Research Article

MULTI-OBJECTIVE INTEGRATED APPROACH FOR DISTRIBUTED GENERATION PLACEMENT AND SIZING TO ENHANCE PERFORMANCE OF RADIAL POWER DISTRIBUTION SYSTEM

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Abstract. *This article proposes an integrated approach combining a novel population-based jellyfish search algorithm (JSA) and loss sensitivity factor (LSF) to optimize single and multiple distributed generation (DG) placement and ratings for total active power loss (TAPL) minimization and total voltage deviation (TVD) reduction. The study considers photovoltaic (PV) and wind turbine (WT) DG systems for optimal integration. The simulation findings are examined for a single and multiple DG allocation on the IEEE 69-bus benchmark radial distribution power network (RDPN). The TAPL of the 69-bus benchmark RDPN is minimized from 225 kW to 77.10 kW, 62.32 kW, 19.52 kW, and 9.94 kW after the single PV, three PV, single WT, and three WT DG systems optimization, respectively. Simultaneously, the TVD is minimized from 1.8369 per unit (p.u.) to 0.7036 p.u. and 0.6698 p.u. for a single and three PV DG systems optimization, respectively, and 0.3934 p.u. and 0.3466 p.u. for a single and three WT DG systems placement, respectively. The performance of the proposed integrated approach is compared to the different optimization techniques, taking TAPL as a comparison metric. The comparison showcases that the integrated approach results in a favorable optimal solution among the compared optimization techniques.*

Keywords

Distributed generation, power loss, voltage deviation, optimization.

1. Introduction

The generating capacities of power stations around the globe are increasing at a rapid rate to satisfy the increased power demand. The utilities may expand their existing power generation capacities to meet this rise in power demand. However, the expansion of transmission and distribution networks is difficult due to the isolated positioning of the power generation station. Additionally, power transmission over a long distance results in more power losses and voltage drops. Therefore, an alternative power generation approach is needed to cut these technical difficulties. The power generation near a load centre could be the wise solution to this problem. Such a power generation technique is termed distribution generation (DG). DG resources can supply required active and reactive power locally without expanding the existing system. DG uses different types of resources for power generation. However, the concern over limited fossil fuel reserves and environmental considerations has led developing countries to move forward with renewable energy-assisted DG. The renewable energy source-based DG inclusion offers power loss minimization, voltage profile and stability improvement, suspended transmission and distribution line extension, and reliability improvement. However, the impact of DG placement in distribution power network (DPN) parameters such as bus voltage, power flow, power losses, and voltage stability has to be explored before and after the allocations. Therefore, an appropriate technique is required for optimal planning of DG into the RDPN to acquire constructive benefits, since inappropriate allocation of DG increases power losses and weakens the reliability and stability of the radial distribution power network (RDPN).

DG placement and sizing problems in RDPN can be solved for single- and multi-objective scenarios. The optimal solution for the DG placement problem was obtained using various conventional and heuristic techniques. The analytical technique incorporates mathematical computation to address the optimization problem [1]. The heuristic technique uses randomness to solve optimization challenges. However, the latter technique has produced better results than the former. Moreover, analytical techniques require more time to converge due to the numerous mathematical computations [2]. An efficient optimization technique should possess faster convergence characteristics and be able to find the best optimal solution, irrespective of the complexity and size of the problem. Heuristic optimization algorithms leverage randomness as an advantage to find the optimal solution rapidly. Over the years, researchers have applied several meta-heuristic algorithms to optimize compensation devices, such as DG, shunt capacitors, and STATCOM, to enhance the performance of RDPN.

A shark optimization algorithm (SOA)-based technique was proposed to optimize DG's location and ratings to minimize the power losses (PL), improve the voltage profile (VP), and enhance the voltage stability (VS) of RDPN [3]. An integrated optimization technique was proposed using LSF and SA to optimize DG systems (PV and WT) in IEEE 33-bus and 69-bus benchmark RDPNs for minimizing PL and voltage deviation (VD) [4]. Optimal positions and ratings for various DGs were optimized via an improved version of the symbiotic organisms search (SOS) algorithm to minimize PL, enhance VP, and improve VS in 33-bus, 69-bus, and 118-bus RDPNs [5]. Multiple DGs were optimally assimilated in IEEE 33-bus and 69-bus benchmark RDPNs using the chaotic sine cosine algorithm (CSCA) for single and multiple objectives [?]. An integrated technique using GWO and PSO algorithms [7] was implemented to identify the suitable locations and ratings of various DG types in 33-bus and 69-bus RDPN. An artificial ecosystem-based optimization approach was implemented to optimize PV and WT DG systems in 33-bus RDPN. The suggested approach makes use of the LSF to find the optimal location for DG placement [8]. A combined optimization technique using genetic algorithm GA and particle swarm optimization (PSO) was introduced to optimize the DG units into the 33-bus and 69-bus balanced RDPNs [9]. DGs were optimized for PL reduction, VP and VSI improvement. GA [10] and PSO [11] techniques were applied to find the optimal position and capacity of multiple DGs in RDPNs. An ant colony optimization (ACO)-based approach was proposed for locating the optimal location and size of a DG system to minimize the TAPL of RPDN [12]. The appropriate sites and sizes for a DG system were finalized with the application of an integrated harmony search (HS) algorithm and LSF technique [13]. The optimal sites were identified using the LSF, and then the optimal sizes were computed with the execution of the HS algorithm. Authors have utilized Tabu search (TS) [14] and the Big Bang Big Crunch algorithm (BB-BCA) [15] to optimize DG placement and size for TAPL minimization and VP enhancement. A hybrid technique was proposed using ABC and ACO to figure out the optimal locations and capacities of DG systems for minimizing operating cost, APL, and emission rate [16]. Likewise, the whale optimization algorithm (WOA) [17], manta ray foraging optimization (MRFO) algorithm [18], salp swarm algorithm (SSA) [19], adaptive particle swarm optimization (APSO) [20], grey wolf algorithm (GWA) [21], ALO algorithm [22,23], Harris hawk optimization (HHO) [24], and hybrid optimization [25] approaches were proposed to optimize different types of DGs to enhance the performance of RDPN. A hybrid technique using teaching-learning and PSO algorithms was addressed in [26] to optimize DGs and STATCOMs simultaneously in RDPNs. The rider optimization algorithm (ROA) meta-heuristic technique was implemented to optimize the position and size of different DG units in RDPNs [27]. Authors have presented an optimization teaching adopting teaching learning strategy to optimize DG units in the RDPNs for minimizing PL, enhancing VP and energy savings [28]. A stochastic mixed-integer linear mathematical model was presented in [29] for optimizing the placement and rating of DG in the DC DPN. The proposed method solves the DG allocation problem, addressing load demand uncertainty and renewable energy source intermittency. Optimal position and capacity of DG units were determined for enhancing the VP and reducing the PL of RDPN [30]. Various loading conditions were considered for different types of DG placement. Generalized PSO methodology was proposed [31] for maximizing the profit of the DPN, taking the impact of harmonics. An integrated analytical and grid search algorithm (GSA) technique was proposed for solving the optimal DG allocation problem [32]. The proposed study considers PL reduction, VP improvement, and voltage stability index (VSI) enhancement as the primary goals. A novel multi-objective GWO optimization approach was introduced [33] to optimally assimilate multiple units of DGs in the RDPN. PL minimization, VD reduction, and VSI enhancement were considered as the primary objectives in this DG optimization study. The appropriate location and size of the PV DG unit were optimized using a new approach [34]. The proposed approach integrates LSF and the bat algorithm to locate the best site and size for the PV DG unit. A non-dominated sorting GA-II optimization technique [35] was employed to optimize the DG and capacitor units. The suggested technique achieved technical performance in the form of PL reduction, VD minimization, and line loading maximization. An enhanced SSA algorithm-assisted optimization approach was presented in [36] to discover the best solution for the DG placement and sizing problem in RDPN. The suggested approach optimizes the DG units for maximizing the economic and technical benefits, including PL minimization, VP improvement, and cost minimization.

