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ORIGINAL RESEARCH

Optimal distributed energy resources accommodation with techno-economic benefits using cheetah optimizer

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Abstract
The planning and operation of radial distribution networks face increasing challenges such as active power losses and voltage instability, prompting a focus on integrating renewable energy resources to mitigate these issues. This study presents a techno-economic optimization framework leveraging the cheetah optimizer, a recently introduced metaheuristic technique, to optimize the accommodation of distributed energy resource units within the IEEE 33-bus radial distribution networks utilizing MATLAB environment. Both single and multi-objective perspectives are explored, demonstrating significant reductions in active power losses, minimized voltage deviation, improved stability, and maximized economic benefits. The cheetah optimizer efficacy is showcased through notable achievements, including a 94.20% reduction in active power losses and annual savings of up to $77,933 for optimal power factor mode in multi-objective optimization, surpassing existing literature. Additionally, reliability analysis conducted with ETAP software underscores the effectiveness of distributed energy resource integration, particularly with wind turbine systems, in enhancing network reliability.

1 | INTRODUCTION

The electrical power system features centralized generation, an interconnected transmission system, and a passive distribution network (DN), but with steadily increasing electricity demand, the electrical power system is evolving [1]. Significant advancements in smart grid technology and decentralized energy generation over the past decade have led to the widespread adoption of renewable energy-based distributed energy resources (DER) at the distribution level. These changes have introduced new technological and financial challenges for the distribution network (DN), including more significant deviations from ideal voltage profiles [2] and up to 70% of the total power system losses in distribution systems and 30% in the transmission systems [3]. The difference is primarily due to lower radial distribution network (RDN) X/R ratio, voltage levels, and higher copper losses [4].

A global trend of promoting deregulated electrical markets is in place to encourage innovation in the electricity sector. This trend offers consumers more choices when selecting their electricity service providers, leading to improved market efficiency. Nevertheless, there are additional aspects of this issue that require attention. Electricity service providers have been continuously developing strategies to manage this evolving situation. The conventional approach involves constructing new substations or expanding existing infrastructure [5]. However, this method has proven economically unviable due to low utilization rates and high operational costs. An intelligent approach involves the integration of renewable energy-based distributed energy resources (DER) at the

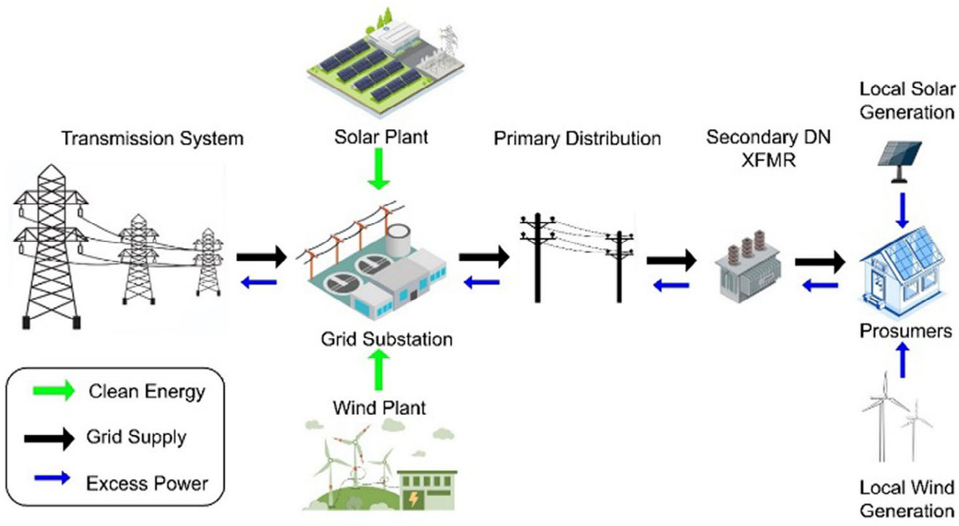

FIGURE 1 RER penetrated RDN.

primary distribution level, as depicted in Figure 1. This approach offers several technical advantages: it is capable of meeting real and reactive power demand of the load, providing support to the grid, has lower investment risk due to the economic advantages [6] and addresses the environmental concerns due to its reliance on renewable energy resources (RER) [7] such as solar and wind, which enhance energy security and mitigate global warming by reducing fossil fuel consumption [8]. In developing countries with significant agricultural activities, integrating renewable energy for irrigation can reduce grid dependency, offering economic and environmental benefits [9].

Several definitions have been proposed for DER based on their technology and parameters. The Electric Power Research Institute (EPRI) has defined it as a “small generation unit from few kilowatts (kW) up to 50 MW and energy storage devices typically sited near customer loads, distribution substations and sub-transmission stations” [10]. Another important classification of DER units based on the real and reactive power generation capability is reported in Table 1 [11].

The literature reveals numerous strategies for penetration of renewable energy into the power grid to enhance sustainability and resilience. One such practical methodology is design of microgrids which play a vital role in integrating renewable energy, offering reliable and sustainable power solutions while mitigating the impacts of climate change [12]. In the shift towards maximizing energy utilization from hybrid renewable energy systems, their sizing is notably impacted by the integration of modern loads such as electric vehicles [13]. The integration of RER based on demand-supply matching is an alternate method that enhances the efficiency of energy utilization by aligning energy production with energy consumption [14].

It is imperative to optimally allocate DER units in the RDN to extract maximum technical and economic benefits. It is a major planning and operation challenge for utilities facing losses since proper accommodation enhances voltage stability, increases system loading, improves power factor, reduces

TABLE 1 DER types based on power generation.

Type	Real power	Reactive power	Examples
Type 1	Capable of only injecting real power into the network	Does not generate reactive power	PV system, microturbines, and fuel cell
Type 2	Does not generate real power	Capable of only injecting reactive power into the network	Synchronous condenser, static var compensators (SVCs),
Type 3	Capable of injecting real power into the network	Capable of injecting reactive power into the network	Synchronous machines, and variable speed DFIG with rotor side converter in WT
Type 4	Capable of injecting real power into the network	Consumes reactive power from the system	Fixed speed and variable speed-based induction generator used in WT

peak load demand on the utility feeder, and prevents protection coordination issues [15, 16]. The grid is relieved from congestion, allowing deferred investment to upgrade facilities. The associated economic benefit of indigenous generation resource accommodation and sustainable energy sector growth [17] is one of the key motivations. It includes a reduction in overall fuel costs due to greater reliance on RER, a massive reduction in reserve capacity requirement by the conventional plants, and a secure supply for the critical loads. Furthermore, RER-based DER can serve as an optimal solution to maintain a balance between energy demand and generation [18]. The power engineers have realized the growing importance of optimizing and modernizing the DN to ensure higher network reliability, defined in [19] as “the ability of a system to perform its required function for given time under steady-state conditions”. Hence, this research aims to explore optimal solutions for the ODERA problem to enhance the performance of RDN.

The paper is structured as follows: Section 2 conducts a comprehensive literature review relevant to the subject. Section 3 outlines the mathematical formulation of the objective functions, constraints, and reliability indices that underpin the research. Section 4 details the mathematical formulation and application of the CO algorithm. Section 5 presents the results of proposed ODERA methodology and offers a thorough analysis. Finally, Section 6 concludes the research and provides recommendations for future work.

