Optimization of Distributed Generation in Radial Distribution Network for Active Power Loss Minimization using Jellyfish Search Optimizer Algorithm

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Abstract *– The inclusion of distributed generation (DG) units in the distribution network (DN) effectively cuts down the power losses (PL) and strengthens the voltage profile (VP). This paper examines the effect of allocating different distributed generation (DG) in radial distribution networks (RDN) through an implementation of an optimization technique using a recently introduced bio-inspired algorithm known as a jellyfish search optimizer (JSO). Unlike the other optimization algorithms, the JSO algorithm evades the local optimal trap and reaches the optimal solution in less time. The DG position(s) and size(s) are optimized for active power loss (APL) minimization with respect to several constraints. The effectiveness and robustness of the proposed optimization technique using JSO algorithm is investigated on a balanced IEEE RDNs with 33, 69 and 118-buses. The simulation outcomes are obtained for different types (type I, II and III) of DG placement. Additionally, a comprehensive comparative study has been performed for the JSO and other algorithms. The comparison exemplifies that the proposed JSO optimization approach produces a better optimal solution with steady convergence than other techniques reported in the literature. Also, the simulation findings show the potentiality of JSO optimization method for solving complex optimization problems.*

Keywords*:* *Distributed Generation, Radial Distribution Network, Jellyfish Search Optimizer, Active Power Losses*

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1. INTRODUCTION

The electrical power system generates electricity and transfers it to consumers through conductors via transmission and distribution systems. The transmission system (TS) carries the electricity from the generating plant to the distribution system (DS) using high-tension conductors. Then, from 'DS' the power is delivered to consumers through low-tension conductors via distribution power networks (DPN). In the process of power transfer, a portion of energy is lost as power losses in transmission and distribution systems. Literature reports [1] that about 70% of power losses (PL) occur in DS and the remaining 30% in TS. The PL in DS is more than TS because of its radial structural design, a higher line R/X ratio and a greater number of load buses [2]. However, an efficient, secure and reliable DPN should account a less PL and voltage drop.

In recent times, a unique power generation technology known as distributed generation (DG) is introduced in DS to achieve numerous technical, economic and ecological benefits including PL minimization (both active and reactive losses), voltage profile (VP) improvement, stability enhancement, operating cost reduction and greenhouse gas emission minimization. DG injects electrical power at/near load points [3]. However, the utility gets benefit through DG placement only when its location and size are optimized in DPN. Numerous optimization techniques implemented by researchers over the years to assimilate DG unit(s) optimally into DPN. A few of them are outlined below.

An analytical methodology [4, 5] and iterative methodology [6] proposed to minimize PL in DPN. A modified aquila optimizer (MAO) technique introduced [7] to reduce the APL and to improve the VP of radial distribution network (RDN) for different types of renewable DG placement. The proposed technique was tested on IEEE 33-bus RDN. The authors [8] implemented an optimization approach using an improved wild horse optimization (IWHO) algorithm to optimize DG units in IEEE RDNs 33, 69 and 119-buses for the APL minimization. A novel hybrid optimization approach proposed [9] combining simulated annealing (SA) and particle swarm optimization (PSO) algorithms to optimize DG position and size into RDN for the APL minimization. The simulation study was executed for IEEE 33-bus RDN. The authors [10] applied a rider optimization algorithm (ROA) for locating the optimal site and computing optimal size for the different renewable energy sources (PV, WT and biomass) in RDN. The proposed ROA approach optimized the DG for minimizing total APL. A novel DG optimization technique proposed [11] using shark optimization algorithm (SOA) to minimize the PL, to enrich the voltage profile and voltage stability of RDN. A hybrid technique based on LSF and SA proposed [12] to optimize PV and WT in IEEE 33 and 69-bus RDNs for APL minimization and voltage enhancement. The authors [13] have implemented an improved version of symbiotic organisms search (SOS) algorithm known as the quasi-oppositional chaotic SOS algorithm to optimally incorporate DGs with different power factor (p.f) into IEEE 33, 69 and 118-buses for the benefit of PL reduction, VP improvement and voltage stability enhancement. An optimization approach using chaotic sine cosine algorithm (CSCA) proposed [14] to optimize multi-DG units into IEEE 33 and 69-bus RDN for solving a single and multiple objectives DG allocation problem. A harris hawks optimization (HHO) algorithm applied [15] to solve single and multi-DG placement problems in RDN. The DGs with different p.f optimized into 33 and 69-buses RDN to reduce PL, enrich VP and improve stability. A new hybrid approach proposed [16] using improved GWO and PSO to optimize DG location and size in RDN to achieve PL reduction, VP enrichment and voltage stability enhancement. The proposed approach adopted a dimension learning hunting method to optimize the DG. Genetic algorithm (GA) and PSO algorithm were proposed [17] to optimally assimilate single and multiple (two) PV and WT DGs into 33-bus RDN. GWO algorithm based DG planning executed [18] for RDN to cut down the PL. The proposed approach optimized the different DGs into IEEE standard test systems with 16, 30, 57 and 118-buses. Water cycle algorithm (WCA) based optimization technique implemented [19] to optimize multi-DGs (FC, PV and WT) into RDN for minimization of total APL, operating cost and greenhouse gas discharge. The authors [20] proposed an integrated technique using LSF and sine cosine algorithm (SCA) to optimize PV and WT for the objectives of PL reduction and VP improvement. The proposed method executed on unbalanced IEEE RDN with 33 and 69-buses.