The meta-heuristic techniques presented in the literature have somehow been able to enhance the performance of RDPN by optimizing the DG location and ratings appropriately. However, most of the meta-heuristic approaches are frequently trapped in local optimal solutions and converge prematurely due to unbalanced exploitation and exploration. Hence, the introduction of new optimization techniques or modifications/hybridization of existing approaches is essential to improve the accuracy of optimal solutions. The present study proposes an efficient integrated approach using LSF and the jellyfish search algorithm (JSA) to solve a single and multiple DG optimization problems. JSA is a population-based algorithm that possesses balanced exploitation and exploration features. This feature makes a valuable reason for its selection in the DG optimization problem. Moreover, to the extended knowledge of the authors, the proposed integrated approach is validated for the first time in the present study for a DG allocation problem.

The significant contribution of the present work is outlined below.

- Implement a novel integrated LSF-JSA optimization technique to assimilate PV and WT DG systems optimally into the RDPN for enhancing the technical performance.
- Investigate the versatility of the proposed LSF-JSA methodology for single and multiple numbers of DG unit optimizations in the 69-bus RDPN.
- Assess the efficacy of the simulation findings of the proposed integrated approach through a comprehensive comparison.

The contribution of the present work is elaborated in different sections. Section 2 presents the problem formulation for a single and multi-DG system placement. Section 3 describes the mathematical modelling of the LSF-JSA integrated approach. Section 4 presents the simulation findings for the IEEE 69-bus benchmark RDPN. A summary of the simulation findings is presented as a conclusion in Section 5.

2. Problem Formulation

The identification of critical bus and selection of rating for DG unit is a complex and non-linear problem. In the present study, DG's locations and ratings are optimized aiming to minimize TAPL and TVD.

2.1. Problem Formulation

Consider an 'n' bus RDPN as shown in Fig. 1.

The flow of current (I) in a distribution line 'k' causes APL and reactive power losses (RPL). However, APL is more than the RPL in RDPN due to high line resistance ($\mathrm{R_k}$). Hence, large the RDPN more will be the power losses. Also, it is crucial to minimize the TAPL for an efficient power transmission network.

Equation (1) gives the mathematical expression for TAPL of RDPN [37].

$$TAPL = \sum_{k=1}^{N_k} \left(3 \times I_k^2 \times R_k\right) \tag{1}$$

where N_k is the number of branches in RDPN.

VP improvement is the secondary objective and is accomplished via minimizing the TVD of an RDPN. Equation (2) gives the objective function for TVD minimization [38]. The voltage deviation measurement between the actual ($\mathrm{V_i}$) and nominal (1 p.u.) bus voltages

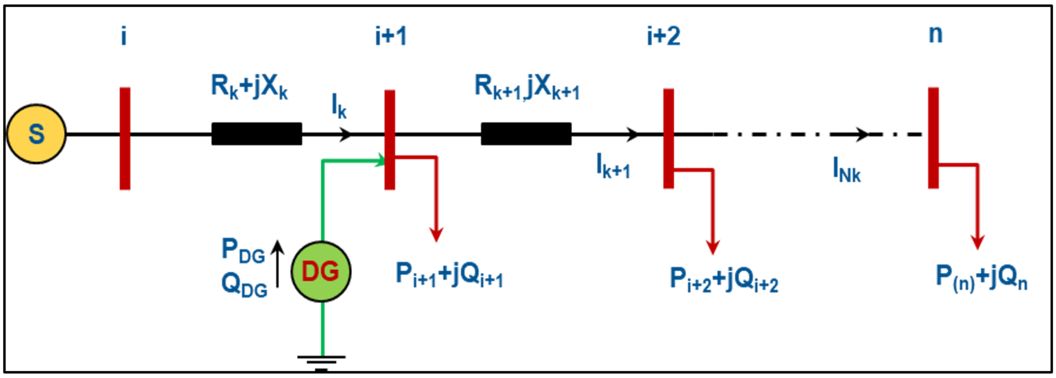

Fig. 1: RDPN with DG placement.

gives the voltage stability state of the system.

$$TVD = \sum_{i=1}^{n} |1 - V_i| \tag{2}$$

where n is the number of buses of RDPN. V_i is the voltage magnitude.