2 | LITERATURE REVIEW

2.1 | Related work

The literature extensively examines the integration of renewable energy-based DER into the RDN from various perspectives. Incorporating renewable energy sources, such as solar, wind, and biomass, with and without hybrid energy storage systems has demonstrated significant improvements in reliability and efficiency, as evidenced by the optimized integration approach for university campuses that achieved nearly 100% renewable energy fraction and substantial cost savings while supplying campus demand of cooling load and electrical appliances as proposed in [20].The objectives that must be achieved for successful power system optimization depend on the nature of the problem. Consequently, the integration of DER can be categorized into single-objective and multi-objective optimization problems. Single-objective optimization primarily focuses on optimizing a single objective and accordingly determining the optimal parameters for DER units. The multi-objective optimization may involve predefined weights or a search for the best possible weights of the multiple objectives that may be technical, economic, environmental, or a combination. This results in an optimal tradeoff between the objectives and serves as the basis for evaluating the optimal parameters for DER. Various optimization methodologies have been employed to determine the optimal location of DER in the network and their size. However, the underlying principles of each method can vary [21].

The first class of optimization methodology, often called analytical techniques, is based on detailed mathematical formulation, and relies on precise equations to obtain exact solutions for the optimal placement and sizing of DER. In the context of single objective optimization, the primary goal is to minimize losses in the RDN, and this is achieved through the application of efficient analytical methodology in [22] and mixed-integer non-linear programming (MINLP) in [23]. Another approach utilizes loss sensitivity factors (LSF) and voltage stability (VS) to pinpoint the optimal location within the RDN, followed by size determination through a mathematical model-based technique utilizing "MATLAB" a high-level programming language environment widely employed for numerical computations in engineering [24]. It is worth noting that analytical techniques perform best when dealing with well-structured problems featuring clearly defined objectives and constraints. However, these techniques encounter challenges and exhibit limited applicability when dealing with highly non-linear problems.

Another class of optimization methodology is referred to as meta-heuristic techniques, which does not require a detailed mathematical representation of the problem except to define objectives and constraints. They explore the objective function's input search space through iterative and heuristic methods and are particularly suited to finding solutions to problems that are difficult to formulate mathematically, and to find an exact solution is computationally infeasible. The authors have employed a multi-objective index-based approach with real power loss, reactive power loss, voltage profile, MVA capacity, and short circuit level index for optimal integration of multi-DER in RDN based on particle swarm optimization (PSO) method [25] and is reported to have better exploration and exploitation capability than the genetic algorithm (GA). A novel swarm intelligence technique proposed in [26] introduces the bacterial foraging optimization algorithm (BFOA) to accommodate DER optimally in the RDN and optimize multiple objectives, including network loss minimization, operational cost minimization, and voltage stability enhancement. Another paper has utilized the backtracking search optimization algorithm (BSOA) [27] that incorporates the concept of bi-objective weighted function-based constrained multi-objective optimization to determine optimal DER parameters and has been encoded using the "MATLAB" software. The stud krill herd algorithm (SKHA) proposed in [28] focuses on minimizing a single objective of line losses subject to various constraints related to voltage, power generation, power balance, and DER unit's location constraints.

Furthermore, an innovative whale optimization algorithm (WOA) [3], inspired by the unique hunting behaviour of humpback whales, is used to optimize the single objective of active power loss reduction (APL) to improve the voltage profile of the IEEE 15, 33, 69, and 85-bus test systems. The flower pollination algorithm (FPA) is another AI method presented in [29] and implemented on IEEE 33 and 69 bus systems to determine suitable DER sizes for multi-objective optimization of loss reduction and cost savings. A multi-objective optimization of total energy cost, total power loss, and average voltage drop is carried out using the artificial bee colony (ABC) optimization algorithm in [2] and it implements the Newton Raphson load flow (NRLF) method on the IEEE-33 and 69 bus RDN as well as the CIGRE medium voltage benchmark grid to perform the power system study. However, it should be noted that for higher-dimensional problems, these techniques result in decreased quality of solutions, and the convergence time increases.

Moreover, a specialized class of optimization methodologies is known as hybrid optimization techniques, which harnesses the strengths of individual techniques and generally yields higher-quality solutions. In [30] a novel quasi-oppositional teaching learning-based optimization (QOTLBO) is applied for multi-objective optimization and aims to reduce power loss, and voltage deviation and enhance voltage stability of the RDN on test networks of 33, 69, and 118 buses. Another hybrid technique is presented in [5] for solving the ODERA problem, employing the quasi-oppositional swine influenza model-based optimization with quarantine (QOSIMBO-Q) for single and various combinations of multi-objectives of active power loss minimization, voltage profile improvement, and voltage stability index enhancement. The research in [31], proposes a novel approach that combines the genetic algorithm (GA) with intelligent water drops technique (IWD) for multi-objective optimization of reduced power losses, reduced total voltage variation, and enhanced voltage stability index to identify the optimal location, and size of DER. It specifically models the DER only to inject active power into the network. In another study, the author employs an improved and multi-objective elephant herding optimization (IMOEHO) [32] to conduct multi-objective optimization for minimization of power losses and node voltage and maximization of voltage stability index and is implemented on smaller 33 bus systems to larger 118 bus to 880 bus DN benchmark systems. The stochastic fractal search algorithm (SFSA) [33] also solves the multiple objective optimization problems and optimizes active power loss, voltage profile, and voltage stability of IEEE 33, 69, and 118 bus systems. It is important to note that this class of optimization methodology demands substantial computational resources and time due to its sophisticated structure.

With evolving RDN and increasing integration of renewable energy-based DER, concerns regarding the reliability of networks have been raised, particularly continuity of supply and availability of the system for the consumers. Consequently, researchers have suggested quantitative metrics for evaluating the network's reliability. In [34], renewable energy-based DER units have been accommodated in an IEEE-13 bus unbalanced system, and the authors assessed the system's reliability before and after DER integration and observed significant improvements. In [35] the reliability of IEEE-14 bus RDN is evaluated following the placement of a PV-based DER unit. The highest value is achieved when the unit is integrated at the weakest bus with the lowest voltage profile. Similarly, the application of artificial neural network (ANN) [36] on Roy–Billinton test system (RBTS) for optimal DER accommodation has proven to be a more efficient methodology compared to trial-and-error approaches as this eliminates the risk of human error and reduces the time required for selection of optimal DER parameters. In [37], the study utilized modified particle swarm optimization algorithm (MOPSO) to optimize a multi-objective function that has considered reducing active power losses and improving voltage profile. The optimized DN configuration with optimally placed and sized DER was implemented in ETAP, and the demonstrated approach has shown superior reliability compared to other optimization methods. Research conducted in [38] indicates that integrating a single DER, whether PV system or WT, leads to greater reliability improvements compared to a higher number of DER units. In [39], a multi-objective model employing modified jellyfish search algorithm (MJFS) is used to enhance an IEEE medium voltage distribution feeder (MVDF). This simple optimization technique builds upon the standard jellyfish search algorithm (JFS) by incorporating quasi-oppositional-based learning and social neighbourhood strategies and the results showcase notable improvements in three reliability measures: the total energy not supplied (TENS), system average interruption duration index (SAIDI), and system average interruption frequency index (SAIFI), with reduction of 44.42%, 30.57%, and 30.78% respectively compared to the base case. Table 2 compares the previous literature with the proposed CO algorithm.

TABLE 2 Comparison of CO with literature.

Ref	[2]	[3]	[15]	[24]	[38]	[40]	[P]
Optimal accommodation	✓	✓	✓	✓	✓	✓	✓
APL reduction	✓	✓	✓	✓	✓	✓	✓
TVD reduction						✓	✓
VSI enhancement				✓		✓	✓
Multi-objective	✓		✓	✓		✓	✓
PF mode		✓	✓	✓		✓	✓
DER types		✓	✓		✓		✓
IEEE 33 bus RDN	✓	✓		✓		✓	✓
MATLAB	✓			✓	✓	✓	✓
ETAP					✓		✓
Reliability					✓		✓
Technique	MH	MH	MH	AL	MH	MH	MH

where MH = meta-heuristic optimization scheme, AL = analytical scheme.

