

Optimal Placement Of PV-Based Distributed Generation And EV Charging Infrastructure In IEEE 33-Bus Distribution Networks Using Superb Fairy-Wren Optimization

J Viswanatha Rao^{1*}, Siddheswar Kar², David Raju Kotapuri³, L Anbarasu⁴

Abstract— Electric vehicles (EVs) and Renewable Energy Systems (RESs) are increasingly growing in popularity, and this requires the application of advanced planning methods for ensuring their optimal integration into modern power distribution networks. This paper outlines a high-level optimization technique for optimal EV charging infrastructure placement and PV-based Distributed Generation (DG) in IEEE 33-bus Radial Distribution Systems (RDS). Proposed approach utilizes the Superb Fairy-Wren Optimization (SFWO) algorithm, nature-inspired metaheuristic widely recognized due to its high resistance against local optima and high convergence speed along with good exploration and exploitation balance. Concurrently the optimization aims for enhanced hosting capacity for PV-based DG units and EV charging stations enhanced voltage profile stability and minimized overall active power losses. The SFWO algorithm optimizes the PV-DG and EV charging node size and location subject to network operational constraints under a deterministic load operating scenario. The reliability measures are employed to comprehensively analyse system performance under a variety of operational conditions. The SFWO-based planning method proposed in this work achieves superior loss minimization and voltage profile improvement compared with benchmark metaheuristic algorithms. The proposed work uses a deterministic load-flow model to assess best locations for PV-DG and EV-CS.

Keywords—Electric vehicles, charging infrastructure placement, distributed Generation, RES, PV, IEEE 33-bus radial distribution systems, SFWO algorithm.

I. INTRODUCTION

RAPID growth of transportation industry has been hand in hand with a simultaneous increase in air pollution, majorly caused by Internal Combustion Engine (ICE) vehicles.

ICE-based transport brings large emissions to atmospheric particulate matter content, nitrogen oxides, and Carbon Dioxide (CO₂), posing serious public health threats and driving global warming [1]. To mitigate this environmental load, governments and industries across the globe are pushing vigorously for the

shift towards low-carbon transportation options, among which EVs have been positioned as a compelling answer [2]. EVs deliver significant tailpipe emissions reductions, ensure cleaner city air, and are a real route to meeting global climate goals like the Paris Agreement's requirement to reduce global warming to less than 2 °C by 2050. A reliance on fossil fuels in transportation industry remains largest sources of GHG emissions. Burning petroleum-based fuels not only exhausts limited natural resources but also hastens climate change by emitting CO₂ and methane, which cause glacier melting, sea level rise, and negative climatic phenomena [3]. Both technology and strict policy measures are needed to address these issues. The International Energy Agency (IEA) has suggested speedy uptake of sustainable mobility solutions with the help of clean energy transitions and robust energy infrastructure [4]. This has stimulated investigation into other propulsion systems, renewable energy integration, and novel power electronics-based charging infrastructure with an emphasis on improving or sustaining overall vehicle performance at the expense of environmental degradation [5].

Transport electrification has therefore emerged as a key element of energy transition plans. The most important advantages of EV adoption are enhanced energy security, oil import reduction, cost savings throughout vehicle lifetime, and technological advancement in electric drivetrain and battery management systems [6]. India, for example, has rolled out National Electric Mobility Mission Plan (NEMMP) 2020 and Faster Adoption and Manufacturing of Hybrid and Electric Vehicles (FAME) initiatives, with a view to mass EV deployment by 2030. The objectives of these plans are to facilitate large-scale EV penetration, thus reducing motor vehicle emissions and fossil fuel dependence [7].

The introduction of EV-CS increases load on RDN, which increase the feeder load, voltage deviation, and system losses, unless proper planning is undertaken [8]. Inclusion of EV chargers lead increase feeder load, voltage variation, power

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loss, and loading of transformers in distribution systems in the absence of appropriate planning methodologies. Also, inclusion of fast charging stations creates high power charging demands that are detrimental to network voltage regulation and Power Quality (PQ). Consequently, proper planning and allocation of the EV chargers ensures reliability and efficiency of RDS [9-10].

In order to counteract these deleterious effects, sound planning of EV charging infrastructure is of paramount importance. Charging systems are typically classified into three levels:

- **Level-1** (up to 3.3 kW) suitable for overnight residential charging,
- **Level-2** (ranging from 7 kW to 22 kW) commonly used in public and workplace charging hubs,
- **Level-3** (50–100 kW or more), also known as DC fast charging, which drastically reduces charging time but requires significant grid reinforcement [11].

Strategic deployment of charging stations not only provides user convenience but also reduces network overload, voltage fluctuation, and operating costs.

The deployment of distributed PV generation in distribution networks is becoming widespread in order to minimize feeder loading, enhance voltage profiles, and decrease real power losses. Proper placement and sizing of PV-DG systems play a vital role in technical efficiency of RDN [12]. Yet, inadequate siting and sizing of PV-DG units cause reverse power flow,

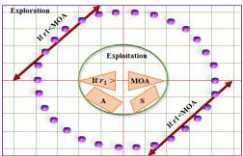
voltage rise problems, and higher power losses, particularly in Radial Distribution Networks (RDNs) with unidirectional power flow design. Hence, coordinated installation and optimal capacity allocation of PV-DG units as well as EV charging stations (EVCSs) are required to achieve techno-economic viability and reliable operations [13].

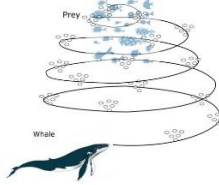
Recent research has utilized reliability-oriented models to assess EVCS integration in distribution networks. For instance, integrating EVCSs with grid-connected solar photovoltaic improves system reliability through sustained supply of load during grid outages [14-16]. Likewise, the planning of mixed-mode charging stations (slow and fast charging) in RDS, highlighting coordinated placement as crucial in minimizing service disruption. Evidence from research also emphasizes that uncontrolled charging in commercial parking areas has the potential to considerably compromise grid reliability [17], thus necessitating controlled load management measures.

For solving the twin challenge of optimal placement of PV-DG and allocation of EVCS, mathematical programming models including Mixed-Integer Nonlinear Programming (MINLP) have been commonly used. Although these models present mathematically optimum solutions, they tend to suffer from scalability challenges with network size and decision variable complexity increase. Therefore, hybrid and metaheuristic optimization methods have become increasingly important as they provide optimum solutions with minimal computational cost within reasonable time [16-18].

II. RELATED WORKS

TABLE I
RELATED WORKS.

Optimization Algorithm	Author & Title	Operations	Limitations
	Naresh Kumar Golla <i>et al</i> (2022) [19] “Optimal Placement of Charging Station and Distributed Generator along with Scheduling in Distribution System using Arithmetic Optimization Algorithm”	<ul style="list-style-type: none"> Performs 24-hour load profile scheduling of DGs using AOA Diminish power losses and increase voltage profile under stochastic EV load conditions. 	However, its scalability is limited due to increased complexity in multi-variable optimization.
	Sainadh Singh Kshatri <i>et al</i> (2025) [20] “An Enhanced Distribution System Performance with optimization Techniques for Location of electrical Vehicle Charging Stations”	<ul style="list-style-type: none"> To determine best EVCS placements, Grey Wolf Optimization (GWO), which draws inspiration from grey wolf hunting behaviour is used Minimizes power losses and enhances voltage profiles. 	Nevertheless, it is limited to static placement; does not address dynamic load variations or real-time scheduling.
	Sami M. Alshareef <i>et al</i> (2023) [21] “Efficient Red kite Optimization Algorithm (ROA) for Integrating the Renewable Sources and Electric Vehicle Fast Charging Stations in RDN”	<ul style="list-style-type: none"> Employs ROA for single-objective optimization and MOROA for multi-objective optimization Targets reduction of active power loss and voltage deviation over 24-hour period. 	Yet, dynamic EV charging durations not yet addressed.
	Isha Chandra <i>et al</i> (2025) [22] “Optimal scheduling of solar-powered EV charging stations in a RDS using Opposition-Based Competitive Swarm Optimization (OCSA)”	<ul style="list-style-type: none"> OCSA manages search space, by conserving its exploration and exploitation characteristics. Demonstrates enhanced grid reliability and reduced carbon emissions. 	Nonetheless, it struggles with premature convergence in highly multimodal landscapes without adaptive control mechanisms.