Above-mentioned techniques have been implemented for solving DG placement problems in RDN and provided reasonable solutions. However, literature [4-6] reported that the analytical techniques suffer from inadequate solutions and convergence problems. Likewise, most of the optimization algorithms offer a chance for premature convergence and produce local optimal solutions. In recent times, many novel algorithms are introduced to solve various complex optimization problems. One such algorithm is known as Jellyfish Search Optimizer (JSO) [21]. The JSO is a swarm-based algorithm that simulates the food-searching manners of jellyfish to produce optimal solutions for a given problem. The JSO has the ability to converge faster than the other algorithms using its stronger searching technique. Also, the JSO requires only few parameter initializations and exhibits better balance between exploration and exploitation. Furthermore, the JSO performance has been tested with numerous benchmark functions and has provided a near optimal solution at rapid convergence [21]. The contribution of the proposed research work is summarized below.

- Propose a new optimization technique using JSO algorithm to optimize the different DG (type I, II and III) units in RDN for APL reduction.
- Apply the proposed JSO algorithm to identify the optimal site (s) and size(s) for different DG types to minimize total APL of RDN.
- Investigate the robustness of the proposed methodology for small (33-bus), medium (69-bus) and large (118-bus) RDN. And, validate the JSO optimized research findings through a comprehensive comparison.

The remaining portion of the manuscript is structured with different sections as follows: Section 2 presents the objective function framework and necessary constraints. Section 3 details the concept and mathematical modelling of the JSO algorithm. Section 4 presents the simulation findings for the IEEE 33-bus, 69-bus and 118-bus RDN for different DG placement and Section 5 highlights the simulation outcome of the JSO technique as a conclusion.

2. PROBLEM FORMATION

The optimal site(s) and size(s) for the *DG* unit(s) are optimized for an objective of minimizing the total *APL* of *RDN*. The total active power loss (APL_T) in a *RDN* represented in Fig. 1 is calculated using Eq. 1.

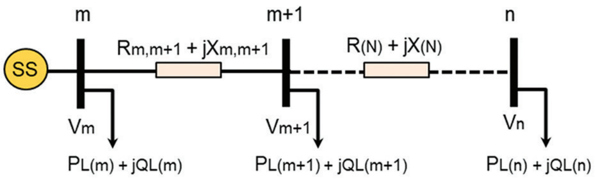

Fig. 1. Radial distribution network

$$APL_T = \sum_{m=1}^{n-1} R_{m,m+1} * \left(\frac{P_m^{\ 2} + Q_m^{\ 2}}{|V_m|^2} \right) \tag{1}$$

Where, R corresponds to distribution line resistance; P_L & Q_L refer active and reactive power demand, respectively, m and n are buses and V is a voltage of buses.

The fitness function or objective function for *APL* minimization is expressed as given in Eq. 2.

$$F = \min \left(\frac{APL_{T(\text{after DG})}}{APL_{T(\text{before DG})}} \right) \tag{2}$$

2.1. CONSTRAINTS

The *DG* sizes are optimized to minimize the APL_T according to several operating parameter constraints of *RDN* including voltage magnitude, feeder current and power flow.

Bus voltage constraint:

$$0.95\text{p.u} \leq V_m \leq 1.05\text{p.u} \tag{3}$$

Thermal constraint:

$$I_{m,m+1} \leq I_{m,m+1}^{\max} \tag{4}$$

***DG* active power (*PDG*) injection constraint:**

$$P_{DG}^{\min} \leq P_{DG} \leq P_{DG}^{\max} \tag{5}$$

***DG* reactive power (Q_{DG}) injection constraint:**

$$Q_{DG}^{\min} \leq Q_{DG} \leq Q_{DG}^{\max} \tag{6}$$

Power balance constraint:

$$P_{swing} + \sum_{i=1}^{N_{DG}} P_{DG}(i) = \sum_{m=1}^{n} P_m + \sum_{m=1}^{N} P_{loss,m} \tag{7}$$

$$Q_{swing} + \sum_{i=1}^{N_{DG}} Q_{DG}(i) = \sum_{m=1}^{n} Q_m + \sum_{m=1}^{N} Q_{loss,m} \tag{8}$$