The present study uses the weighted sum method (WSM) to define the above two objectives as a single objective function [34].WSM assign an appropriate weights to individual objectives as per the level of importance. Equation (3) gives the objective function for the DG optimization study expressing the TAPL and TVD.

$$MOF = \quad Minimize \quad (\delta_1 * TAPL + \delta_2 * TVD) \tag{3}$$

where δ_1 and δ_2 are the appropriate weightage factors of TAPL and TVD, respectively. δ_1 and δ_2 values are chosen based on the level of significance.

2.2. Constraints

The optimal solution to a multi-objective DG allocation problem must fulfill several operational constraints, viz., real and reactive power balance constraints (equality) and RMS bus voltage, thermal capacity, and DG capacity (inequality constraints).

1) Power Balance

The net power injection in RDPN, including DG rating, must satisfy the expression presented in Eq. (4).

$$P_S + \sum_{i=1}^{N_{DG}} P_{DG}(i) = TAPL + \sum_{j=1}^{n} P(j) \tag{4}$$

where 'P_s' is the substation active power (AP) capacity. 'P_{DG}' is the injected AP capacity of DG unit; 'P' is the AP demand; 'N_{DG}' is the number of DG units.

2) Bus Voltage

The voltage magnitude of individual buses must be kept inside the recommended minimum and maximum values as expressed in Eq. (5) for security and safety reason in the RDPN.

$$V_{\min} \le V_i \le V_{\max} \tag{5}$$

where 'V_{min}' and 'V_{max}' are the minimum and maximum recommended levels of bus voltage, respectively. The voltage variation of $\pm5\%$ is considered nominal in RDPN.

$$0.95p.u. \le V_i \le 1.05p.u \tag{6}$$

3) Thermal Capacity

The optimized solution must ensure that the branch current does not increase beyond the maximum current capacity limit of a feeder line.

$$|I_k| \le |I_{k,\max}| \tag{7}$$

4) DG Rating

The DG sizes are optimally planned into the RDPN obeying the constraints expressed in Eq. (8)-(10) to ensure safer operation and prevent reerse power flow [34].

$$P_{\min}^{DG} \le P_T^{DG} \le P_{\max}^{DG} \tag{8}$$

$$P_{\min}^{DG} \le 0.1 \left(TAPL + \sum_{i=2}^{n} P(i) \right) \tag{9}$$

$$P_{\max}^{DG} \le 0.8 \left(TAPL + \sum_{i=2}^{n} P(i) \right) \tag{10}$$

5) Power Flow: Overview

Power flow (PF) is important for assessing line flows, node voltages, and power losses in RDPN. Also, it is

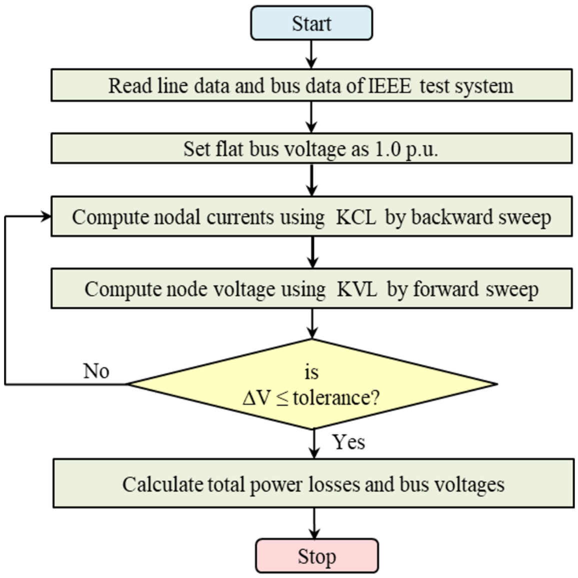

Fig. 2: Flowchart of BFS algorithm.

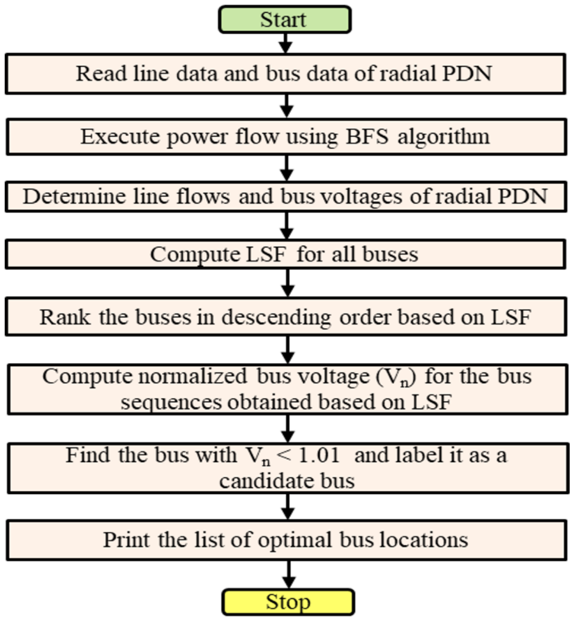

Fig. 3: Optimal DG placement selection.

necessary to compute the fitness values of the objective functions (TAPL and TVD). The orthodox PF techniques applied in transmission power networks are unsuitable for RDPN because of their poor convergence and inaccuracy. Therefore, for an accurate PF solution in RDPN, researchers typically adopt a backward-forward sweep (BFS) algorithm [39]. The BFS algorithm implements a two-step simple process known as a backward sweep (BS) and forward sweep (FS). In BS, branch currents are determined, whereas node voltages are computed in FS. During BS execution, the bus voltages are presumed to be the known values. During the FS execution, voltage is calculated, and it starts from the upstream node and moves toward the downstream node [39]. The flowchart illustration for the BFS algorithm is shown in Fig. 2.