2.2 | Research contributions

The examination of current literature has revealed significant gaps in research. To the best of author's knowledge, prior research has avoided exploration of distribution network optimization considering both technical and economic objectives, as well as the analysis of different DER modes of operation and their effect on network performance and reliability analysis has been inadequately explored using trial and error methods:

- The proposed ODERA methodology utilizes the novel meta-heuristic cheetah optimizer (CO) algorithm introduced in 2022 for techno-economic optimization of the IEEE 33-bus RDN to accommodate renewable energy resources in compliance with IEEE 1547–2018. It determines the optimal location and capacity of DER units based on single and multi-objectives, incorporating the minimization of APL, TVD minimization, and VSI enhancement within the network.
- The methodology conducts economic optimization to identify the DER mode that maximizes economic benefits. This involves calculating AEL_{woDER} and AEL_{wDER} to determine ACS (annual cost savings).
- The optimization specifically examines various DER modes of operation with different power factors, emphasizing their impact on system performance.
- The study assesses the reliability of DER accommodation through PV and WT cases, to determine optimal RDN configurations in compliance with IEEE 1366–2022.
- This research leverages the strengths of two specialized software tools, MATLAB and ETAP.

3 | PROBLEM FORMULATION

The primary objective of this research is to optimize distributed energy resource (DER) accommodation within RDNs to enhance network performance, economic feasibility and ensure a reliable power supply to consumers. This section provides the mathematical formulation of objectives, constraints, and the essential indices necessary for conducting optimal accommodation of DER and reliability analysis of RDN.

3.1 | Objective functions

The optimization of the radial distribution network (RDN) is achieved through strategic DER accommodation, aimed at improving system efficiency and annual profit. In single-objective optimization, the focus lies on mitigating the network's active power losses (APL), while in multi-objective optimization, objectives extend to reducing total voltage deviation (TVD) and maximizing the voltage stability index (VSI). Through technical optimization, optimal parameters for DER location and size are determined, further refined based on economic criteria. Hence, proposed methodology is represented in Figure 2.

3.1.1 | Reduction of APL

A lower value of DN X/R ratio and lower voltage levels significantly increase the active power loss as a greater magnitude of current flows through the conductors from the sending end (utility) to the receiving end (consumer). Therefore, APL

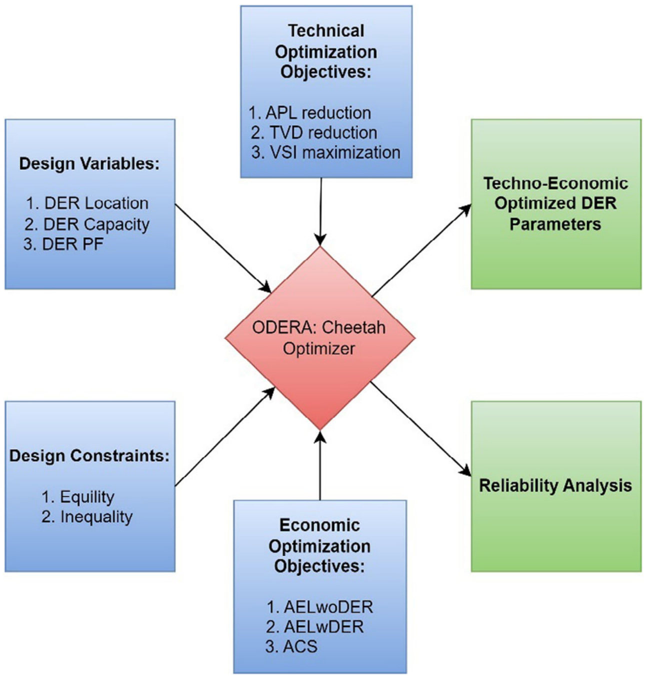

FIGURE 2 Proposed DER accommodation strategy.

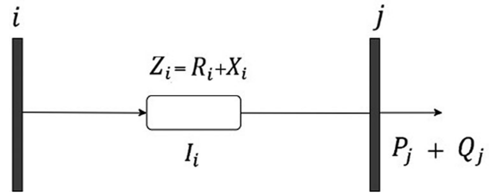

FIGURE 3 Equivalent circuit of a branch in RDN.

denotes the summation of active power loss values of all branches of a RDN, and equivalent circuit of a branch is shown in Figure 3 and evaluated by following Equation (1) as in [41]:

$$\mathrm{APL} = \sum_{i=1}^{N_{\mathrm{br}}} |I_i|^2 R_i \tag{1}$$

where index $\boldsymbol{i}$ denotes branch that emerges from respective bus, N_{br} gives total number of branches, $|I_i|^2$ is the square of value of current flowing and R_i is resistance of $\boldsymbol{i}$th branch. Hence, first objective function ($\boldsymbol{of}_1$) is given in Equation (2):

$$of_1 = \min\ (\mathrm{APL}) \tag{2}$$

3.1.2 | Minimization of TVD

TVD represents the collective span of voltage fluctuations for all the buses in the network over a specified duration with reference to the ideal voltage profile. The reduction of TVD within RDN is significant to both customers and utility companies. This reduction ensures that the devices sensitive to voltage variation operate within the prescribed limits. Consequently, utilities can provide power in adherence to quality regulations, mitigating the risk of penalties. The following Equation (3) determines the value of TVD, and it is quoted from [30]:

$$\mathrm{TVD} = \sum_{i=1}^{N_{\mathrm{bus}}} (V_{\mathrm{ref}} - V_i) \tag{3}$$

where index i denotes the bus number, N_{bus} gives the total number of buses in the distribution network under consideration, V_{ref} is taken to be 1 p.u since it serves as a convenient reference point, and V_i is the voltage of ith bus. Hence, second objective function (of_2) is given in Equation (4):

$$of_2 = \min\ (\mathrm{TVD}) \tag{4}$$

3.1.3 | Maximization of VSI

For voltage stability and reliable operation of the DN, it is necessary to maintain the numerical measure of VSI within acceptable limits as per the standards. Therefore, the VSI value at the receiving end bus must be greater than zero, and the VSI is calculated using Equation (5) [42]:

$$\mathrm{VSI}_j = V_i^4 - 4\left(P_j R_i + Q_j X_i\right) V_i^2 - 4\left(P_j X_i - Q_j R_i\right) \quad (5)$$

where, i and j denote the sending and receiving ends, P_j and Q_j represent the load's active and reactive power, and R_i, X_i are the impedance and reactance of the line emanating from bus i. To prevent voltage collapse, we maximize the lowest VSI value, and the third objective function (of_3) is given in Equation (6):

$$of_3 = \max\left(\min\left(\mathrm{VSI}_j\right)\right) \quad (6)$$

3.2 | Problem constraints

Constraints of optimal DER integration within RDN exist to ensure that the accommodation process is conducted effectively considering various technical, operational, and regulatory aspects and to preserve network stability, reliability, and safety.

3.2.1 | Equality constraints

It is crucial to maintain power balance to ensure the successful operation of the power system while keeping it stable in terms of frequency and voltage and ensuring safety for both the public and the utility. This means that the total power generated must be equal to the sum of power demand and losses as given in Equation (7):

$$\sum_{j=1}^{N_{\mathrm{DER}}} P_{\mathrm{DERj}} = P_{\mathrm{D}} + \mathrm{APL} \quad (7)$$

where N_{DER} is the number of DER units installed in the RDN, P_{DERj} is the $\boldsymbol{j}$th DER unit's real power generation, and P_D represents the power demand of the load.

3.2.2 | Inequality constraints

The following constraints should be considered for the security consideration of DN and system operation within limits.