Where, 'I' is the magnitude of branch current; P_{DG}, $P_{DG\text{-}min}$ and $P_{DG}^{\ max}$ are the optimal, minimum and maximum real power capacity of *DG* unit, respectively; Q_{DG}, $Q_{DG}^{\ min}$ and $Q_{DG}^{\ max}$ are the optimal, minimum and maximum reactive power capacity of *DG* unit, respectively; n and N refer to a total number of buses and branches in *RDN*, respectively.

The power flow (*PF*) analysis in *DPN* is important for assessing the various parameters including power losses and bus voltages. The power flow methods suitable for transmission power networks such as Gauss-Seidel and Newton Raphson algorithms have become inappropriate for *RDPN* due to its unique radial structure and higher line *R/X* value. Hence, for an accurate and optimal power flow solution, *RDPN* implements *PF* study using the backward/forward sweep (*BFS*) algorithm [9]. In this study, *BFS* algorithm is executed for *PF* study.

3. SOLUTION METHODOLOGY: JELLYFISH SEARCH OPTIMIZER ALGORITHM

Jellyfish search optimizer (JSO) [21] is a recent algorithm inducted into the group of metaheuristic algorithms for solving an optimization problem. JSO is a swarm-based algorithm and it makes use of the food searching process of jellyfish. The jellyfish search food (fish eggs, larvae, etc.,) stochastically in the ocean. The jellyfish follow two types of search movement: (i) Ocean current (OC) and (ii) Jellyfish swarm [21]. The JSO incorporate two phases of search technique such as diversification and intensification. It also has a time control mechanism to switch between these two search phases. The mathematical modelling of different phases of the JSO algorithm is discussed in the subsequent subsections.

3.1. POPULATION INITIALIZATION

The JSO adopt a unique approach called chaotic map [21] to initialize the population size rather than a typical random process. This effectively eliminates the probability of local optima stagnation and premature convergence as in the case of random process initialization. Equation 10 expressed the population initialization in JSO.

$$X_{i+1} = \eta X_i (1 - X_i), \quad 0 \leq X_i \leq 1 \tag{10}$$

Where, X refers to the logistic chaotic value of jellyfish, X_0∈("0,1") X_0∈{"0,0.25,0.75,0.5,1.0" } and η is a constant.

3.2. FOLLOWING OCEAN CURRENT

The OC has rich quantities of nutrients and the jellyfish follows OC to search food. The aggregation of all the vectors from populated jellyfish to best (current) jellyfish is used to determine the direction of OC ($\overrightarrow{trend}$). Equation 11 simulates the OC direction [21].

$$\overrightarrow{trend} = X^* - \beta \times rand(0,1) \times \mu \quad (11)$$

Where, X^* points to the best position of jellyfish (current best); β and μ refer to distribution coefficient concerning to the length of ($\overrightarrow{trend}$) and mean position of all jellyfish, respectively. Typically, β value is more than zero. Consequently, the position of each jellyfish is updated using Eq. 12 and Eq. 13.

$$X_i(t+1) = X_i(t) + rand(0,1) \times \overrightarrow{trend} \quad (12)$$

$$X_i(t+1) = X_i(t) + rand(0,1) \times X^* - \beta \times rand(0,1) \times \mu \quad (13)$$

3.3. JELLYFISH SWARM

The jellyfish move around the swarm in two motions [21]: passive and active. The passive and active movements of the jellyfish are termed as type A and type B motions, respectively. During the early stages of the swarm formation, the majority of jellyfish follow the type 'A' motion and after a period of time they tend to follow the type 'B' motion. The type 'A' motion refers to the movement of jellyfish around its own position. The updated position of jellyfish after type 'A' motion is given by Eq. (14).

$$X_i(t+1) = X_i(t) + \gamma \times rand\ (0,1) \times \lfloor Ub - Lb \rfloor \quad (14)$$

Where, L_b and U_b correspond to the lower and upper search space limit, respectively; γ is a motion coefficient and depends upon the length of motion around individual jellyfish.