	Natsawat Pompern <i>et al</i> (2023) [23] “Optimal Placement and Capacity of Battery Energy Storage System in Distribution Networks Integrated With PV and EVs Using Metaheuristic Algorithms”	<ul style="list-style-type: none"> African Vulture Optimization Algorithm (AVOA) performs well in loss reduction and high demand mitigation in IEEE 33-bus system. Provides best standard deviation in statistical analysis. 	Slightly inferior objective values and less effective in peak demand reduction.
	Ferry Rahmat Astianta Bukit <i>et al</i> (2024) [24] , “Optimizing electric vehicle charging station placement integrates distributed generations and network reconfiguration”	<ul style="list-style-type: none"> Backward-forward sweep (BFS) load flow approach is used to predict power losses using Whale Optimization Algorithm (WOA), metaheuristic inspired by social foraging behaviour of whales. 	Conversely, it gets sensitive to initial parameter settings and convergence control.
	Muhammad Haris Khan <i>et al</i> (2022) [25] , “Optimal Sizing and Allocation of Distributed Generation in the Radial Power Distribution System Using Honey Badger Algorithm (HBA)”	<ul style="list-style-type: none"> By efficiently reducing active power losses, HBA's application greatly improved voltage profile and system reliability. It also establishes the ideal DG sizing for IEEE 33-bus RDS. 	On the other hand, it is limited exploration of multi-objective trade-offs beyond loss and voltage metrics.

Among the diverse metaheuristic methods employed in power system planning, the optimization algorithm proposed, stands out as a novel and biologically inspired method specifically suited to multi-objective distribution system optimization. Its adaptive search strategy, inspired by the cooperative and exploratory nature of the superb fairy-wren species, provides better capabilities to navigate the nonlinear, multimodal, and high-dimensional domains characteristic of RDNs. In contrast to traditional algorithms like PSO, which are plagued with premature convergence and local optima entrapment, SFWO presents dynamic role-switching and information-exchange mechanisms that enhance solution diversity, exploration-exploitation balance, and convergence reliability. These characteristics make SFWO especially well-suited for solving complicated infrastructure planning problems involving DG and EVCS.

This research introduces novel contributions to strategic planning of EV-CS and DG within modern power distribution systems. In particular, emphasis is made on best placement and sizing of the EV charging facilities and DG under the deterministic operation condition, in order to improve voltage control and reduce active power losses in the IEEE 33-bus RDS. This planning approach simultaneously optimizes the sites and sizes of EV charging facilities and distributed generation by employing a deterministic power flow model.

III. CONTRIBUTION

Proposed study aims to introduce new ideas and make significant contributions in this area, such as;

- ✓ Optimal configuration and size of EVCS and PV-based DGs for minimizing active power losses and enhancing voltage profile stability of IEEE 33-bus RDS in a deterministic operational environment.
- ✓ With the highly coupled effect between EVCS and distribution system, work studies various placements of DG-enabled EVCS and assesses their combined effects.
- ✓ A weighted sum multi-objective optimization approach using SFWO method is proposed in article

for assessing optimal number, configuration, and size of EVCS and PV-based DGs.

- ✓ The current work examines G2V EV charging under deterministic operating conditions; whereas, V2G feature is considered a potential extension and is not yet enabled within the optimization process.

IV. PROBLEM FORMULATION

A. Assumptions for Optimal DG and EVCS Allocation

Due to time-varying nature of loads in distribution networks, determining ideal location and capacity for EVCS and DG units under fluctuating conditions is challenging. To simplify the optimization process, the following assumptions are made:

- The radial distribution system is considered balanced.
- EVCS units are considered to be constant active power loads throughout the optimization process. The demand for charging is considered in the form of deterministic load that corresponds to the selected operating scenario.
- DG units are considered to be operating with unity Power Factor (PF) throughout the optimization process. Reactive power contribution by the smart PV inverters is not considered in this current research and will be investigated in future research.
- The optimization process considers the deterministic steady-state operating conditions. The power generation of PV is considered in the form of expected power based on the selected operating condition.
- Base load is considered in the form of fixed active and reactive powers. The demand for EV charging is considered in the form of deterministic load based on the selected operating condition.

B. Direct Load Flow Approach

Conventional load flow techniques such as Gauss-Seidel and Newton-Raphson are inappropriate for most distribution systems due to their radial topology and high resistance-to-reactance (R/X) ratio. Rather, a straightforward matrix-based strategy is used:

Matrixes for Branch Current to Bus Voltage (BCBV) and Bus Injection to Branch Current (BIBC) are built.

Load flow is solved by multiplying these matrices:

$$[P] = [BIBC][I] \quad (1)$$

$$[\Delta V] = [BCBV][P] \quad (2)$$

Combining both gives:

$$[\Delta V] = [DLF] \cdot [I] \quad (3)$$

Where, DLF is Distribution Load Flow matrix. Current at bus t is calculated as:

$$I_i = \left(\frac{P_i + jQ_i}{V_i} \right)^* \quad (4)$$

and decomposed into real and imaginary components using voltage angle θ_i . The deterministic operating point derived from the anticipated PV generation and equivalent EV charging demand is used for the load-flow computations.

C. Multi-Objective Optimization Framework

The optimization aims to identify best locations for DGs and EVCSs to:

- Reduce active power losses
- Maintain voltage levels within acceptable limits
- Improve Voltage Stability Index (VSI)

EVCSs are modelled to supply only real power for EV charging. Their placement affects real power demand at the connected bus, and optimal siting is preferred at buses with minimal branch current to reduce losses. In this paper, sizing and locating of PV-based DG and EV-CS are modelled as a deterministic multi-objective optimization problem under representative operating conditions. The objective is to minimize real power losses and voltage deviation at same time.

Proposed approach makes use of a weighted sum method that minimizes real power losses and voltage deviation at once through multi-objective optimization. The general objective function is computed as:

$$F(x) = w_1 F_1(x) + w_2 F_2(x) \quad (5)$$

Where, $F_{1(x)}$ real power loss objective and $F_{2(x)}$ voltage deviation objective. Weights w_1 and w_2 show the priority of the objectives and satisfy the constraint ($w_1 + w_2 = 1, 0 \leq w_1, w_2 \leq 1$).

Formulation considered here emphasizes better voltage profile stability, hosting capacity enhancement, and reduction in active power losses. Novel optimization algorithm is utilized in finding optimal placement and sizing of DG and EV-CS nodes.

D. Objective Functions

Reducing real power loss while preserving acceptable voltage profiles is the goal of the optimization.

1) Real Power Loss Reduction

Efficiency of DG is increased by lowering active power losses. Objective function for real power loss minimization is:

$$F_1(x) = \min \sum_{b=1}^{N_b} R_b \cdot |I_b|^2 \quad (6)$$

Where, R_b refers to branch b resistance and I_b refers to current flow through the branch. This formula measures by how much actual power is lost as heat in distribution lines.

2) Minimization of Voltage Deviation

Voltage deviation index is related as:

$$F_2(x) = \min \sum_{n=1}^{N_{bus}} (V_{ref} - V_n)^2 \quad (7)$$

V_{ref} is nominal reference voltage (1.0 p.u.), while V_n is voltage magnitude at bus n . Squared difference measures how much the actual bus voltages diverge from the ideal reference.

E. Constraints

The optimization procedure needs to fulfil both equality and inequality constraints in order to ensure system feasibility and dependability.

1) Equality Constraints

These constraints keep active and reactive power balance throughout system:

$$\sum_{g=1}^{N_{DG}} P_g^{act} - P_{loss} = P_{load} \quad (8)$$

Active Power Balance ensures that power generated exactly equal's consumption to avoid over generation or deficit situations.

$$\sum_{g=1}^{N_{CB}} Q_g^{react} - Q_{loss} = Q_{load} \quad (9)$$

Reactive power balance constraint ensures reactive power supplied by PV inverters balances network reactive power losses. Sustaining this balance enhances system power factor, hence minimizing voltage drops and enhancing stability.