Der output power limits

DER output power limit: Maintaining DER power within specified limits is crucial, as overvoltage can stress equipment, wear down insulation, and pose hazards, while undervoltage can lead to malfunctions and reduced efficiency, impacting power system reliability and safety. Equations (8) and (9) define these limits.

$$\text{Real power limits}: \; P_{\mathrm{DER}j}^{\mathrm{Min}} \le P_{\mathrm{DER}j} \le P_{\mathrm{DER}j}^{\mathrm{Max}} \quad (8)$$

$$\text{Reactive power limits}: \; Q_{\mathrm{DER}j}^{\mathrm{Min}} \le Q_{\mathrm{DER}j} \le Q_{\mathrm{DER}j}^{\mathrm{Max}} \quad (9)$$

Voltage limit

The voltage at each bus needs to be maintained within the specified limit for regulatory compliance and optimized distribution network operation. The absolute value of the difference between the maximum and minimum voltage limit is reported in [43] and given in Equation (10).

$$0.95\; p.u \le V_j \le 1.05\ \mathrm{p.u} \quad (10)$$

Power factor limit

According to the IEEE 1547–2018 standard, PV system inverters are required to support voltage regulation [44] as this reduces the cost of adding dedicated equipment for the purpose of voltage regulation. It also suggests that all DER units are required to adjust the amount of reactive power they inject into the system. Hence, maintaining a good power factor is essential as it enhances power quality, prolongs equipment lifespan, and ensures compliance with utility regulations. These limits are given in Equation (11) and quoted from [45].

$$\mathrm{PF}_{\mathrm{DER}j}^{\mathrm{Min}} \le \mathrm{PF}_{\mathrm{DER}j} \le \mathrm{PF}_{\mathrm{DER}j}^{\mathrm{Max}} \quad (11)$$

3.3 | MCDM technique

Multiple approaches for solving multi-objective optimization problems have been employed in literature. However, the search process has become computationally demanding due to the increasing complexity of optimization problems. Multi-criteria decision-making (MCDM) techniques offer an ideal combination of optimal solutions and efficient computational processes. Among these techniques, the 'weighted sum method' is the most widely used, which enables decision-makers to assign appropriate weights to multiple criteria. It accurately represents the designer's preference for the trade-off between multiple objectives if appropriately assigned. This approach is particularly suitable for generating an initial, strongly non-dominated solution, which may be a foundation for other approaches [46].

The mathematical representation of the integrated objective function created by the weighted sum of distinct objectives is given in Equations (12) and (13):

$$\mathrm{FIT} = \min\left(w_1 \times of_1 + w_2 \times of_2 + w_3 \times of_3\right) \quad (12)$$

$$\mathrm{FIT} = \min\left(w_1 \times \frac{\mathrm{APL}}{\mathrm{APL_{base}}} + w_2 \times \frac{\mathrm{TVD}}{\mathrm{TVD_{base}}} + w_3 \times \frac{\mathrm{VSI}^{-1}}{\mathrm{VSI}_{\mathrm{base}}^{-1}}\right) \quad (13)$$

This function determines the fitness of multiple objectives integrated into a single fitness function and the sum of all weights equals one (w_1+w_2+ w_3= 1). In this research, all the objectives have the same weight of one-third (1/3) due to equal importance in decision-making. The terms $\mathrm{APL_{base}}$, $\mathrm{TVD_{base}}$, and $\mathrm{VSI}_{\mathrm{base}}^{-1}$ denote total active power loss, total voltage deviation, and the inverse of voltage stability index determined from the base case network without DER.

TABLE 3 RDN parameters for economic analysis.

Parameters	Value
C_e	0.05 $/kWh
C_{DER}	$30.00/kW
L_{DER}	10 years

3.4 | Economic objective functions

Integrating distributed energy resources (DER) into the radial distribution network (RDN) offers significant advantages by considering the economic objectives, ensuring the feasibility of the optimization process. The assessment of economic benefits primarily revolves around calculating the annual economic loss (AEL) attributed to the distribution network. Through a comparative analysis, which involves the annual economic loss without DER (AELwoDER) reflecting the energy loss attributable to power distribution costs when DER units are not integrated into the RDN, and the annual economic loss with DER (AELwDER) representing the annual economic loss resulting from the additional load due to DER unit integration and losses in the RDN, the study provides valuable insights into annual cost savings (ACS) achieved through network optimization [7]. The total annual economic loss without DER (AELwoDER) is given in Equation (14).

$$\mathrm{AEL}_{\mathrm{woDER}} = P_L^{\mathrm{woDER}} \times C_e \times 8760 \tag{14}$$

where the term C_e refers to cost in dollars ($) of energy loss per kWh, P_L^{woDER} refers to active power loss in the RDN without DER integration. While the total annual economic loss with DER ($\mathrm{AEL}_{\mathrm{wDER}}$) is given in Equation (15).

$$\mathrm{AEL}_{\mathrm{wDER}} = P_L^{\mathrm{wDER}} \times C_e \times 8760 + \frac{C_{\mathrm{DER}} \sum_{i=1}^{N_{\mathrm{DER}}} P_{\mathrm{DER}i}}{L_{\mathrm{DER}}} \tag{15}$$

where N_{DER} refers to number of DER units in RDN, C_{DER} refers to cost incurred in USD ($) due to DER for each kWh energy generated and also includes capital, deployment, operation, and maintenance costs, L_{DER} refers to life span of DER in years and to include the long term effect of ODERA this will also be considered as the planning period of given system, $P_{\mathrm{DER}i}$ refers to ith DER unit's real power generation, P_L^{wDER} refers to active power loss in RDN with DER installed and total annual cost saving (ACS) due to optimal DER integration is given by Equation (16). Table 3 provides the parameters for RDN economic analysis.

$$\mathrm{ACS} = \mathrm{AEL}_{\mathrm{woDER}} - \mathrm{AEL}_{\mathrm{wDER}} \tag{16}$$

3.5 | Reliability evaluations

The accommodation of DER into RDN offers several advantages, such as decreased power losses, enhanced voltage profile, and increased system stability. However, it is essential to maintain a balance between the reliability and performance of the RDN to achieve regulatory compliance and ensure sustainable operation. Hence, IEEE 1366–2022 standard [47] defines multiple indices as in Table 4.

where, λ_i represents the average failure at load point i, $j \varepsilon N_e$ denotes the total number of faulty equipment, $\lambda_{e,j}$ represent average failure rate, r_{ij} represents failure duration due to faulty elements. N_i and N_T represent the total number of customers interrupted and served.

4 | OVERVIEW OF CO ALGORITHM

Cheetah optimizer (CO) is a recently introduced novel metaheuristic optimization technique inspired by the hunting strategies of cheetahs [48]. The CO algorithm represents the hunting process and mimics the main strategic behaviour of cheetahs: searching, sitting and waiting, and attacking. Furthermore, it incorporates the “leave the prey and go back home” strategy to enhance population diversification, convergence performance, and robustness. Cheetahs patrol and scan their surroundings; similarly, the algorithm actively explores its search space to locate promising prey (solutions). Upon detecting potential prey, the algorithm may patiently wait for optimal conditions before initiating an attack. During the attack phase, it swiftly converges towards promising solutions with maximum speed and efficiency. If hunting attempts fail or energy limits are reached, the algorithm may adjust its strategy or return to its territory for reassessment and rest. This adaptive approach ensures the algorithm's resilience and effectiveness in navigating complex optimization landscapes. The CO can be applied to combinatorial and NP-hard optimization problems, including those related to power systems, such as optimal siting and sizing of Distributed Energy Resources (DER) in the RDN. Figure 4 is a graphical representation of the proposed ODERA algorithm using CO, and the tags represent the operators of the scheme. Table 5 provides the parameters of the cheetah optimizer.