The direction of jellyfish movement in type 'B' motion is determined by considering a jellyfish (*j*) beside the one selected in the random process and a vector from ith jellyfish to jth jellyfish. The jellyfish (*i*) will move towards the direction of jellyfish (*j*) when the quantity of food available in jellyfish (*j*) is more than the position of jellyfish (*i*). However, the jellyfish (*i*) moves away from jellyfish (*j*) if food availability at the position of jellyfish (*j*) is lower than jellyfish (*i*). Likewise, all jellyfish move around the swarm to locate a better position for finding food. The mathematical representation for jellyfish motion and its position updation is given in Eq. 15, Eq.16 and Eq.17.

$$\overrightarrow{Step} = rand(0,1) \times \overrightarrow{Direction} \quad (15)$$

$$\overrightarrow{Direction} = \begin{cases} X_j(t) - X_i(t) & \text{if} \quad f(X_i) \geq f(X_j) \\ X_i(t) - X_j(t) & \text{if} \quad f(X_i) < f(X_j) \end{cases} \quad (16)$$

Hence

$$X_i(t+1) = X_j(t) + \overrightarrow{Step} \quad (17)$$

Where, f is an objective function of location X.

3.4. TIME CONTROL MECHANISM

The jellyfish forms a swarm and search food in the ocean current (OC). The OC changes, whenever the temperature or the wind direction changes. Under this circumstance, the jellyfish creates one more swarm and moves toward another OC. This motion of jellyfish within the swarms can be categorized into a type 'A' and type 'B' motion where a jellyfish typically moves or switches position. A jellyfish follows type 'A' motion especially at the beginning of the hunt and after a while, it gets favor from type 'B' motion. In order to simulate this switchover mechanism, a time control technique is introduced in the JSO algorithm. A time control function (TCF), c (t) and a constant, c_0 are introduced to regulate the movement of a jellyfish between OC and swarm. The TCF is a random number between 0 and 1 which fluctuates over time. The mathematical illustration of TCF is given in Eq.18. The jellyfish move towards C when the TCF value is more than c_0. But, a jellyfish move within the swarm if TCF is less than c_0. The value of c_0 is unknown and it will vary randomly between 0 and 1. However, the c_0 value is taken as 0.5, taking the average values of 0 and 1.

$$c(t) = \left| \left(1 - \frac{t}{Iter_{max}}\right) \times (2 \times rand(0,1) \ - 1) \right| \quad (18)$$

Where, t and $Iter_{max}$ correspond to iteration time and a maximum number of iterations, respectively. The expression (1- c (t)) represents the motion of jellyfish inside a swarm. The jellyfish follows type 'A' motion when rand (0, 1) exceeds (1- c (t)), if not then the jellyfish follows type 'B' motion. Initially, the probability of rand (0, 1) > (1- c (t)) is higher than later. Hence, jellyfish prefer type 'A' motion at the beginning of the search and then switch over to type 'B' motion after a while.

3.5. BOUNDARY CONDITIONS

The movement of jellyfish inside an ocean is a random process and its position should be normalized whenever it violates the boundary condition for better performance. Equation 19 illustrates the random process and boundary condition.

$$X'_{i,d} = \begin{cases} (X_{i,d} - U_{b,d}) + L_{b,d} & \text{if} \quad X_{i,d} > U_{b,d} \\ (X_{i,d} - L_{b,d}) + U_{b,d} & \text{if} \quad X_{i,d} < L_{b,d} \end{cases} \quad (19)$$

Where, $X_{i,d}$ and $X_{i,d}'$ denote i^{th} jellyfish's actual position and updated position after boundary normalization, respectively. $L_{b,d}$ and $U_{b,d}$ are the lower and upper boundary conditions of the search area, respectively. Fig. 2 illustrates the flowchart of the JSO algorithm.

4. TEST RESULTS AND DISCUSSION

This section presents the simulation findings of JSO algorithm optimized DG units for IEEE standard 33-bus, 69-bus and 119-bus RDNs. The necessary codes of programming are executed in MATLAB software version 2020b. The simulation study was executed 30 times for 100 iterations. The control parameter and the necessary constraints for the JSO algorithm is presented in Table 1.