2) Inequality Constraints

Solution Space is also subjected to the following operational constraints for IEEE 33-bus RDS, which ensures safe and secure operation.

Active Power Generation Limitation of DG Systems

Active power generation of DG system of each bus is subjected to the generation limit between minimum and maximum generation capacity.

$$P_g^{min} \leq P_g^{act} \leq P_g^{max} \quad (10)$$

Voltage Bound of Bus

Voltage magnitude at each bus is in permissible operating zone of voltages to provide voltage regulation.

$$0.95 \leq V_n \leq 1.05 \quad (11)$$

PF Constraint

PV based DG systems are assumed to operate at unity PF, DGs supply active power and they have no role in reactive power regulation. Therefore,

$$pf = 1.0 \quad (12)$$

Total Active Power Generation Limit

Total active power generation from all PV based DG units must be less than or equal to the total active load demand.

$$\sum_g P^{act} \leq P_{load}^{total} \quad (13)$$

V. MODELLING OF PV POWER GENERATION

Historical solar irradiance data collected over a specific period is used to construct a frequency distribution representing a typical day. To simulate PV power generation, the Beta distribution is employed.

A. Solar Irradiance Modeling

For each hour t of a representative day, the Beta PDF models the probabilistic behaviour of solar irradiance s^t (in kW/m²) as:

$$f_b(s^t) = \begin{cases} \frac{\Gamma(\alpha^t + \beta^t)}{\Gamma\alpha^t \Gamma\beta^t} (s^t)^{\alpha^t-1} (1-s^t)^{\beta^t-1}, & 0 \leq s^t \leq 1, \alpha^t, \beta^t > 0 \\ 0, & \text{otherwise} \end{cases} \quad (14)$$

The parameters α^t and β^t derived from mean μ_s^t and standard deviation σ_s^t of irradiance at time t :

$$\beta^t = (1 - \mu_s^t) \left(\frac{(1 - \mu_s^t) \mu_s^t}{(\sigma_s^t)^2} \right) \quad (15)$$

$$\alpha^t = \frac{\mu_s^t \beta^t}{(1 - \mu_s^t)} \quad (16)$$

B. PV Power Output Estimation

To estimate the PV array's power output for each hour t , the continuous irradiance distribution is discretized into multiple

states. The expected hourly power P_{PV}^t is computed by summing the contributions from all irradiance states:

$$P_{PV}^t = \sum_{i=1}^{n_s} P_0(s_i^t) f_b(s_i^t) \quad (17)$$

Here $P_0(s_i^t)$ is output power of a PV module, calculated as,

$$P_0(s_i^t) = N_m \times V_c \times I_c \left(\frac{V_{MPP} \times I_{MPP}}{V_0 \times I_s} \right) \quad (18)$$

Here, N_m Number of PV modules, V_{MPP}, I_{MPP} are voltage and current at peak power point, V_0, I_s are open-circuit voltage and short-circuit current, V_c, I_c are cell voltage and current, determined by:

$$V_c = V_0 - K_v \times T_c \quad (19)$$

$$I_c = s^t (I_s + K_i (T_c - 25)) \quad (20)$$

Where, K_v, K_i are temperature coefficients for voltage and current, T_c is cell temperature, computed as:

$$T_c = T_A + s^t \left(\frac{T_0 - 20}{0.8} \right) \quad (21)$$

This study uses irradiance data to derive hourly mean and standard deviation values for μ_s^t and σ_s^t . For the analysis irradiance values divided into 20 discrete states per hour at 0.05 kW/m² intervals. The resulting PV power outputs are illustrated in Figure 1(a), and a normalized daily profile (in per unit) is generated as displayed in Figure 1(b). Expected hourly generation by PV derived using the Beta distribution is converted to a representative operating point prior to performing load flow and optimization.

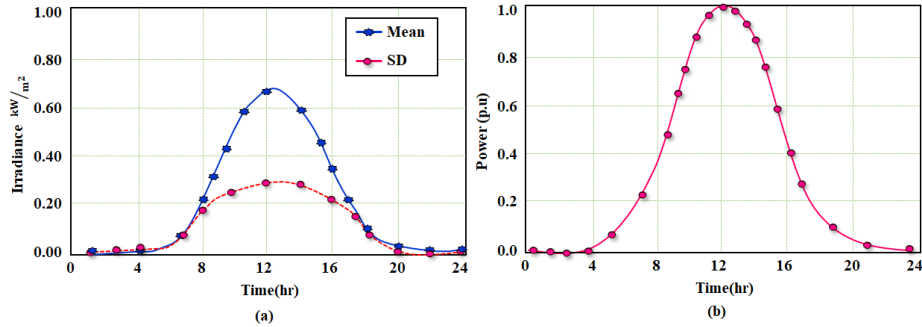


Fig. 1. Schematic modelling of PV power generation (a) Mean and Standard Deviation (c) Expected PV output normalized power.

VI. SUPERB FAIRY-WREN OPTIMIZATION (SFWO) ALGORITHM

Placement of EVCSs and PV based DGs is a process of choosing an optimal bus location along with sizing of DG units based on certain constraints. The difficulty of arriving at optimal solution is compounded by the nonlinearity and mixed discrete and continuous characteristic of the optimization problem. To resolve this issue, the proposed SFWO algorithm [26] presents a reliable mechanism of searching for optimal location and sizing of DG units and EVCSs within IEEE 33-bus RDN.

A. Initialization

SFOA, population-based metaheuristic mimics intelligent search behaviour over iterative evaluations. Each member of

SFOA population represents candidate solution, encoded as a vector of decision variables. The initial population is randomly distributed within the defined search space using:

$$X = \begin{bmatrix} X_1 \\ \vdots \\ X_i \\ \vdots \\ X_N \end{bmatrix}_{N \times D} = \begin{bmatrix} x_{1,1} & \cdots & x_{1,d} & \cdots & x_{1,D} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i,1} & \cdots & x_{i,d} & \cdots & x_{i,D} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{N,1} & \cdots & x_{N,d} & \cdots & x_{N,D} \end{bmatrix}_{N \times D} \quad (22)$$

$$X = (ub - lb) \times rand(0,1) + lb \quad (23)$$

Here, X global matrix of candidate solutions, ub, lb upper and lower bounds of decision variables, $rand$ random number in $[0, 1]$, N number of population members, D dimensionality problem.

B. Behavioural Modeling of SFOA

Position of each member in search space is updated through three biologically inspired phases:

Phase 1: Growth and Exploration

In this phase, young birds simulate learning through movement and experience. This behaviour enhances global exploration and prevents premature convergence. The position update is given by:

$$X_{new\ i,j} = X_{i,j}^t + ((ub - lb) \times rand), r > 0.5 \quad (24)$$

Phase 2: Breeding and Feeding

When environmental risk is low, birds engage in cooperative breeding and feeding. Members take turns caring for eggs and teaching identification behaviours. This phase promotes local exploitation. The danger threshold s computed by:

$$s = r_1 * 20 + r_2 * 20 \quad (25)$$

Here, r_1, r_2 are normally distributed random variables. The updated position is:

$$X_{new\ i,j} = X_G + (X_b X_{i,j}^t) \times p, r < 0.5, s < 20 \quad (26)$$

$$X_G = X_b \times C \quad (27)$$

Here, X_b is the current best position, $C = 0.8$, constant, p is maturity factor based on teaching cycle.

$$P = \sin((ub - lb) \times 2 + (ub - lb) \times m) \quad (28)$$

Where,

$$m = \left(\frac{FES}{MaxFES} \right) \times 2 \quad (29)$$

Current number of evaluations FES , Maximum evaluations $MaxFES$

Phase 3: Predator Avoidance

When danger is detected, birds rapidly change position to evade predators. This phase introduces randomness and diversity in search process. Position update is:

$$X_{new\ i,j} = X_b + X_{i,j} \times l \times k, r < 0.5, s > 20 \quad (30)$$

Here, l is Lévy flight step size, k is adaptive flight factor, Call frequency (w), specified by:

$$k = 0.2 \times \sin\left(\frac{\pi}{2} - w\right), \quad w = \frac{\pi}{2} \times \frac{FES}{MaxFES} \quad (31)$$

C. Implementation Summary

Population Initialization: Define N, D, FES, ub and lb .