3. LSF-JSA Integrated Technique: Modelling and Implementation

The proposed integrated optimization technique employs LSF to optimize the DG's locations and JSA to optimize the ratings. This section details the adoption of the proposed integrated approach for the DG placement and sizing problem.

3.1. Optimal Bus Selection using LSF

LSF reflects the impact of AP flow on the power losses. Hence, the present study makes use of LSF information to identify the optimal bus location for DG placement [37]. Also, optimal bus selection via LSF index computation significantly cut down the search space of the optimization algorithm. The mathematical equation for the LSF index is given in Eq. (11). The buses with a high LSF index and minimum normalized voltage (V_N) are selected as the ideal sites for DG placement. The bus voltages are normalized to a minimum constraint voltage (V_{min}). The flowchart for optimal bus selection is illustrated in Fig. 3.

$$LSF_i = \frac{2Q_i R_k}{|V_i|^2} \tag{11}$$

3.2. Optimal Sizing using JSA

JSA is a novel metaheuristic algorithm introduced to solve numerous optimization problems. JSA addresses complex optimization problems effectively through its diverse search ability, an adaptive search approach, and a balanced exploration-exploitation process. These unique features greatly evade local optima entrapment and fast convergence. Noticeably, the JSA has reported superior performance to several benchmark functions [40]. JSA mimics the food search behaviors of jellyfish. Jellyfish adopt two types of search mechanisms, viz., diversification and intensification, to capture nutrition like fish eggs, larvae, etc., in the ocean current and jellyfish swarm. JSA switches between search mechanisms via a time control mechanism (TCM). The mathematical background of JSA implementation is presented as follows.

1) Population Initialization

A unique tactic known as a chaotic map is adopted for initializing the population. Equation (12) expresses the population initialization.

$$Y_{i+1} = \eta Y_i (1 - Y_i) \quad , \quad 0 \leq Y_i \leq 1 \tag{12}$$

and

$$Y_0 \in (0, 1) \quad , \quad Y_0 \notin \{0, 0.25, 0.75, 0.5, 1.0\} \tag{13}$$

where 'Y' refers to the logistic chaotic value of jellyfish and 'η' is a constant.

2) Ocean Current (OC) Search Movement

The OC has rich quantities of nutrients. Hence, Jellyfish follows the OC in search of nutrition. The direction of OC, ($\overrightarrow{trend}$) is discovered using Eq. (14).

$$\overrightarrow{trend} = Y^* - \beta \times rand\,(0, 1) \times \mu \tag{14}$$

where 'Y^*' points the best (current) jellyfish position; 'β' and 'μ' refer to distribution coefficient and mean position of all jellyfish, respectively. The jellyfish upgrades its location via Eq. (15) and Eq. (16).

$$Y_i(t+1) = Y_i(t) + rand(0, 1) \times \overrightarrow{trend} \tag{15}$$

$$\begin{aligned} Y_i(t+1) = &Y_i(t) + rand(0, 1) \times Y^* \\ &- \beta \times rand(0, 1) \times \mu \end{aligned} \tag{16}$$

3) Jellyfish Search Movement

Jellyfish swarm moves in two different motions, viz. active and passive. JSA characterizes the jellyfish's passive motion as type 'A' and active motion as type 'B,' respectively. In the beginning of the optimization process, jellyfish swarms tend to follow type 'A' motion. But, later it follows type 'B' motion. Type 'A' motion epitomizes the jellyfish movement inside the swarm. Equation (17) gives the jellyfish movement following a type 'A' motion.

$$Y_i(t+1) = Y_i(t) + \gamma \times rand(0, 1) \times [H_b - L_b] \tag{17}$$

where 'L_b' and 'H_b' correspond to the lower and upper limit of the search area, respectively; 'γ' refer motion coefficient.

In type 'B' motion, the jellyfish movement direction is explored via considering a jellyfish, 'j,' alongside the one chosen (jellyfish, 'i') in a random process. If the nutrition around the jellyfish, 'j,' is more compared to the location of jellyfish, 'i,' then jellyfish, 'i,' directs towards jellyfish, 'j.' Otherwise, jellyfish, 'i' directs away from jellyfish, 'j.' Similarly, remaining jellyfish inside the swarm move and occupy the best position to consume the food. The mathematical illustration for the jellyfish movement and its updated position is given in Eq. (18)-(20).

$$\overrightarrow{Step} = rand(0, 1) \times \overrightarrow{Direction} \tag{18}$$

$$\overrightarrow{Direction} = \begin{cases} Y_j(t) - Y_i(t) & if \quad f(Y_i) \geq f(Y_j) \\ Y_i(t) - Y_j(t) & if \quad f(Y_i) < f(Y_j) \end{cases} \tag{19}$$

$$Y_i(t+1) = Y_j(t) + \overrightarrow{Step} \tag{20}$$

where f (Y) refers to a fitness function.

4) Time Control Mechanism (TCM)

The OC embraces a bulk quantity of nutrition for jellyfish. Therefore, the jellyfish creates a swarm to search for food in the OC. The OC changes its direction for a temperature or wind direction change. Under this circumstance, the jellyfish crafts another swarm and directs its movement towards the OC. However, to regulate the movement of jellyfish inside and outside the swarm, a TCM is added in the JSA. TCM introduces a time control function (TCF) and constant c_0 to regulate the movement of jellyfish. Equation (21) expresses TCF used in JSA. 'c_0' is an unknown value that varies from 0 to 1.

$$c(t) = TCF = \left| \left(1 - \frac{t}{Iter_{\max}}\right) \times (2 \times rand(0, 1) - 1) \right| \tag{21}$$

where 't' and '$Iter_{max}$' correspond to iteration time and a maximum number of iterations, respectively. $(1 - c(t))$ signifies the movement of jellyfish inside a swarm.