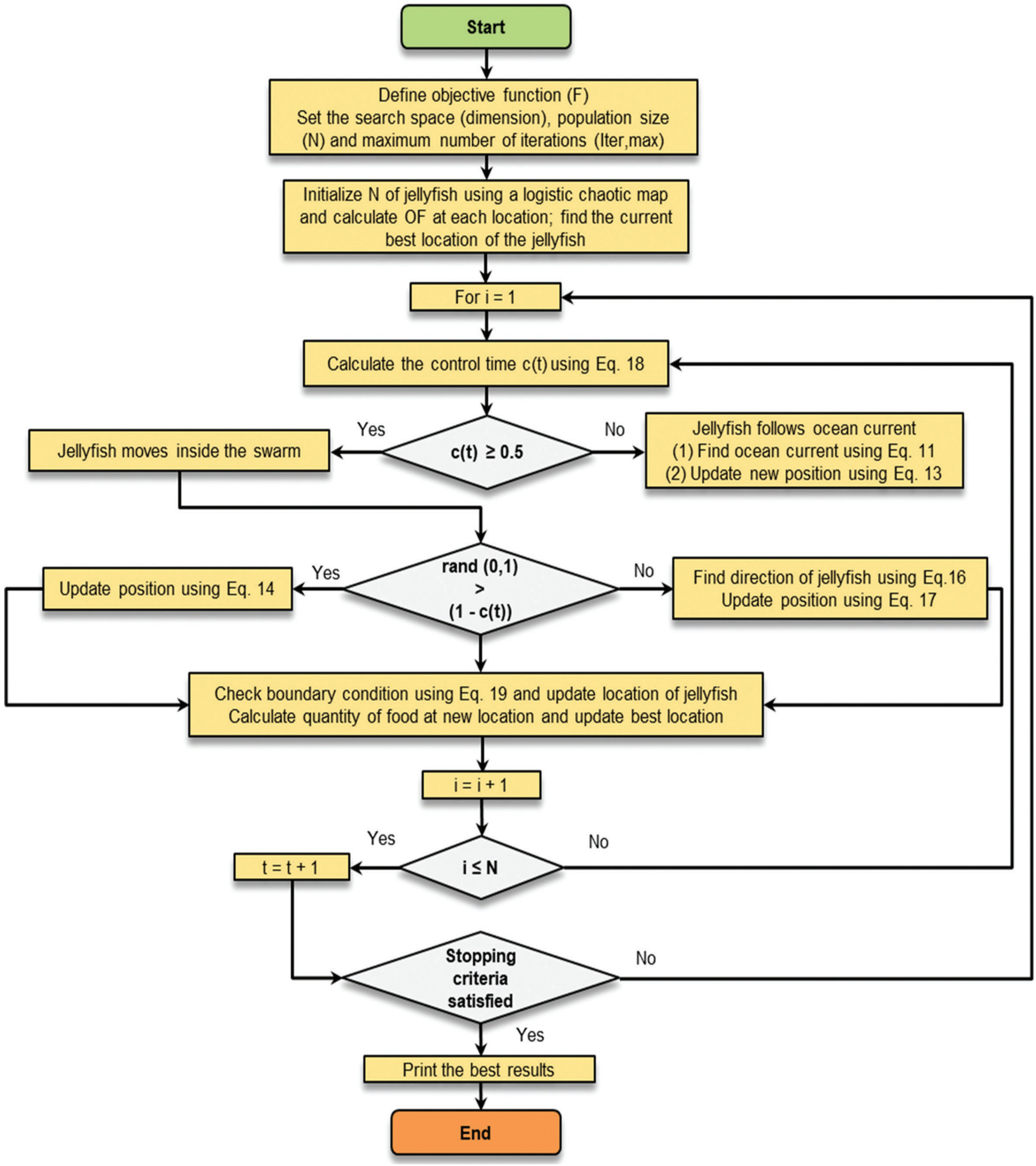

Fig. 2. Flowchart of JSO algorithm

Table 1. Control parameter and constraints

Variable	Values
No. of populations	30
No. of iterations	100
Base MVA	100
Bus voltage constraint	0.95 p.u<V_i<1.05 p.u
DG capacity limit	33-bus *RDN* - 400<P_{DG}<3000 250<*QDG*<1830 69-bus *RDN* - 400<P_{DG}<3100 300<*QDG*<2100 118-bus *RDN* - 2400<P_{DG}<18000 1750<*QDG*<13250

The simulation study is executed considering the following assumptions.

- The *RDN* power demand is constant and balanced.
- The environmental climate irregularity for *DG* modelling is ignored.
- The *PF* results of *RDN* without *DG* accommodation are referred as base case results.

The proposed simulation study has been executed to optimize the location and size for type I (photovoltaic), II (capacitors) and III (synchronous generator) *DG* to minimize total *APL* of *RDN*.

The following subsections present the simulation findings of different *RDN*s with and without *DG* accommodation.

4.3 SIMULATION OUTCOME WITH NO DG PLACEMENT

The simulation outcome for different IEEE *RDN*s with no *DG* placement is presented in Table 2. The *PF* execution using *BFS* algorithm for 33-bus, 69-bus and 118-bus *RDN*s without *DG* results in 210.98 kW, 225 kW and 1296.3 kW total *APL*, respectively. Noticeably, 21 out of 33-bus, 9 out of 69-bus and 45 out of 118-bus *RDN*s violates the minimum bus voltage (V_{min}) constraint and register V_{min} 0.9038 p.u, 0.9092 p.u and 0.8688 p.u, respectively.