Growth Phase: Wide exploration using formula (22)

Breeding Phase: Local exploitation using formula (23)

Avoidance Phase: Randomized movement using formula (25)

The final position update rule integrates all three behaviours:

$$X_{new\ i,j} = \begin{cases} X_{i,j}^t + ((ub - lb) \times rand), r > 0.5 \\ X_b \times C + (X_b X_{i,j}^t) \times p, r < 0.5, s < 20 \\ X_b + X_{i,j} \times l \times k, r < 0.5, s > 20 \end{cases} \quad (32)$$

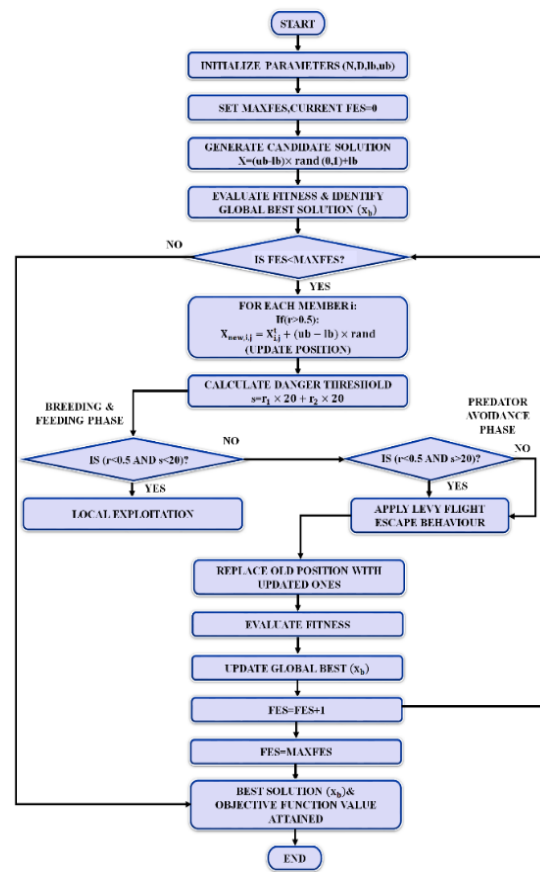


Fig. 2. Flowchart of proposed SFWO algorithm.

This new swarm intelligence algorithm figure.2, based on the lifecycle and society dynamics of the superb fairy-wren, has improved exploration and exploitation functions. Its biologically inspired framework makes it an effective means to tackle complex optimization issues such as strategic location of PV-based DG units and EVCS in RDNs.

VII. RESULT AND DISCUSSION

Proposed system is assessed on a benchmark RDS: IEEE-33 bus network. Proposed SFWO algorithm is implemented over 100 iterations with population size of 50, across 10 independent trials. The maximum generation capacities were set at 1000 kW for RES (PV) and 1500 kW for FCS.

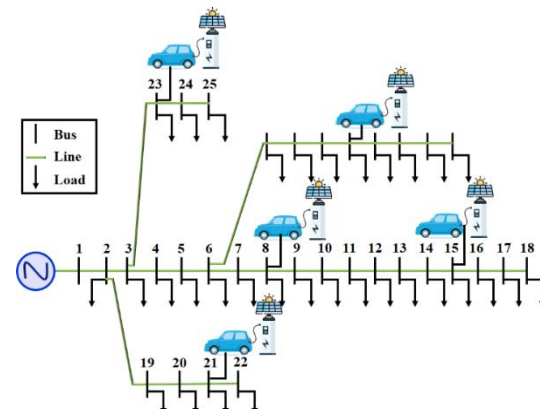


Fig. 3. IEEE bus system with solar powered EVCS.

IEEE-33 Bus Network Configuration and Simulation Setup

IEEE 33-bus RDS, consisting of 33 nodes and 32 branches, operates at nominal voltage level of 12.66 kV with base power rating of 100MVA, as depicted in Figure 3. In this research, PV-based RES units were strategically integrated into network. System's base load is defined as 3.715MW and 2.3MVar, with initial power losses recorded at 3905.628kW and

2604.031kVar. All simulations were conducted on a computational platform featuring an 11th Gen Intel® Core™ i7-11370 processor operating at 3.30 GHz, supported by 16 GB of RAM.

First, Ant Colony Algorithm's (ACA) performance is assessed using several network reconfiguration and DG deployment scenarios.

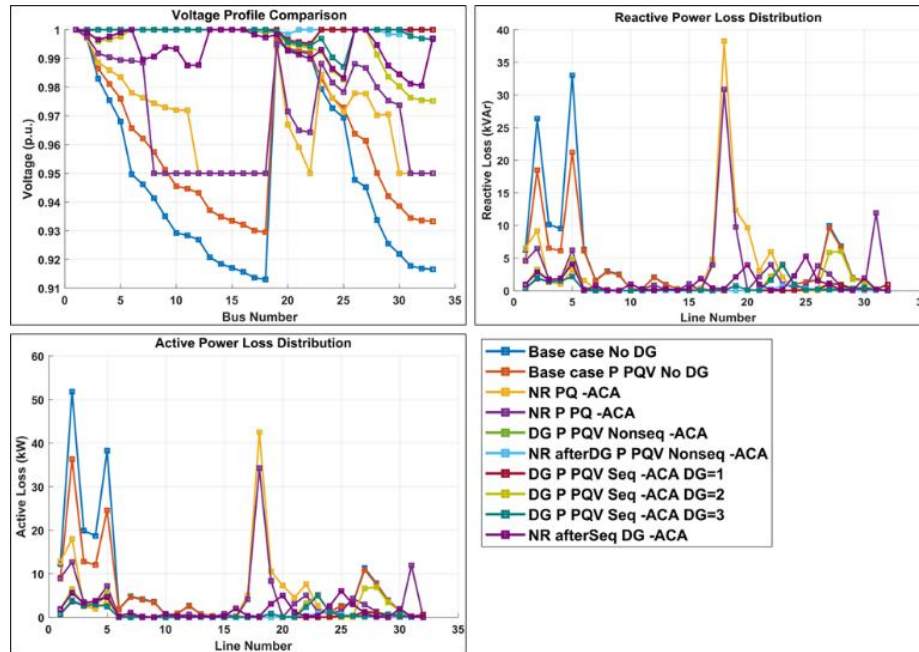


Fig. 4. Performance analysis of ACA for optimal DG and EV-CS placement in IEEE 33-bus distribution network

Figure.4 presents performance comparison of ACA using different network reconfiguration schemes and DG placements based on distribution profiles of voltage profile, reactive power losses, and active power losses. When compared to the baseline scheme, ACA shows remarkable improvements in terms of the improvement of minimum bus voltage from around 0.914 p.u.

to nearly 0.998 p.u. of best sequential DG placement and reduction of major loss peaks of around 33 kVA and 52 kW for the reactive and active power losses, respectively. However, localized voltage instabilities and loss peaks still be seen near Line 18 to Line 30.