4.1 | Operators of the co algorithm

4.1.1 | Search strategy of cheetah

The search strategy employed by cheetahs involves two primary modes: scanning and active patrolling. Scanning mode is favoured when prey is densely distributed and grazing, while active patrolling is preferable in the presence of scattered and active prey. During the hunting period, cheetahs dynamically alternate between these modes based on factors such as prey density, area coverage, and their own condition. Mathematically modelling this strategy involves defining the current position ($X_{i,j}^t$) of each cheetah (i) in each dimension (j), where n represents the cheetah population and D signifies the dimensionality of the optimization problem. To update the position of cheetah i in arrangement j at each hunting time $\boldsymbol{t}$, a random search equation is proposed by Equation (17):

$$X_{i,j}^{t+1} = X_{i,j}^t + r_{i,j}^{-1} \times \alpha_{i,j}^t \tag{17}$$

TABLE 4 RDN reliability indices.

Reliability indices	Description	Mathematical expression	Unit
Reliability indices for load point			
Average failure rate	Electrical equipment failure rate	$\lambda_i = \sum_{j\epsilon N_e}^{\infty} (\lambda_{e,j})$	Failure per year (f/year)
Annual outage duration	Total time of electricity supply interruptions in 1 year.	$\mu_i = \sum_{j\epsilon N_e}^{\infty} (\lambda_{e,j}.r_{ij})$	Hours per year (h/year)
Average output duration	Ratio of annual outage duration over average failure rate.	$r_i = \frac{\mu_i}{\lambda_i}$	Hours (h)
System based reliability indices			
System average interruption frequency index (SAIFI)	Estimated number of power interruptions for an average customer in 1 year.	$\text{SAIFI} = \frac{\sum_i^{\infty} (N_i)}{N_T}$ $1 \leq \text{SAIFI} \leq 10$	f/customer.year
System average interruption duration index (SAIDI)	Estimated number of power interruption hours for an average customer for 1 year.	$\text{SAIDI} = \frac{\sum_i^{\infty} (r_i N_i)}{N_T}$	h/customer interruption
Customer average interruption duration index (CAIDI)	A measure of utility's reaction time to system contingency.	$\text{CAIDI} = \frac{\sum_i^{\infty} (r_i N_i)}{\sum_i^{\infty} (N_i)} = \frac{\text{SAIDI}}{\text{SAIFI}}$	h/customer.year
Average system availability index (ASAI)	Measure of how often power system is operational and available to customer.	$\text{ASAI} = 1 - \sum_i^{\infty} \left(\frac{r_i N_i}{N_T . T} \right)$	p.u
Average system unavailability index (ASUI)	Average time duration for which system is unavailable due to power interruptions.	$\text{ASUI} = 1 - \text{ASAI}$	p.u

TABLE 5 Parameters of CO algorithm.

Parameter	Value
Search agents	50
Dimensions	num*3
Optimally allocated DER (num)	3
Maximum iterations	num*50
DER power generation limit	$0 \leq P_{\text{DER}j} \leq 2000$
DER power factor limit	$0.71 \leq PF_{\text{DER}j} \leq 1$

where, $X_{i,j}^{t+1}$ denotes the next position, $X_{i,j}^{t}$ represents the current position, t signifies the current hunting time, and T is the maximum hunting time. $r_{i,j}^{-1}$ and $\alpha_{i,j}^{t}$ denote the randomization parameter and step length, for cheetah i respectively. The randomization parameter $r_{i,j}^{-1}$ is generated from a standard normal distribution, while the step length $\alpha_{i,j}^{t}$ can be set based on the cheetahs' slow-walking behaviour.

4.1.2 | Sit and wait strategy

The Sit-and-wait strategy employed by cheetahs involves remaining stationary and patiently waiting for prey to approach, thereby minimizing the risk of alerting the prey to their presence. This strategy is adopted when the prey is within the cheetah's field of vision during the search mode. By lying low or concealing themselves among bushes, cheetahs aim to get close enough to their prey without triggering their escape response. Mathematically modelling this behaviour involves updating the position of cheetah i in arrangement j as represented by Equation (18):

$$X_{i,j}^{t+1} = X_{i,j}^{t} \tag{18}$$

where, $X_{i,j}^{t+1}$ represents the updated position, and $X_{i,j}^{t}$ signifies the current position of cheetah i in arrangement j. This strategy ensures that the cheetah remains stationary, allowing it to patiently await the prey's approach without making any sudden movements that could alert the prey.

4.1.3 | Attack strategy

The Attack strategy employed by cheetahs capitalizes on two fundamental elements: speed and flexibility. When initiating an attack, a cheetah accelerates to its maximum speed in pursuit of the prey. As the chase ensues, the prey becomes aware of the impending threat and begins to flee. The cheetah, relying on its keen eyesight, tracks the prey's movements and adjusts its trajectory to intercept the fleeing target. The objective is to cut off the prey's escape route by strategically positioning itself in the prey's path, compelling the prey to change its direction suddenly to evade capture. Mathematically, this attacking tactic of cheetah is represented in Equation (19):

$$X_{i,j}^{t+1} = X_{B,j}^{t} + r_{i,j} \times B_{i,j}^{t} \tag{19}$$

where, $X_{i,j}^{t+1}$ represents the updated position of cheetah i in arrangement j, with $X_{B,j}^{t}$ denoting the current position of the prey in the same arrangement. The first term of the equation signifies the cheetah's rapid approach toward the prey's

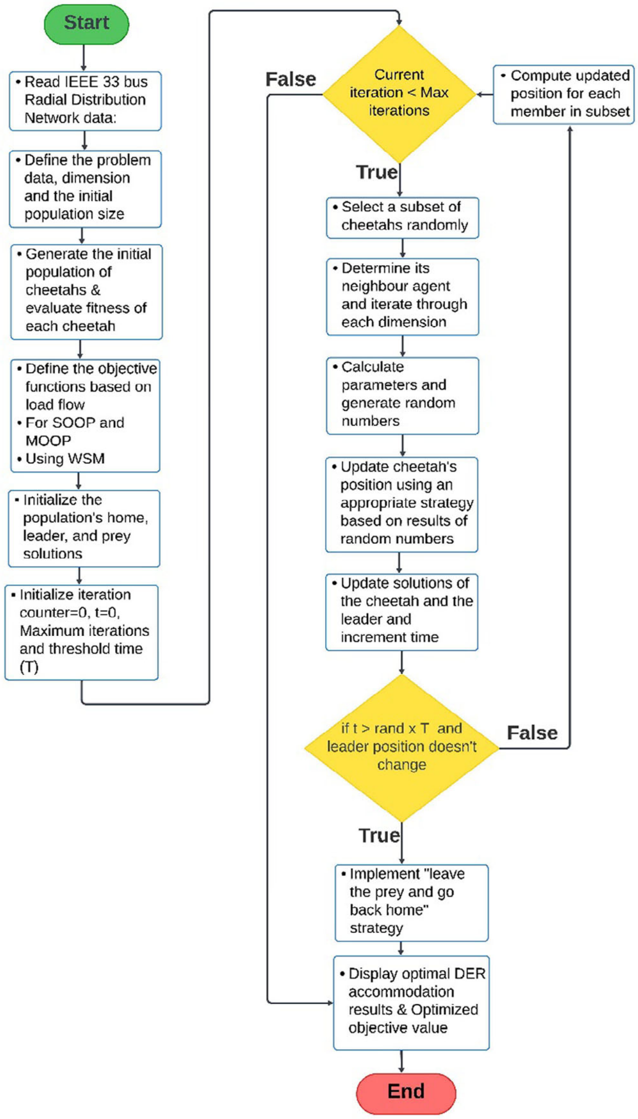

FIGURE 4 Flowchart of CO based ODERA.

position, utilizing maximum speed to close the distance swiftly. The second term, involving the turning factor $r_{i,j}$ captures the interaction between a cheetah and a leader during the capture phase.