The jellyfish movement is characterized as a type 'A' motion, if rand (0, 1) is more than $(1 - c(t))$; otherwise jellyfish follow type 'B' motion.

5) Boundary Conditions

The jellyfish circulates randomly inside an ocean. Hence, its position must be regularized within a specified boundary condition whenever it goes beyond the search area to have a better solution. Equation (22) illustrates the boundary condition normalization.

$$Y'_{i,d} = \begin{cases} (Y_{i,d} - H_{b,d}) + L_{b,d} & \text{if } Y_{i,d} > H_{b,d} \\ (Y_{i,d} - L_{b,d}) + H_{b,d} & \text{if } Y_{i,d} < L_{b,d} \end{cases} \tag{22}$$

where '$Y_{i,d}$' and '$Y'_{i,d}$' denote jellyfish's actual position and updated position, respectively. The concept of JSA algorithm is presented graphically as flowchart in Fig. 4.

The step-by-step implementation of LSF-JSA integrated approach is presented below.

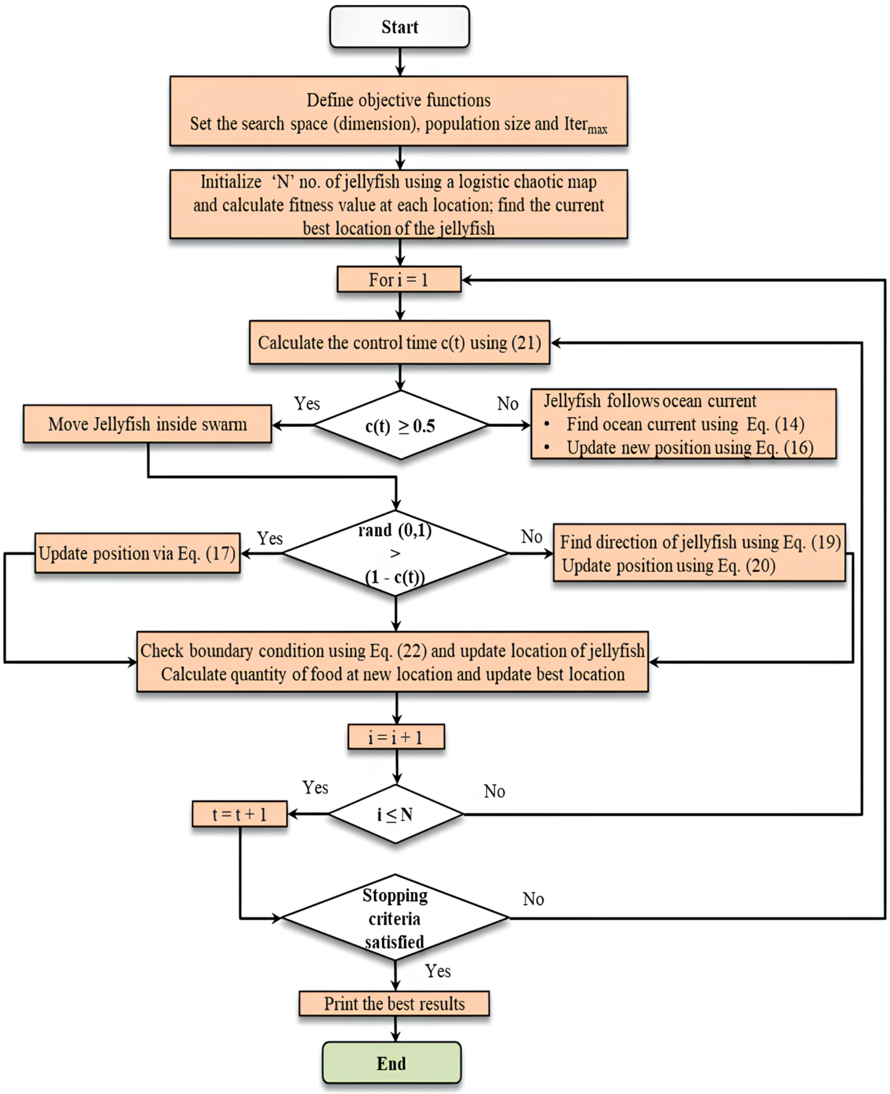

Fig. 4: JSA flowchart.

Step 1) Provide the necessary data for 69-bus IEEE benchmark RDPN.

Step 2) Run the power flow and find TAPL and TVD for the benchmark test system (without DG placement).

Step 3) Execute the following steps to locate optimal buses.

a) Compute LSF index for all buses of a benchmark test system.

b) Sort the buses in descending order based on the LSF index.

c) Calculate VN for all buses.

d) Locate the buses with VN less than 1.01 and consider them as potentially weaker buses for DG placement.

e) Select the buses with a high LSF index and minimum 'VN' as the optimal buses for compensation device placement.

Step 4) Execute the JSA to optimize rating(s) of DGs.

a) Get the optimal buses for DG placement.

b) Set the population size, number of iterations, and initialize relevant constraints.

c) Find the initial candidate solutions using Eq. (12), and map the solution with jellyfish location.

d) Run the BFS algorithm or PF method to compute the fitness value for every candidate solution.

e) Set the iteration count to 1.

f) Update the location of jellyfish using Eq. (15)-(16).

g) Run the PF and determine the fitness value for the updated jellyfish location.

h) Compare the fitness values of present and previous locations of jellyfish. Assign the jellyfish solution that gives the minimum fitness value as the elite solution.

i) Check for constraint violation and iteration number.

j) If the iteration count is less than the maximum value, increase the iteration by 1 and go to Step 4d.