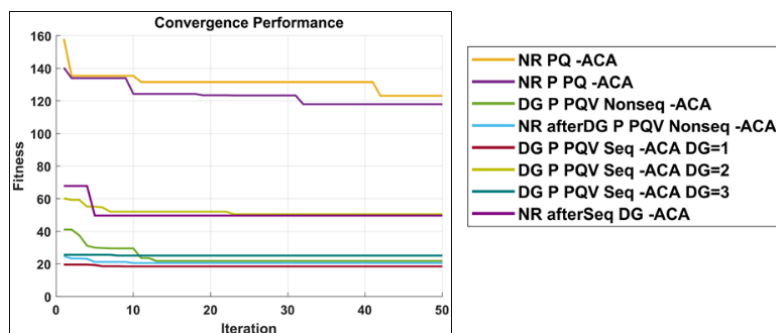


Fig. 5. Convergence characteristics of ACA

Figure. 5 represents the convergence features of ACA, for network reconfiguration cases, the optimization is initialized with the fitness values of about 158 and 136 and converges to around 123 and 118 respectively after about 42–45 iterations. Non-sequential DG allocation converges from about 41 to 24, while the sequential DG allocation cases converge in the range of 19–23 after about 8–12 iterations. Post sequential network reconfiguration converges from around 68 to 50 within about 5 iterations and does not change afterward. ACA has a stable

convergence behavior with consistent fitness reduction and adequate optimization capability. But, in the end of the iterations, the convergence rate tends to slow down especially for network reconfiguration cases, wherein any significant improvement does not be achieved after 30 iterations.

As done with ACA, the performance of HBA is examined through different operating conditions of the network, such as network reconfiguration and sequential and non-sequential DG allocation.

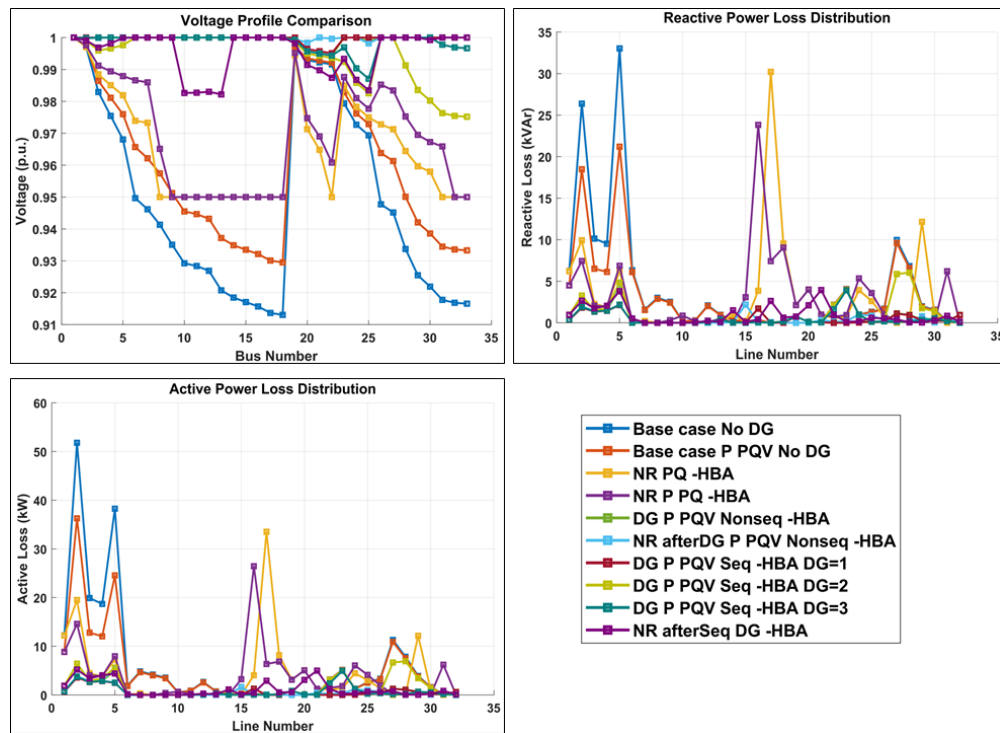


Fig. 6. Performance analysis of HBA for optimal DG and EV-CS placement

Figure.6 displays results of voltage magnitude, active power loss, and reactive power loss when using HBA for various reconfigurations and DG locations. It is seen that HBA outperforms the base scenario through improving minimum bus voltage from about 0.914p.u. to around 0.997p.u., decreasing

maximum active and reactive power losses from approximately 52kW to 34kW and 33kVar to 30kVar, respectively. While HBA gives a better voltage control and loss reduction than ACA, their exist voltage fluctuations and losses' peaks.

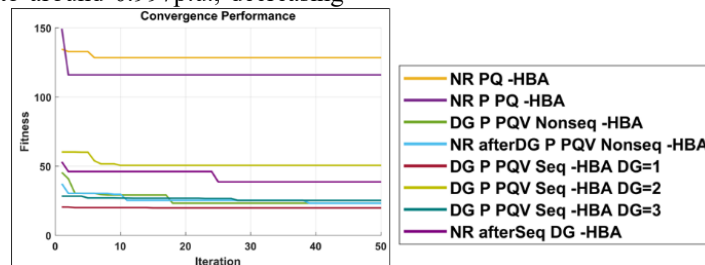


Fig. 7. Convergence Performance of HBA

Figure.7 depicts the convergence properties of the HBA in various configurations of DG placement and network reconfiguration. The converged values in the reconfiguration problems start from around 150 and 135 and stabilize at 128 and 116, respectively. For the sequential DG placement problem, the algorithm converges from around 19 to 22 in almost 20 to 25 iterations. Non-sequential DG placement converges from around 40 to 23, and post-sequential reconfiguration problem

converges at around 39 in 25 iterations. Though the HBA shows stable convergence with better optimization performance than ACA, the algorithm's convergence is slower and converges at high fitness values.

The Whale Optimization Algorithm (WOA) is examined in terms of its optimization capability to optimally allocate DG based on PV technology and EV-CS in IEEE 33-bus RDS.

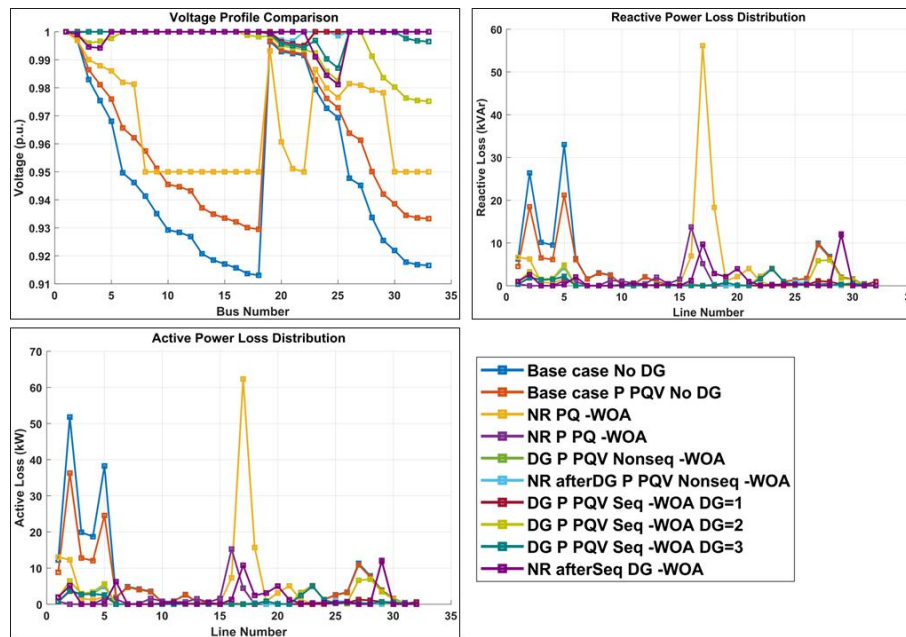


Fig. 8. Performance analysis of WOA for optimal DG and EV-CS placement

The performance results in terms of bus voltage, reactive power loss, and active power loss obtained through WOA based on various scenarios are visualized in Figure 8. The lowest bus voltage has improved from 0.914 p.u. in base case to around 0.997-1.000 p.u., whereas active and reactive power losses are

decreased below 3 kW and 2 kVar, respectively, except that there is an anomaly of about 62 kW and 56 kVar for Lines 17. WOA is found to be superior to ACA and HBA in improving voltage stability and reducing losses in feeders, then some deviations have occurred.