4.1.4 | Leave the prey and go back home

This strategy encompasses two key scenarios for cheetahs in their hunting endeavours. Firstly, if a cheetah's hunting attempt proves unsuccessful, it undertakes a positional adjustment or retreats to its territory, recognizing the need to reassess the situation. Secondly, in cases where prolonged hunting yields no success, the cheetah relocates to the vicinity of the last known prey location and resumes its search, employing a strategic approach to optimize hunting efficiency and maximize prey capture opportunities.

5 | RESULTS AND ANALYSIS

This section implements the proposed ODERA methodology utilizing the CO algorithm on the comprehensive IEEE 33-bus RDN benchmark. DERs are optimally accommodated based on the results of single-objective optimization for reducing active power losses (APL) and with additional objectives, including the reduction in total voltage deviation (TVD) and the enhancement of the voltage stability index (VSI).

The proposed system is developed using MATLAB R2023a for programming the ODERA algorithm. Subsequently, the system is simulated using the industry-grade software ETAP 19.0.1, specialized for electrical power system design. The computational process is executed on a device equipped with an Intel Core i7-8565U CPU (1.99 GHz) with 8.00 GB RAM processor.

5.1 | IEEE 33 bus test system

The IEEE 33-Bus RDN is implemented to benchmark distribution studies, and it is proposed in [49]. The system is assumed to be balanced with 12.66 kV (base voltage) and 100 MVA (base power), has one grid sub substation (GSS), and total active and reactive power load is considered as 3.715 (MW) and 2.3 (MVAR) respectively. The characteristics of the test feeder, including overhead conductor, ground wire and 3-phase system configuration data is taken from this document. Single line diagram of the test system is given in Figure 5.

The originally proposed 'IEEE 33-bus benchmark distribution network' is considered the base system without any capacitor or DER units installed. The load flow results are as follows, which will be used as a reference in the next sections.

- Active power loss = 210.89 kW
- Voltage deviation index = 0.1164
- Voltage stability index = 0.6934

5.1.1 | Single objective optimization

In this section, three DER units for each of the three different AC operation modes (PF) would be accommodated based on the optimization of a single objective function: 'reduction of APL in the RDN'. The optimization technique is tested on the following modes of DER units:

- Unity power factor mode (UPF)
- 0.95 lagging power factor (0.95PF)
- Optimal power factor (OPF)

The OPF values represent the values of DER units aligning with that of the RDN power factor at the point of accommodation, adhering to the principles of the maximum power transfer theorem. This theorem suggests that alignment is crucial for optimizing energy transfer, reducing losses, and improving system efficiency.

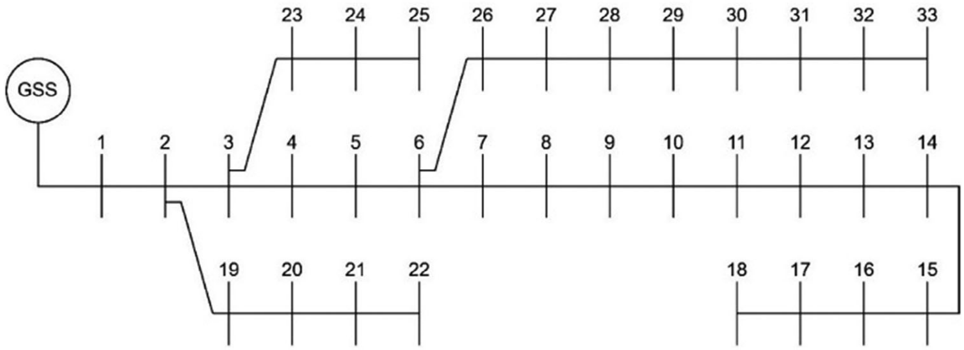

FIGURE 5 IEEE 33 bus benchmark RDN.

Optimal der accommodation

Table 6 presents the results of three DER units accommodated based on SOOP at unity power factor. The proposed optimization scheme "CO" has determined three optimal locations of 14, 24 and 30 and a 759, 1071 and 1100 kW capacity, respectively. This configuration achieves a decrease in losses from 210.89 kW in the base case to 70.58 kW and the percentage loss reduction of 66.55 % which is greater than IGWOPSO [50] with 66.51%, SFSA [33] with 65.49%, IHHO [42] with 65.50% and SIMBO-Q [5] with 65.21%. It could be concluded that the proposed CO [P] has outperformed the mentioned optimization schemes for UPF mode by producing the maximum power loss reduction in RDN.

The next recorded results in Table 7 compare the effect of 0.95 lagging PF on single objective optimization-based accommodation, and the proposed scheme 'CO' achieves a power loss of 28.94 kW, equivalent to a loss reduction of 86.28%. The achieved result is an improvement over the standard HHO [42] with 85.92% loss reduction and SIMBO-Q [5] with 86.26% but with a slightly lower value than IHHO [42] with 86.49%, IGWO [50] with 86.84% and IGWOPSO [50] with 86.88%.

To analyse the effect of different DER power factor modes on active power loss reduction in the RDN, DER accommodation using CO algorithm is performed based on optimal power factor (OPF) mode. Table 8 presents the calculated results in comparison with other techniques. CO achieves an APL of 13.29 and loss reduction (LR) up to 93.70% which is greater than standard HHO [42] with 92.92%, BFOA [52] with 86.97%, and BSOA [27] with 85.97%.

These results of optimal DER accommodation indicate that among three different AC operation modes, CO has been able to show the best performance and maximum loss reduction in UPF case and slightly lower value of power loss reduction than IHHO [42], IGWO [50] and IGWOPSO [50] only in single objective optimization for 0.95 lag PF and OPF. Figure 6 displays the variation in PF for the SOOP case, and it could be noticed for UPF that maximum %LR is achieved compared to other modes.

Voltage profile of RDN

The enhanced version of IEEE 33 bus benchmark DN is reported in [49] which states that during the system operation, voltages should be retained within the range 0.95 to 1.05 p.u, an acceptable range for practical distribution systems as per grid code and the usual voltage control range for on-load tap changers (OLTC) with ±5% of the nominal voltage. To ensure efficient system operation, it's essential to analyse overvoltage and undervoltage conditions across the network. Therefore, effect of AC operation mode of DER units on the network's voltage profile is investigated.

In this analysis, the results are depicted in Figure 7 and the weakest point is bus 18 with a minimum voltage of 0.9134 p.u, and maximum voltage at the bus 1 known as slack bus or utility bus which maintains the highest voltage value at 1 p.u, serving as a reference point for the entire network. When operating DER units in UPF mode, the overall voltage profile improves, and the voltage magnitude at bus 18 increases to 0.9758 p.u however it is the lowest a network voltage and the maximum voltage occurs at the bus 1 with 1 p.u. Transitioning to 0.95 lagging PF, enhances the voltage profile, with bus 18 improving to 0.9917 p.u and bus 8 experiences the lowest voltage at 0.9893 p.u, and maximum voltage at the slack bus. Further operation of DER units at OPF produces a voltage profile ranging from 0.9923 p.u (lowest network voltage at bus 8) to 1.0006 p.u (bus 30). This data indicates that the OPF mode corresponding to SOOP maintains optimal voltage profile among the three PF modes and maintains voltage within ± 1% of the nominal system voltage. This signifies robust voltage control and minimizes overvoltage or undervoltage conditions at any bus.

Statistical analysis for SOOP

The statistical analysis of CO is performed by carrying out 10 successive runs and determining the best values for power loss reduction, average value and the worst value obtained for loss reduction and the results are presented in Table 9. For UPF, CO shows greater performance with lowest value from the best case with 70.58 for power loss reduction in comparison to mentioned methodologies. However, for 0.95 PF and OPF, IHHO has a slightly lower power loss value with CO at second. However, average, and worst value obtained by CO in 0.95 PF and OPF case shows greater performance in comparison and indicates greater stability, robustness, and qualification of being a superior technique. These results have been graphically presented in Figure 8 for all three AC operation modes, each

TABLE 6 ODERA results for UPF based SOOP.