Table 2. Simulation outcome: Without *DG* accommodation

Outcome	IEEE 33-bus RDN	IEEE 69-bus RDN	IEEE 118-bus RDN
Active power demand in MW	3.72	3.8	22.71
Reactive power demand in MVAr	2.3	2.69	17.04
Total APL in kW	210.98	225	1296.3
Vmin in p.u.	0.9038	0.9092	0.8688

4.3 SIMULATION OUTCOME WITH DG PLACEMENT

The simulation findings for different *RDN*s with *DG* units are presented in Table 3.

Table 3. Simulation outcome: With *DG* accommodation

Outcome	IEEE 33-bus RDN			IEEE 69-bus RDN			IEEE 118-bus RDN		
	DG Type			*DG* Type			*DG* Type		
	I (kW)	II (kVAr)	III (kVA)	I (kW)	II (kVAr)	III (kVA)	I (kW)	II (kVAr)	III (kVA)
Location	30	30	30	61	61	61	61,17,65,12,13	61,17,65,12,13	61,17,65,12,13
Size	2133.67	1647.12	2689.43	1798.65	1328.25	1957.54	2660.1,1796.5, 2353.2,1636.7, 1786.9	1850.1,1923.5, 2003.2,1696.7, 2326.9	2650.1,1995.5, 2103.2,1896.7, 2006.9
Total *APL* in kW	101.8	146.1	60.46	71.24	133.24	20.38	456.78	678.23	187.46
V_{min} in p.u.	0.9522	0.9512	0.965	0.9776	0.9855	0.9845	0.9785	0.9932	0.9894

4.3.1. IEEE 33-bus RDN:

Graphical illustrations for APL and VP of IEEE 33-bus RDN before and after DG deployment are presented in Fig. 3 and Fig.4, respectively. The optimal allocation of DGs results in significant power loss reduction. The total APL of the test network has reduced to 101.8 kW, 146.1 kW and 60.46 kW respectively for type I, II and III optimized DG allocation. Also, the Vmin of the 33-bus RDN enhanced to 0.9522p.u, 0.9512p.u and 0.965p.u after the addition of type I, II and III DG, respectively and no buses of the power network fall below 0.95p.u.

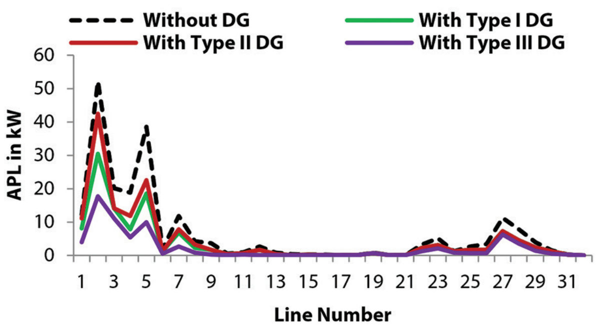

Fig. 3. APL of IEEE 33-bus RDS prior and after DG allocation

Moreover, JSO optimized DG placement converges to optimal result taking 7, 9 and 12 iterations and consuming 12, 14 and 17 seconds of CPU time for type I, II and III DG respectively. Fig. 5 shows the convergence characteristic of JSO algorithm for 33-bus RDN.

