yielded 66.35% and 91.99% of TRPL reduction respectively in test system -1. Likewise, multiple Type I DG allocations in IEEE 69 bus RDS at the bus locations 61, 17 and 65 with sizes 1289.3 kW, 520.4 kW and 273.1 kW, respectively have resulted 66.86% of TRPL reduction. Whereas, for optimized Type III DG placement with capacities 1583.8 kVA, 498.6 kVA and 259.5 kVA 95.29% of TRPL reduction has been achieved. The optimized test outcome of the proposed hybrid method has been compared to PSO, GA, CSA and BSOA methods. The comparison study witnessed a maximum percentage of power loss reduction in the proposed method. Also, inclusion LSF approach significantly improved convergence rate of CSA. This shows the superiority of proposed method over other methods. Therefore, the suggested hybrid method can be recommended for effective DG allocation in RDS.

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