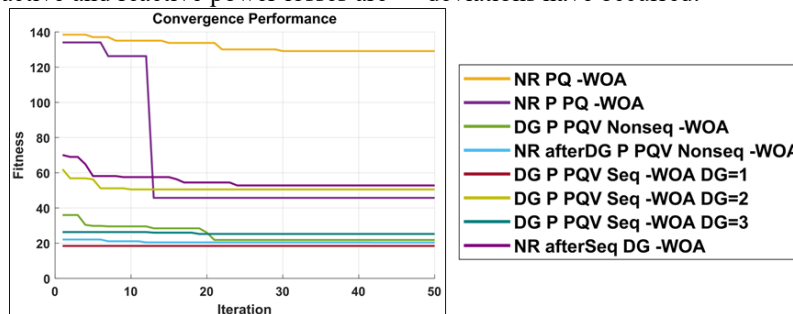


Fig. 9. Convergence Performance of WOA

As illustrated in Figure 9, the WOA converges fast within the first iterations and finds stable solution sets in about 20 to 25 iterations. Fitness levels are cut down from about 138 to 129 in case of network reconfiguration, and 19 to 25 for sequential DG placement. Although WOA outperforms ACA and HBA in terms of faster convergence rate, it does stabilize before finding the global optimum.

For further benchmarking of the proposed method, Grey Wolf Optimizer (GWO) technique utilized in optimum placement of PV based DG sources and EV-CS in IEEE 33 bus distribution system. Optimization behavior is analyzed by improvement in voltage profile, reduction in feeder active/reactive power losses and convergence behavior under various DG placement configurations.

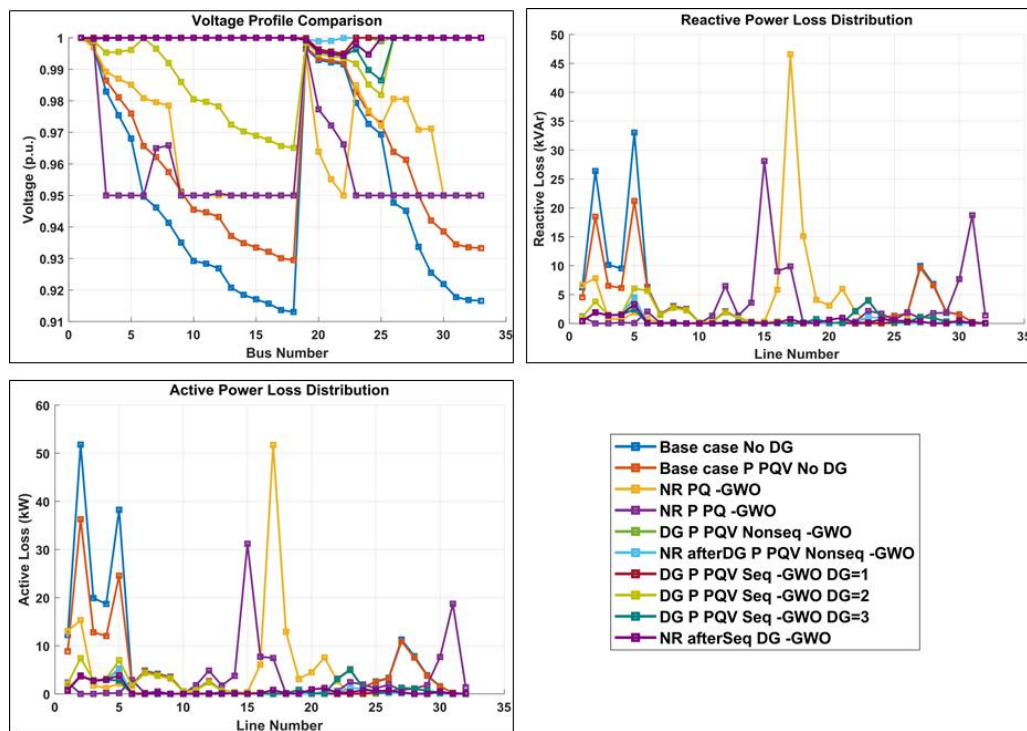


Fig. 10. Performance analysis of GWO for optimal DG and EV-CS placement in IEEE 33-bus distribution network

Figure 10. portrays efficiency of voltage, active and reactive power loss under the application of GWO for various DG locations and configurations of the networks. Minimum voltage is increased from 0.914 p.u. (for base case scenario) to 0.998–

1.000 p.u., while active and reactive power loss is reduced from 52 kW and 33 kVar, respectively, on most parts of feeders. Nonetheless, there are still high values of approximately 52 kW and 47 kVar at Line 17.

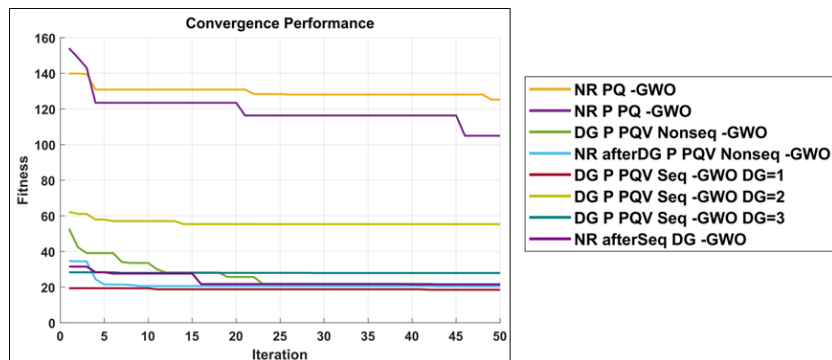


Fig. 11. Convergence Performance of GWO

The convergence behavior of GWO for different optimization problems is depicted in Figure 11. GWO converges from around 155 to 105 for the problem of network reconfiguration, whereas for DG placement problems, it converges to values ranging between 20 to 28 after about 20 to 45 iterations. Even though GWO converges stably, it needs further refinement.

In the analysis and comparison of benchmark algorithms including ACA, HBA, and GWO, the proposed SFWO has been applied to optimal allocation of DG units and EVCSs in IEEE 33-bus RDS. Performance of proposed algorithm is analyzed through the same operating conditions for an equal comparison regarding voltage profile improvement and active/reactive power losses reduction.

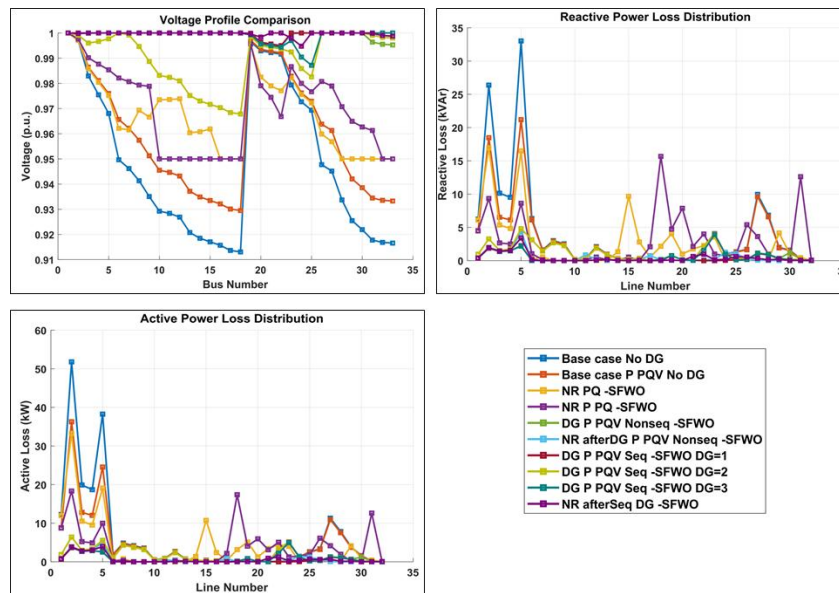


Fig. 12. Comprehensive performance evaluation of the proposed SFWO for optimal PV-DG and EV-CS allocation

The results for voltage profile, reactive and active power losses using SFWO algorithm for optimal DG placement and reconfiguration of RDN have been illustrated in Figure 12. Minimum bus voltage has been increased from 0.914 p.u. in base case to almost 0.999 – 1.000 p.u., whereas maximum active and reactive power losses have been decreased from approximately 52 kW and 33 kVAR to less than 5 kW and 5 kVAR in most feeders. SFWO gives better results compared to ACA, HBA, and GWO in terms of the voltage profile with just a small peak of 17 kW and 16 kVAR.