Method	DER location	DER size (kW)	Power loss (kW)	LR%
Fuzzy-IAS [40]	32 30 31	2071 1113 150.3	117.36	42.45
BSOA [27]	13 28 31	632.0 486.0 550.0	89.050	57.76
LSF [51]	18 33 25	720.0 810.0 900.0	85.070	59.72
TLBO [30]	10 24 31	824.6 1031 886.2	75.540	64.20
QOTLBO [30]	12 24 29	880.8 1059 1071	74.100	64.88
BFOA [52]	14 25 30	779.0 880.0 1083	73.530	65.14
SIMBO-Q [5]	14 24 29	763.8 1042 1136	73.400	65.21
QOSIMBO-Q [5]	14 24 30	770.8 1096 1066	72.800	65.49
HHO [42]	14 24 30	745.7 1022 1135	72.980	65.40
IHHO [42]	14 24 30	775.5 1081 1067	72.790	65.50
QOCSOS [53]	13 24 30	801.7 1091 1054	72.787	65.50
SFSA [33]	13 24 30	802.0 1092 1054	72.785	65.49
CSCA [54]	13 24 30	871.0 1092 954.1	71.940	65.90
IGWO [50]	14 24 30	758.0 1073 1099	70.640	66.51
IGWOPSO [50]	14 24 30	786.0 1032 1094	70.640	66.51
CO [P]	14 24 30	759.0 1071 1100	70.580	**66.55**

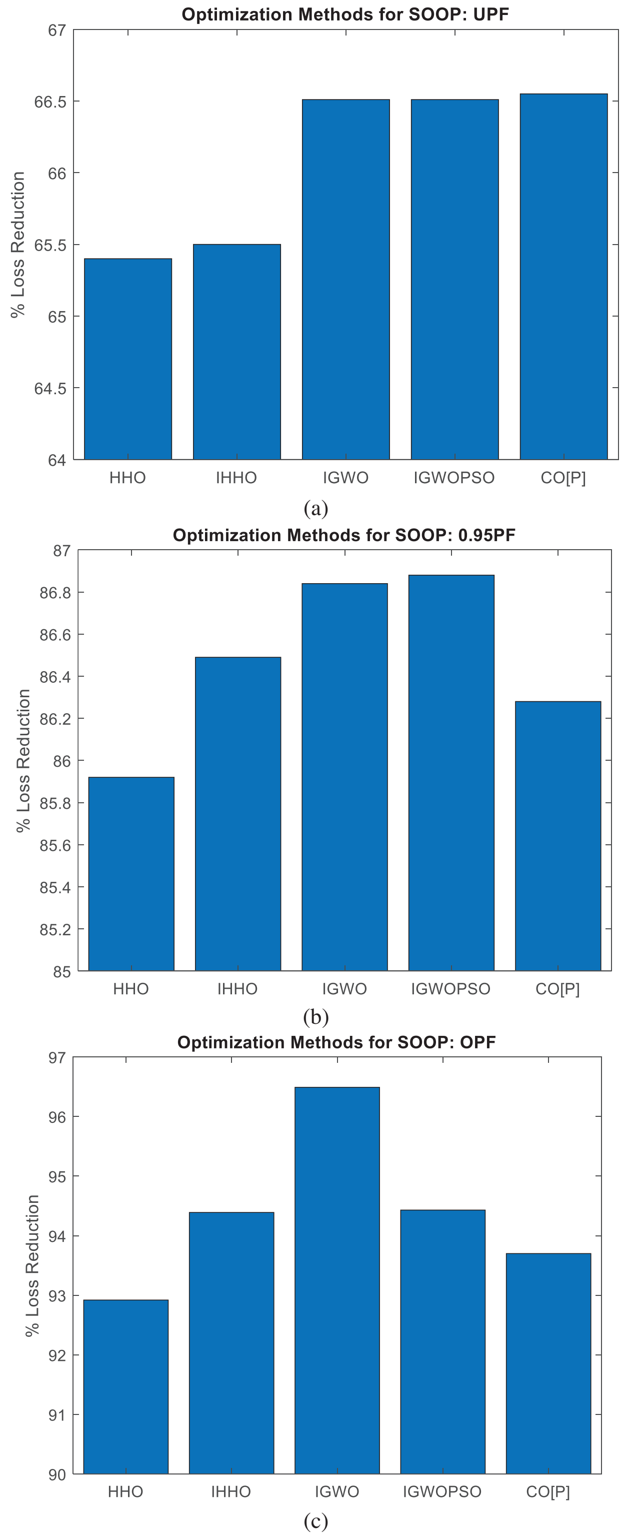

FIGURE 6 %LR for DER PF modes in SOOP.

with best, average, and worst case scenarios. Figure 9 displays the convergence characteristics of the CO algorithm for the integration of three DER units in the IEEE 33-bus benchmark radial distribution network. The graph illustrates the efficiency of CO algorithm to converge to optimal solution in minimum number of iterations.

5.1.2 | Multi objective optimization

This section extends the DER accommodation problem using CO to multiple objectives. In addition to the objective function of reduction in active power loss (APL), voltage deviation

TABLE 7 ODERA results for 0.95 PF based SOOP.

Method	DER bus	DER size (kW)	DER size (kVar)	Power factor (PF)	Power loss (kW)	LR%
HHO	13	871.34	286.40	0.95	29.71	85.92
[42]	24	1326.8	436.08	0.95		
	30	1076.1	353.68	0.95		
SIMBO-Q	13	887.50	291.70	0.95	29.00	86.26
[5]	24	1085.3	356.70	0.95		
	30	1309.2	430.30	0.95		
CO	14	778.00	256.00	0.95	28.94	**86.28**
[P]	24	1124.0	369.00	0.95		
	30	1268.0	417.00	0.95		
IHHO	14	793.81	260.91	0.95	28.50	86.49
[42]	24	1132.4	372.21	0.95		
	30	1257.8	413.41	0.95		
IGWO	13	835.00	274.00	0.95	27.77	86.84
[50]	24	1083.0	354.00	0.95		
	30	1252.0	410.00	0.95		
IGWOPSO	14	803.30	272.90	0.95	27.68	86.88
[50]	24	1123.9	369.40	0.95		
	30	1239.8	407.50	0.95		

TABLE 8 ODERA results for OPF based SOOP.

Method	DER bus	DER size (kW)	DER size (kVar)	Power factor (PF)	Power loss (kW)	LR%
BSOA	13	698.0	414.0	0.86	29.65	85.97
[27]	29	402.0	399.0	0.71		
	31	658.0	671.0	0.70		
BFOA	14	600.0	307.0	0.89	27.50	86.97
[52]	25	598.0	402.0	0.83		
	30	934.0	504.0	0.88		
HHO	12	913.0	557.0	0.85	14.94	92.92
[42]	24	882.9	616.6	0.82		
	30	1079	734.2	0.83		
CO	14	748.0	348.0	0.90	13.29	**93.70**
[P]	24	1079	520.0	0.90		
	30	1050	1019	0.71		
IHHO	14	761.8	373.5	0.90	11.83	94.39
[42]	24	1142	536.0	0.91		
	30	1014	1003	0.71		
IGWOPSO	13	793.0	374.0	0.87	11.74	94.43
[50]	24	1066	519.0	0.90		
	30	1038	1000	0.72		
IGWO	14	751.0	340.0	0.91	11.64	96.49
[50]	24	1070	526.0	0.85		
	30	1054	1018	0.72		

(VD) reduction and voltage stability index (VSI) enhancement are also considered for the optimal DER size and position in the network.