Step 5) Print the elite solution.

4. Simulation Results and Discussion

The efficacy of the proposed integrated approach was tested on the IEEE benchmark 69-bus RDPN. Further, the performance of the proposed LSF-JSA integrated approach was investigated for different cases: i) single DG and three DG placements. The simulation findings were obtained using MATLAB 2022b software. The proposed optimization approach was simulated for 50 independent times to explore the best (global) optimal solution. The simulation studies were conducted for 30 numbers of population and 100 iterations (max.). Also, the natural uncertainties associated with solar and wind energy was ignored in this work.

The integrated LSF-JSA solves the multi-objective function using a WSM; hence appropriate selection of weightage factors (δ_1 and δ_2) is critical for computation of optimal solutions. The weighted factors are chosen based on the significance of objective functions. The present study gives more priority to TAPL minimization than TVD minimization. Therefore, δ_1 should be chosen greater than δ_2. The appropriate value for weightage factors is selected based on the fitness value of the objective function. The combination of δ_1 and δ_2 for which the fitness value results least is considered to be the appropriate value. In the present study, δ_1 and δ_2 are approximated as 0.6 and 0.4, respectively, since this combination results in the least fitness value for a single DG allocation (PV) in a 69-bus radial RDPN.

4.1. IEEE 69-bus RDPN

Figure 5 presents the single-line diagram (SLD) for the IEEE 69-bus benchmark system [41]. The test system is connected with 3800 kW of real power and 2690 kVAr of reactive power. The substation operates at 12.66 kV. The PF execution on the test system without DG placement results in 225 kW of TAPL and 1.8369 p.u of TVD. The test system experiences a V_{min} of 0.9092 p.u. in the 65th bus (far end). It is also found that 9 out of 65 buses have voltage magnitudes less than 0.95 p.u.

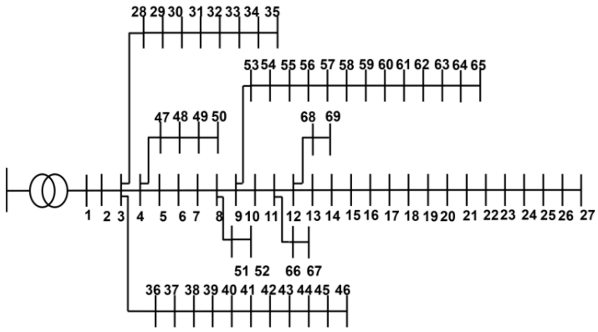

Fig. 5: SLD of IEEE 69-bus RPDN.

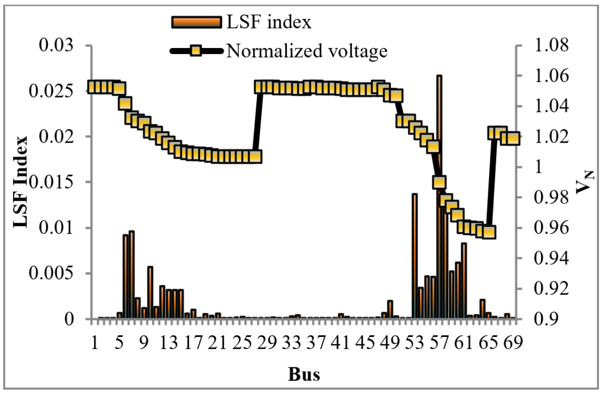

Fig. 6: LSF and VN of IEEE 69-bus RDPN.

4.2. Identification of Optimal Bus

The appropriate buses for DG placement are optimized based on the LSF index. Figure 6 illustrates the LSF index for the 69-bus RDPN. First, the sequences of buses for optimal DG placement are obtained based on the LSF index and VN. Then, the buses are listed in descending order based on the LSF index to find the candidate bus sequences for DG placement. The candidate bus sequences for the 69 bus benchmark system are 57, 58, 61, 60, 59, 64, 17, 65, 16, 21, 19, 63, 20, 62, 25, 24, 23, 26, 27, 18, and 22. For a single DG placement, bus 57 is picked as an optimal location, and likewise, buses 17, 61, and 65 are picked as optimal locations for multiple (three) DG placements.

4.3. Optimal Solution

This subsection discusses the optimal solution obtained for different cases of DG placement. Table 1 present the simulation findings for single and three DG placements.

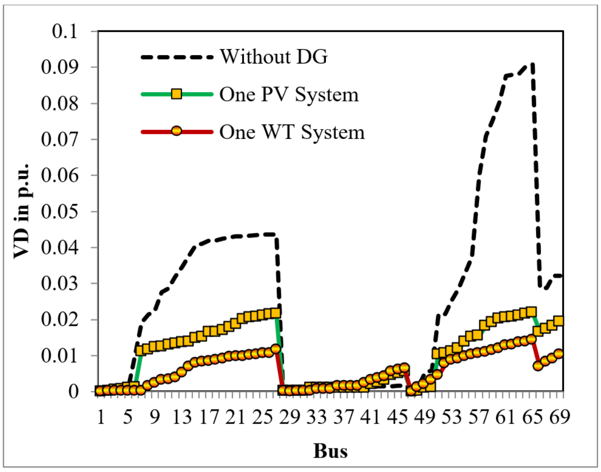

Fig. 7: VD of IEEE 69 bus- RDPN with and without optimized single PV and WT system.