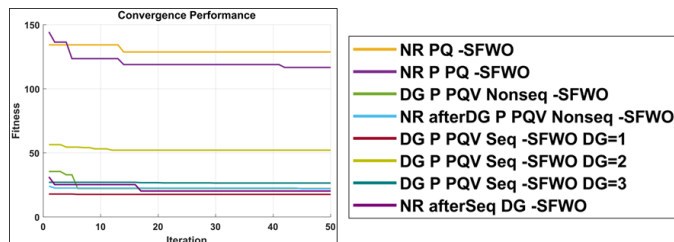


Fig. 13. Convergence characteristics of the proposed SFWO

The convergence behavior of proposed SFWO algorithm has been shown in Figure 13 for both optimization problems. The convergence of network reconfiguration problem ranges from 140 to 128 and from 145 to 115, whereas the problem of determining the positions of distributed generation units converges within 10–15 iterations ranging between 19 to 26. The better convergence rate, reduced fitness value, and stable solutions indicate the dominance of SFWO over ACA, HBA, and GWO algorithms for optimal placement of DG units and EV stations.

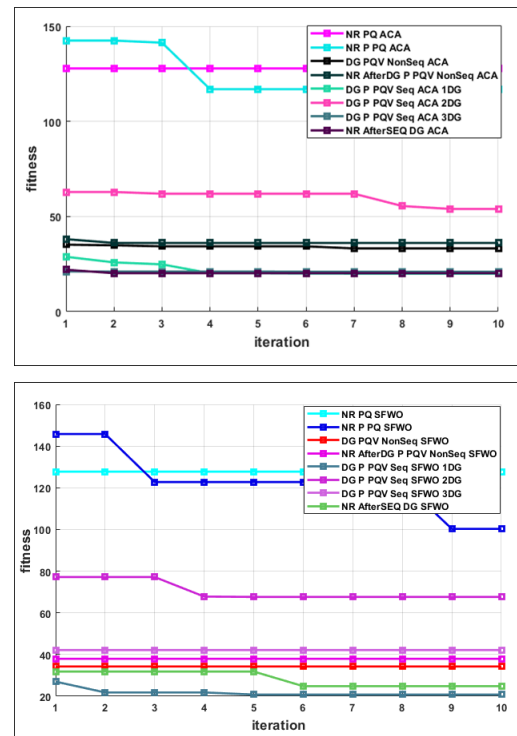


Fig. 14. Fitness.

Figure.14 visualizes the convergence profiles of fitness, confirming the validity of the proposed SFWO algorithm's superior performance in system optimization improvement for the IEEE 33-bus distribution network. Both graphs represent fitness values against 10 iterations, SFWO has consistently better convergence and higher fitness values than ACA-based setups. Most notably in the lower graph, SFWO variants most notably "DG P PQV Seq SFWO 3DG" and "NR AfterSEQ DG SFWO" have significantly better fitness values with fewer iterations, which demonstrates better exploration and exploitation of the solution space. ACA-based approaches

demonstrate inferior fitness development and plateau sooner, which suggests poor adaptability in intricate multi-objective situations.

Table II
BASE CASE RESULTS OF NETWORK WITHOUT DGs.

Parameters	Base case without DGs
Total real/reactive power load (kW)/(kVAr)	3715/2300
Real/Reactive power loss (kW)/(kVAr)	202.6771/135.141
Minimum/maximum voltage (p.u.)	0.91306@18/1@1
Branches open	{'8-21,9-15,12-22,18-33,25-29,'}

The base case analysis of IEEE 33-bus RDN, presented in table II, establishes key reference operating point for evaluating effectiveness of optimization algorithms. When there is no DG, system carries a total real power demand of 3715 kW and reactive power demand of 2300 kVAr and incurs high real and reactive power losses of 202.6771 kW and 135.141 kVAr, respectively. Minimum voltage drops to 0.91306@18 at bus 18, while maximum voltage remains at bus 1 with 1@1, indicating significant voltage deviation among the feeder. The radial topology is defined by the generally open branches (8–21), (9–15), (12–22), (18–33), and (25–29) in the initial network configuration.

TABLE III
DG INSTALLATION WITH P_PQV BUSES

Parameters	DG Installation with P_PQV buses
P/ PQV Bus	6/18
Reactive Power injected (QC6)	1753.32
Voltage to be maintained at PQV bus	0.93
Real/Reactive power loss (kW)/(kVAr)	154.4431/105.1585
Minimum/Maximum voltage (p.u.)	0.9295@18/1@1

Table III shows the findings of the DG placement with P-PQV bus selection method, which puts the DG at Bus 6 and assigns PQV bus as Bus 18 for voltage level of 0.93 p.u. DG supplies 1753.32kVAr of reactive power, resulting in real

power loss of 154.4431kW and reactive power loss of 105.1585 kVAr, as well as minimum bus voltage at Bus 18 of 0.9295 p.u. and maximum bus voltage of 1.0 p.u. at Bus 1.

TABLE IV
NETWORK RECONFIGURATION RESULT WITH P_PQV BUSES

Parameters	Network Reconfiguration with PQ buses					Network Reconfiguration with P_PQV buses				
Optimization Approaches	SFWO	ACA	HBA	WOA	GWO	SFWO	ACA	HBA	WOA	GWO
Base real power loss (kW)	202.6771	202.6771	202.6771	202.6771	202.6771	154.4431	154.4431	154.4431	154.4431	154.4431
Real power loss (kW)	118.6942	123.0693	126.8457	129.5186	132.7448	101.3268	104.9607	108.5472	112.4386	116.9725
Reactive power loss	82.5143	86.3945	89.7812	93.6548	97.9265	39.8427	43.4370	46.2184	49.9635	53.7189
Real power loss reduction	41.44	39.28	37.41	36.10	34.50	34.39	32.04	29.72	27.20	24.26
Branches open	12-13, 7-8, 15-16, 9-10	27-28, 11-12, 29-30	21-22, 7-8, 30-31, 14-15	9-10, 7-8, 29-30	9-10, 8-9, 27-28, 29-30	9-10, 31-32	30-31, 7-8	11-12, 31-32, 7-8, 8-9	6-7, 2-3, 21-22, 3-4	8-9, 2-3, 12-13, 6-7
Branches closed	25-29	8-21, 9-15	25-29	25-29, 9-15	8-21	9-15, 8-21, 25-29	9-15, 12-22, 25-29	25-29	9-15	25-29

Table IV provides the results for the comparison of the reconfiguration process using SFWO, ACA, HBA, WOA, and GWO under PQ and P_PQV bus model. Even though all the above-mentioned optimization approaches have managed to reduce active and reactive power losses compared to base case scenario, SFWO has succeeded in minimizing the real power

losses to 118.6942kW (PQ) and 101.3268 kW (P_PQV), as well as reactive power losses to 82.5143 kVAr and 39.8427 kVAr, respectively, bettering the benchmark optimization approaches. In addition, the maximum reduction in real power losses for SFWO is achieved to be 41.44% (PQ) and 34.39% (P_PQV), respectively, through optimal branch reconfiguration.