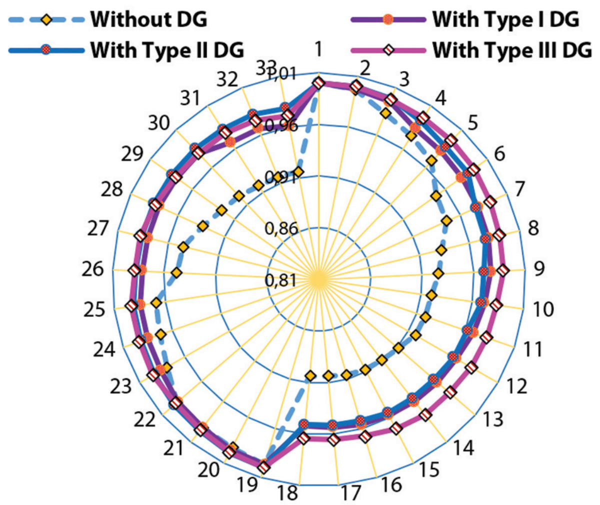

Fig. 4. VP of IEEE 33-bus RDS prior and after DG allocation

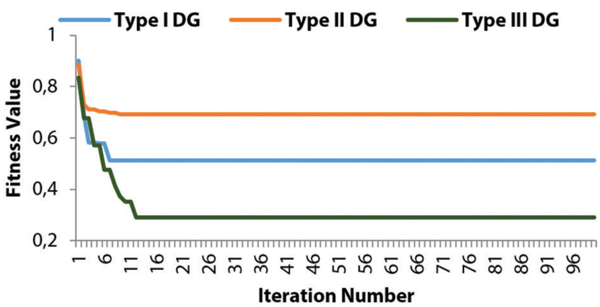

Fig. 5. Convergence curve of JSO algorithm for 33 bus RDS

4.3.2. IEEE 69-bus RDN:

PF execution for the 69-bus RDN with optimal type I, II and III DG placement results in a total APL of 71.24 kW, 133.24 kW and 20.38 kW, respectively. Furthermore, the Vmin of the test network increased to 0.9776p.u, 0.9855p.u and 0.9845p.u for type I, II and III DG respectively. Figs. 6 and 7 illustrate the APL and VP of 69-bus RDN prior and after DG allocation, respectively.

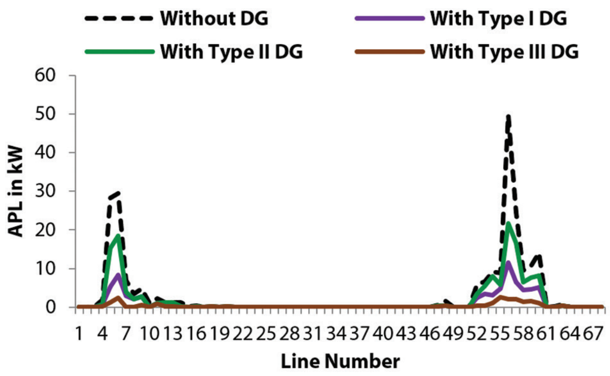

Fig. 6. APL of IEEE 69-bus RDS prior and after DG allocation

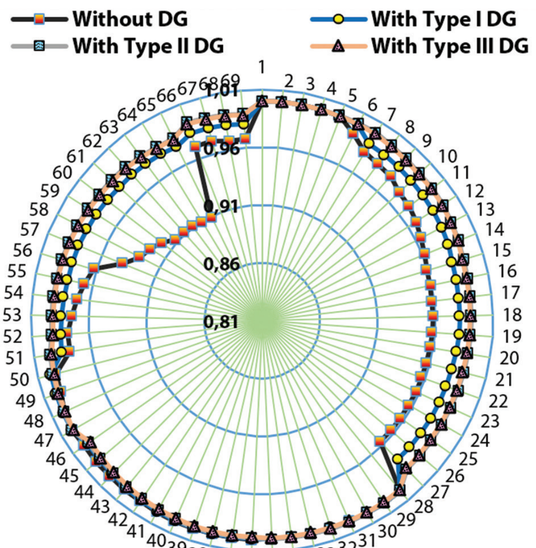

Fig. 7. VP of IEEE 69-bus RDS prior and after DG allocation

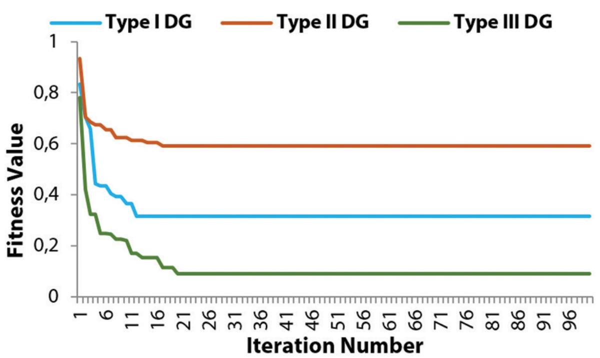

Fig. 8. Convergence curve of JSO algorithm for 69-bus RDS

The JSO converges to optimal result taking 11, 17 and 20 iterations and consumes 15, 25 and 31 seconds of CPU time respectively for type I, II and III optimized DG placement. The convergence characteristic of the JSO algorithm for 69-bus RDN is shown in Fig. 8.

4.3.3. IEEE 118-bus RDN:

The robustness of the JSO algorithm is examined by extending the simulation study to a large and complex 118-bus RDN. The number DGs for optimization are increased to five considering a large RDN. Table 3 presents optimal locations and the corresponding sizes of multi-DG for IEEE 118-bus RDN. The PF execution of a test network after multiple type I, II and III DG allocation minimized the total APL to 456.78 kW, 678.23 kW and 187.46 kW, respectively. The DG allocation also enriched the Vmin of the test network significantly to 0.9785p.u for type I, 0.9932p.u for type II and 0.9894p.u for type III. The VP of 118-bus RDN prior and after the allocation of multiple DGs is presented in Fig. 9.