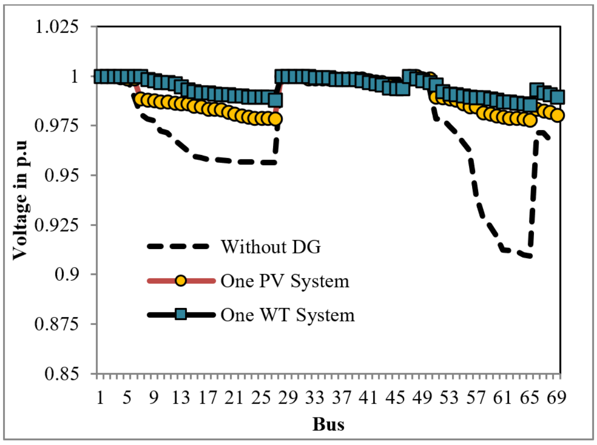

Fig. 8: VP of IEEE 69-bus RDPN with and without optimized single PV and WT system.

1) Case-1: Single DG System Placement

In case-1 investigation, a single DG system is optimally integrated into the RDPN. The simulation findings for the case-1 DG allocation are presented in Table 1 and Figures 7, 8, and 9. Figures 7 and 8 illustrate VD and VP of the IEEE 69-bus RDPN without and with a single PV and WT system, respectively. Figure 9 gives the convergence characteristic of JSA for a 69-bus RDPN with optimized single DG placement.

The placement of PV system at the 57th bus of a test system with a 1785.58 kW rating minimized the TAPL from 225 kW to 77.10 kW and reduced the TVD from 1.8369 p.u. to 0.7036 p.u. Furthermore, the TVD reduction has enhanced the VP significantly. Noticeably, optimized PV system placement enhanced the Vmin from 0.9092 p.u. (without DG) to 0.9781 p.u. Similarly, optimized positioning of a single WT system at the 57th bus with 1885.56 kVA reduced the TAPL to 19.52 kW and TVD to 0.0.3934 p.u. The least bus voltage magnitude of the test system is increased to 0.9856 p.u., after the optimized inclusion of the WT system. The JSA has taken 24 and 31 iterations and 57 and 65 seconds of CPU time for optimal solution convergence for single PV and WT system allocation, respectively.

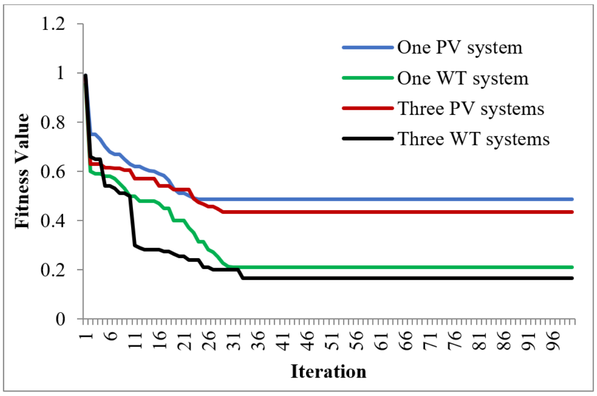

Fig. 9: Convergence characteristics of JSA for optimized placement of single and multiple DGs in IEEE 69-bus RPDN.

The proposed optimization approach is executed for 50 runs in MATLAB software. The best, maximum, mean, and standard deviation values obtained for the multi-objective function are outlined in Table 2.

2) Case 2: Three DGs Placement

Table 3 presents the MATLAB simulation findings for three units of DG allocations. The VD and VP of the test network after the three DG optimizations are presented in Figures 10, and 11, respectively. The proposed integrated approach finds the optimal solution by optimizing the PV systems for 1567 kW, 727 kW and 596.9 kW capacities at 61st, 17st and 65st buses, respectively; and WT systems for 1007.1 kVA, 884.7 kVA, and 997.7 kVA ratings at 61st, 17st and 65st buses, correspondingly. The JSA converges in 29 iterations and 63 seconds for a multi-PV systems allocation and 33 iterations and 68 seconds for optimal multi-WT systems integration. TAPL is reduced to 62.32 kW and 9.94 kW after the optimized inclusion of multi-PV and WT systems, respectively. Simultaneously, TVD is minimized to 0.6698 p.u and 0.3466 p.u immediately after the optimized three PV and WT systems allocation, respectively. Moreover, the Vmin is enhanced to 0.9798p.u and 0.98993p.u after the PV and WT systems optimization, respectively.

3) Comparative Analysis

The effectiveness of the LSF-JSA integrated approach is examined by relating its simulation findings with several optimization methodologies reported in the literature. Tables 3 and 4 present the simulation findings of

Tab. 1: Simulation results of IEEE 69-bus RDPN for different cases of DG placement.

	DG Capacity in kW/kVA (bus)	TAPL in kW	% TAPL Reduction	TVD in p.u	V_{min} in p.u	No. of Iterations	CPU Time (s)
No DG	-	225	-	1.8369	0.9092	-	-
With PV Placement							
Single PV	1785.58 (57)	77.10	65.73	0.7036	0.9781	24	57
Three PVs	1567 (61) 727 (17) 596.9 (65)	62.32	72.30	0.6698	0.9798	29	63
With WT Placement							
Single WT	1885.56 (57)	19.52	91.32	0.3934	0.9856	31	65
Three WTs	1007.1 (61) 884.7 (17) 997.7 (65)	9.94	95.58	0.3466	0.9899	33	68

Tab. 2: Optimal solution for different cases of DG placement.

Stats	One PV	One WT	Three PVs	Three WTs
Best	0.4870	0.2094	0.4341	0.1651
Maximum	0.5261	0.2457	0.4702	0.2116
Mean	0.4956	0.2188	0.4519	0.1802
Standard deviation	0.0131	0.0123	0.0128	0.0130

Tab. 3: Simulation results comparison: one DG placement.