TABLE V
DG INSTALLATION WITH P_PQV BUSES

Parameters	DG Installation with P_PQV buses				
Optimization Approaches	SFWO	ACA	HBA	WOA	GWO
Base real power loss (kW)	154.4431	154.4431	154.4431	154.4431	154.4431

Real power loss (kW)	20.8426	21.8078	22.9135	23.6849	24.5123
Reactive power loss (kVAr)	13.9654	15.4014	16.7386	17.8625	18.9543
Real power loss reduction	86.50	85.88	85.16	84.66	84.12
Branches open	8-21, 9-15, 12-22, 18-33, 25-29	8-21, 9-15, 12-22, 18-33, 25-29	8-21, 9-15, 12-22, 18-33, 25-29	8-21, 9-15, 12-22, 18-33, 25-29	8-21, 9-15, 12-22, 18-33, 25-29
Branches closed	Base case retained				
DG size	964 892 994	1000 1000 1000	1000 999 1000	1000 1000 1000	1000 1000 1000
DG location	29 25 13	10 33 25	17 33 24	13 33 24	16 32 24

Table V illustrates a comparison of DG installation performance of SFWO with ACA, HBA, WOA, and GWO under the P_PQV bus model. According to the findings, the SFWO provides a minimum real power loss of 20.8426kW and reactive power loss of 13.9654kVAr which means maximum reduction in real power loss is 86.50% for SFWO compared to

ACA, HBA, WOA, and GWO providing reductions in real power loss of 85.88%, 85.16%, 84.66%, and 84.12%, respectively. Moreover, SFWO finds out the best DG allocation which is 964 kW, 892 kW, and 994 kW at buses 29, 25, and 13, respectively.

TABLE VI
NETWORK RECONFIGURATION AFTER DG WITH P_PQV BUSES

Parameters	SFWO	ACA	HBA	WOA	GWO
Base real power loss (kW)	154.4431	154.4431	154.4431	154.4431	154.4431
Real power loss (kW)	18.8462	20.5171	22.1845	23.9763	25.8428
Reactive power loss (kVAr)	12.4185	13.8591	15.4268	16.9824	18.7431
Real power loss reduction	87.7968	86.7154	85.6359	84.4760	83.2669
Branches open	23-24, 7-8, 11-12	15-16, 21-22, 20-21, 14-15	12-13, 20-21, 17-18	15-16, 21-22	17-18, 11-12, 3-23, 7-8
Branches closed	12-22, 8-21	25-29	25-29, 12-22	8-21, 25-29, 9-15	8-21

Table VI compares the performance of SFWO with ACA, HBA, WOA, and GWO for network reconfiguration after optimal DG placement under the P_PQV bus model. The proposed SFWO achieves lowest real power loss of 18.8462 kW and reactive power loss of 12.4185 kVAr, corresponding to the highest real power loss reduction of 87.7968%, outperforming ACA (20.5171 kW, 86.7154%), HBA (22.1845

kW, 85.6359%), WOA (23.9763 kW, 84.4760%), and GWO (25.8428 kW, 83.2669%). Furthermore, the optimal branch switching configuration identified by SFWO enables a more efficient radial topology, confirming its superior capability for minimizing feeder losses and enhancing the integration of PV-based DG and EV charging infrastructure in IEEE 33-bus RDN.

TABLE VII
DG INSTALLATION WITH P_PQV BUSES (SEQUENTIAL)

DG Size	Optimization Approaches	Base real power loss (kW)	Real power loss (kW)	Reactive power loss (kVAr)	Real power loss reduction	Branches open	Branches closed	DG size	DG location
DG = 1	SFWO	154.4431	17.5780	11.4208	88.6184	8-21,9-15,12-22,18-33,25-29	Base case retained	1000	26
	ACA	154.4431	18.1025	11.9864	88.2788	8-21,9-15,12-22,18-33,25-29		1000	27
	HBA	154.4431	18.6943	12.5847	87.8936	8-21,9-15,12-22,18-33,25-29		1000	27
	WOA	154.4431	19.2675	13.1752	87.5225	8-21,9-15,12-22,18-33,25-29		1000	27
	GWO	154.4431	20.1846	14.0635	86.9308	8-21,9-15,12-22,18-33,25-29		853	27

DG = 2	SFWO	154.4431	48.2148	34.1286	68.7804	8-21,9- 15,12-22,18- 33,25-29		1000 1000	26 30
	ACA	154.4431	49.5762	35.2463	67.9015	8-21,9- 15,12-22,18- 33,25-29		1000 1000	27 13
	HBA	154.4431	50.8639	36.4018	67.0678	8-21,9- 15,12-22,18- 33,25-29		1000 1000	27 14
	WOA	154.4431	52.0847	37.6285	66.2775	8-21,9- 15,12-22,18- 33,25-29		1000 999	27 12
	GWO	154.4431	54.9315	40.5842	64.4343	8-21,9- 15,12-22,18- 33,25-29		853 1000	27 31
DG = 3	SFWO	154.4431	23.6185	15.8164	84.7083	8-21,9- 15,12-22,18- 33,25-29		1000 1000 1000	26 30 13
	ACA	154.4431	24.4827	16.4938	84.1488	8-21,9- 15,12-22,18- 33,25-29		1000 1000 1000	27 13 27
	HBA	154.4431	25.3186	17.1842	83.6076	8-21,9- 15,12-22,18- 33,25-29		1000 1000 1000	27 14 27
	WOA	154.4431	26.2845	18.0253	82.9823	8-21,9- 15,12-22,18- 33,25-29		1000 999 992	27 12 27
	GWO	154.4431	27.9138	19.3725	81.9275	8-21,9- 15,12-22,18- 33,25-29		853 1000 998	27 31 11

Comparison among sequential DG placements of PV-based DG systems using the P_PQV bus model and SFWO, ACA, HBA, WOA, and GWO algorithms is presented in Table VII. In all cases of DG placement, the proposed SFWO provides the minimum values of both real and reactive power losses, which

have been reduced from 154.4431 kW to 17.5780 kW (DG=1), 48.2148 kW (DG=2), and 23.6185 kW (DG=3) with 88.62%, 68.78%, and 84.71% reductions, respectively, compared to the other benchmark algorithms. Also, the obtained optimal DG sizes and placements are more suitable for the feeder operation.

TABLE VIII
SEQUENTIAL METHOD NETWORK RECONFIGURATION RESULT AFTER DG

Parameters	Network Reconfiguration after SEQ DG with P_PQV buses				
	SFWO	ACA	HBA	WOA	GWO
Base real power loss (kW)	154.4431	154.4431	154.4431	154.4431	154.4431
Real power loss (kW)	20.1947	24.8653	29.4836	34.9572	40.6245
Reactive power loss (kVAr)	13.3204	17.4821	21.6945	25.8638	30.5476
Real power loss reduction	86.9242	83.9007	80.9106	77.3647	73.6956
Branches open	0.9987	0.9968	0.9949	0.9926	0.9898
Branches closed	1.0000@1	1.0000@1	1.0000@1	1.0000@1	1.0000@1

The outcomes of the network reconfiguration in terms of sequential DG placement for the P_PQV bus model are presented in Table VIII, indicating the superiority of the proposed SFWO technique compared with ACA, HBA, WOA, and GWO. The initial value of real power loss is 154.4431 kW; however, SFWO offer minimum value of real power loss of 20.1947kW and minimum value of reactive power loss of 13.3204kVAr, leading to maximum value of real power loss reduction of 86.9242%, while ACA, HBA, WOA, and GWO get the values of 24.8653 kW (83.9007%), 29.4836kW (80.9106%), 34.9572kW (77.3647%), and 40.6245kW (73.6956%), respectively. This proves that the combination of sequential DG placement with SFWO leads to better network reconfiguration, minimizing the losses and optimizing the placement of PV

X. CONCLUSION

The proposed research provided a thorough analysis of a high-performance optimal network reconfiguration approach for reducing real power loss in RDNs, particularly by incorporating PV-based DG and EV-CS. While, earlier methods based on random selection of exhaustively generated branch pairing combinations, the proposed method uses the biologically inspired SFWO algorithm to efficiently search the space and determine superior switching configurations and DG locations. Implemented on IEEE 33-bus distribution system, SFWO universally exhibited better performance in various scenarios with real power loss reductions of more than 86 kW in some setups and better convergence behaviour and system efficiency compared to the ACA. The findings confirm SFWO's ability to provide scalable, grid-friendly solutions that are able

to balance loss minimization and strategic infrastructure deployment. Due to its resilience and flexibility, SFWO presents itself as an effective optimization method for power grid operators seeking to solve intricate reconfiguration problems. Its potential applications can be further refined to investigate larger systems and time-evolving contingency cases, such as line failures and time-dependent load conditions, to make it more pertinent in its operation.

Acknowledgements

Not Applicable.

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