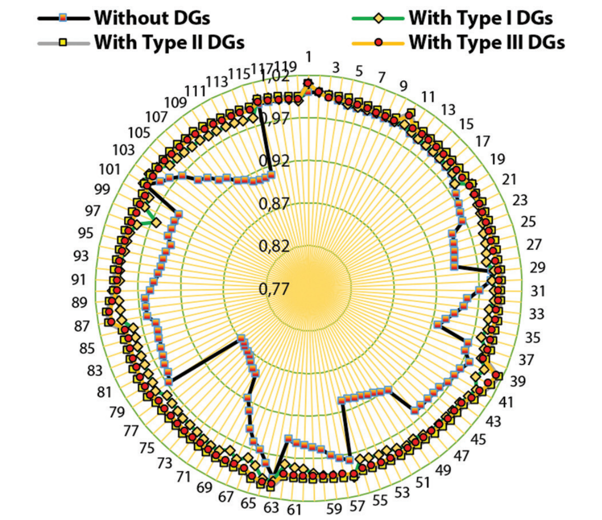

Fig. 9. VP of IEEE 118-bus RDS prior and after DG allocation

The proposed optimization technique converges to optimal solution taking 37, 36 and 41 iterations and consumes 52, 49 and 63 seconds of CPU time respectively for multiples of type I, II and III DG placement. Fig. 10 shows the convergence curve of the JSO algorithm for 118-bus RDN.

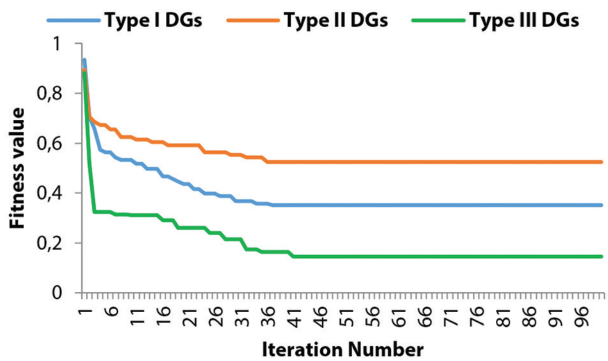

Fig. 10. Convergence curve of JSO algorithm for 118-bus RDS

The simulation findings presented in Table 3 also highlight that Type III DG deployment results more power loss reduction than type I and II DGs by injecting both active (P) and reactive (Q) powers into RDN.

4.4. COMPARATIVE ANALYSIS

In order to showcase the supremacy of the JSO algorithm, the simulation findings of the JSO algorithm are compared with the other algorithms cited in the literature. Table 4 presents the comparative results for type I and type III DG placement in 33-bus RDN. A comparison has revealed that the proposed JSO algorithm outclassed other optimization algorithms (SOA [11], ROA [10], SCA [20], HHO [15], LSF-SA [12] and WHO [8]) delivering a higher percentage of APL reduction at reduced DG capacity. Furthermore, JSO algorithm seamlessly converges to the best solution without trapping in local optima solution and tool less no. of iteration for convergence.

Table 4. Comparison result: IEEE 33-bus RDN with type I and III DG

Parameter	Type I DG				Type III DG					
	SOA [11]	ROA [10]	SCA [20]	Proposed	SOA [11]	ROA [10]	HHO [15]	LSF-SA [12]	WHO [8]	Proposed
Location	6	6	6	30	6	6	26	6	6	30
Size	2600	2590.2	2590.1	2133.67	2550	3144.6	2952.95	3098.2	3081.7	2689.43
Total APL in kW	102.8	111.02	111.02	101.8	65.1426	67.83	69.443	67.8118	61.3147	60.46
No. of iterations	NR	NR	NR	7	NR	17	28	28	15	12
CPU time (sec)	NR	NR	NR	12	NR	NR	NR	NR	NR	17

5. CONCLUSION

In this work, a novel optimization technique has been introduced using a jellyfish search optimizer (JSO) algorithm to optimize DG into RDN to minimize total APL. The optimal site and size for different DG (type I, II and III) were optimized using the JSO algorithm. The simulation study has been implemented on IEEE 33, 69 and 118-bus RDNs for different DG allocation. JSO optimized type I, II and III DG allocation in IEEE 33-bus RDN result 51.74%, 30.75% and 71.34% of total APL, respectively. For IEEE 69-bus RDN, type I, II and III DG placement reduced the total APL by 68.33%, 40.78% and 90.94%, respectively. Likewise, for multiple allocation of type I, II and III DGs in 118-bus RDN cut down the APL by 64.76%, 47.67% and 85.53%, respectively. In addition, the optimized solution enhanced the voltage profile of the RDNs significantly above the specified level (0.95p.u). The simulation finding of JSO for optimized DG allocation emphasizes its ability to find better solutions for complex optimization problems.

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