Methodology	DG Capacity in kW/kVA (@bus)	TAPL in kW	% TAPL Reduction
PV System Placement			
ALOA [23]	1800 (61)	81.77	63.64
ROA [27]	1872.7 (61)	83.19	63.01
GA [10]	1872 (61)	83.18	63.02
PSO [11]	1337.8 (61)	83.20	63.01
SOA [3]	1890 (61)	81.50	63.76
Proposed	1785.58 (57)	77.10	65.73
WT System Placement			
ALOA [23]]	2227.9 (61)	23.16	89.70
ROA [27]	1828.47 (61)	23.16	89.70
SOA [3]	2250 (61)	23.15	89.70
Proposed	1885.56 (57)	19.52	91.32

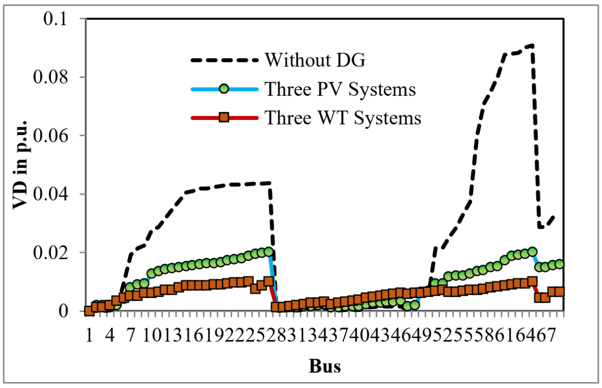

Fig. 10: VD of IEEE 69-bus RDPN with and without optimized three PV and WT systems.

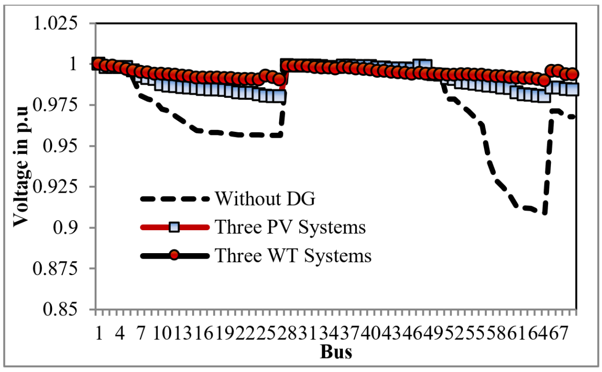

Fig. 11: VP of IEEE 69-bus RDPN with and without optimized three PV and WT systems.

the proposed LSF-JSA approach and other popular optimization approaches for a single and three DG placements in the IEEE 69-bus benchmark RPDN. The comparison has been performed taking percentage TAPL reduction as a comparison parameter. The comparison witnessed that the proposed LSF-JSA approach yields a maximum percentage of TAPL reduction with 65.73% and 91.32% for a single PV and WT system allocation, respectively. Also, the PSO [11] approach yields the least percentage of PL reduction at 63.01% amongst the other methodologies for a single PV system allocation. At the same time, the proposed integrated approach reduced 72.30% and 95.58% of TAPL following the multi-PV and WT systems allocation, respectively, which are the maximum amongst the reported methodologies in Table 4. Furthermore, GA [11] and IMOHS [42] approaches have reported minimum PL reduction in the literature for optimized three units of PV and WT DG placements, respectively.

5. Conclusion

In this work, an efficient LSF-JSA integrated optimization technique has been applied for optimizing single and multiple DG systems. The best placement and ratings for DG systems were optimized for TAPL reduction and TVD minimization. Optimal placements for the DG systems were identified via the LSF index, and the ratings were optimized via the application of JSA. The performance of an LSF-JSA integrated technique was assessed on the 69-bus IEEE benchmark RDPN for single and three units of PV and WT system placements. TAPL of the benchmark RPDN was reduced by 65.73% and 72.30% after the allocation of single and three PV systems, respectively. Furthermore, the PL was further reduced by 91.32% and 95.58% after the optimized inclusion of one and three units of WT systems, respectively. The optimized inclusion of DGs also reduced the TVD of RDPN significantly and enhanced the VP above the recommended V_{min}. Besides, to evaluate the effectiveness of the simulation findings of the integrated technique, the test results were compared to the simulation findings of several optimization techniques published in the literature. The integrated approach overcomes the limitations of existing optimization techniques and produces superior outcomes with better convergence characteristics. The proposed integrated approach showed its ability to discover the best locations and ratings for DG allocations, and hence it can be recommended for implementation in the practical RDPN in the future.

Data Availability

The datasets used and/or analyzed during the current study available from the corresponding author on reasonable request.

Author Contributions

J. R. developed the theoretical formulation; R. K. J. drafted the manuscript; S. K. M. and S. A. performed simulation; V. S. and S. R. analyzed the results and R. P. suggested the methodology and supervised the manuscript.

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Tab. 4: Simulation results comparison: three DG placement.

Methodology	DG capacity in kW/kVA (@bus)	TAPL in kW	% TAPL reduction
PV Systems Placement			
Proposed	1567 (61) 727 (17) 596.9 (65)	62.32	72.30
GA [11]	929.7 (21) 1075.2 (62) 984.8 (64)	89.00	60.42
PSO [11]	1199.8 (61) 795.6 (63) 992.5 (17)	83.20	63.01
GA/PSO [11]	884.9 (63) 1192.6 (61) 910.5 (21)	81.10	63.90
TLBO [43]	1013.4 (13) 990.1 (61) 1160.1 (62)	82.17	63.46
QOTLBO [43]	811.4 (15) 1147.0 (61) 1002.2 (63)	80.58	64.17
CTLBO [28]	560.3 (11) 427.4 (18) 2153.4 (61)	76.37	66.04
CTLBO ε-method [28]	965.8 (12) 230.7 (25) 2133.6 (61)	79.66	64.57
WT Systems Placement			
Proposed	1007.1 (61) 884.7 (17) 997.7 (65)	9.94	95.58
IMOHS [42]	1455.2 (61) 476.9 (11) 312.4 (21)	10.50	95.33
LSFSA [3]	549.8 (18) 1195.4 (60) 312.2 (65)	16.26	92.77
PSO [11]	1278.0 (61) 301.0 (64) 324.0 (21)	12.80	94.30

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