Optimal DER accommodation

The result of multiple objective functions-based accommodation of 3 DER is presented in Table 10, and DER units are operating at UPF mode. CO obtains the location for three DER as 14, 24, 30 and real power generation capacity of 869, 1133 and 1444 kW, respectively. The active power loss achieved is 70.7331 kW compared to base case with 210.89 kW and LR % of 66.47, the highest value in comparison to IGWO [50] with 64.16% LR, IGWOPSO [50] with 63.67% LR, QOCSOS [53] with 63.48% LR, MOIHHO [42] with 56.28% LR and MOHHO [42] with 55.94% LR. CO also achieves a lower value of VD equivalent to 0.0066 p.u that is lower than QOSIMBO_Q

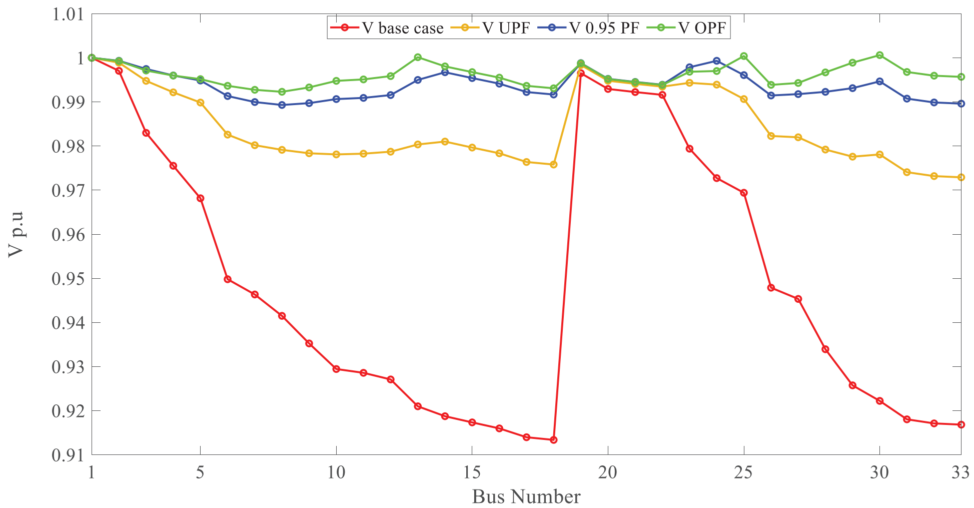

FIGURE 7 Voltage profile of IEEE RDN for SOOP.

TABLE 9 Statistical analysis for SOOP methods.

Power factor	Method	Best case (%)	Average case (%)	Worst case (%)
UPF	CO	66.53	66.51	66.43
	HHO	65.39	62.22	59.70
	IHHO	65.48	63.66	62.16
0.95PF	CO	86.28	85.29	82.43
	HHO	85.91	82.29	78.17
	IHHO	86.46	82.56	78.11
OPF: 0.90, 0.90, 0.71	CO	93.70	93.13	90.08
0.85, 0.82, 0.83	HHO	92.92	89.73	87.08
0.90, 0.91, 0.71	IHHO	94.39	92.56	88.09

[5] with 0.0088, GA/PSO [55] with 0.0124, PSO [55] with 0.0335 and GA [55] with 0.0407. Additionally, the CO has achieved a moderately higher value of VSI which is superior to that obtained by QOCSOS [53] with 0.9168 p.u. These results suggest the effectiveness of CO, particularly with respect to APL and VD. It is most capable of minimizing dissipation of electrical energy, maintaining a more consistent stable voltage level and is moderately resilient to disturbances.

To determine the effect of PF variation on multi-objective DER accommodation, 0.95 lagging PF operation mode is analysed and the results are presented in Table 11. CO achieves maximum power loss reduction with active power loss of 27.73 and LR % of 86.86. It is followed by IGWOPSO [50] with 85.77 % LR, IGWO [50] with 85.57 % LR, MOIHHO [42] with 85.50 % LR, MOHHO [42] with 85.12 % LR and QOSIMBO-Q [5] with 84.97 % LR.

Table 12 presents the optimal accommodation result of DER at OPF. CO performs the best when it comes to active power loss reduction with APL of 12.2367 kW and % LR of up to 94.20 and is greater than IGWOPSO [50] with 93.88 % LR, IGWO [50] with 93.87 % LR, MOIHHO [42] with 92.89 % LR and MOHHO [42] with 91.09 % LR.

CO has been able to outdo other techniques in the literature for all the three AC operation modes in terms of APL reduction and secures the highest value of %LR in the OPF mode. Compared to other power factors, in this mode, it maintains minimum TVD of 0.0015 p.u and maximum VSI of 0.951 p.u and able to maintain high system stability, however slightly behind the maximum value. Figure 10 represents the modified IEEE 33 bus RDN after optimally accommodating DER, suggesting it is able to meet real and reactive power load demand in line with IEEE 1547–2018 standard [44]. The optimization results are visualized in the Figure 11 which compares the results of %LR achieved by CO and other techniques while considering multiple objectives.

Voltage profile of RDN

Based on the findings presented in Tables 10–12, the MOOP based integration of DER for three distinct power factor scenarios has exhibited a substantial improvement in minimizing power losses compared to SOOP. Consequently, it is required to investigate the impact on voltage profiles, as illustrated in Figure 12. In the base case, it is observed that bus 18 is characterized as the weakest point in the network, with a minimum voltage of 0.9134 p.u, while bus 1, known as the utility bus, maintains the highest voltage at 1 p.u. Under UPF mode for DER, the voltage profile of the network experiences improvement, however it results in bus 8 being the weakest bus with a voltage magnitude of 0.9857 p.u and the utility bus maintains a maximum voltage of 1 p.u. In the context of 0.95 PF the lowest voltage magnitude is observed at bus 33 with a value of 0.9945 p.u, whereas bus 10 records the highest voltage at 1.0095 p.u. For OPF mode, the minimum voltage is registered at bus 18 with a magnitude of 0.9940 p.u, while bus 11 maintains the highest voltage at 1.0090 p.u. Hence, based on these observations it could be concluded that, for all three PF modes, both 0.95PF and OPF modes effectively maintain the voltage within a narrow range of ±1% deviation from the nominal system voltage, however with OPF mode holding a slight advantage due to its lower overvoltage levels.

TABLE 10 ODERA results for UPF based MOOP.

Method	DER bus	DER size (kW)	Power loss (kW)	Loss reduction %	TVD	VSI
GA [55]	11 29 30	1500 422.8 1071	106.3	49.62	0.0407	0.9490
PSO [55]	8 13 32	1177 981.6 829.7	105.3	50.09	0.0335	0.9255
GA/PSO [55]	11 16 32	925.0 863.0 1200	103.4	50.99	0.0124	0.9508
TLBO [30]	12 28 30	1183 1191 1186	124.7	40.89	0.0011	0.9503
QOTLBO [30]	13 26 30	1083 1188 1199	103.4	50.99	0.0011	0.9530
TM [56]	15 26 33	719.9 719.9 1440	102.3	51.51	0.0040	0.9371
MOTA [56]	7 14 30	980.0 960.0 1340	96.30	54.36	0.0014	0.9551
SIMBO-Q [5]	13 24 31	140.0 919.8 1400	104.3	50.56	0.0011	0.9615
QOSIMBO-Q [5]	12 25 31	1437 826.2 1443	101.9	51.70	0.0009	0.9669
MOHHO [42]	13 25 31	1207 763.0 1400	92.95	55.94	0.0020	0.9654
MOIHHO [42]	14 24 31	1223 1144 1290	92.25	56.28	0.0019	0.9580
QOCSOS [53]	13 24 30	956.4 1131 1294	77.04	63.48	0.0065	0.9168
IGWO [50]	13 24 30	987.0 1101 1330	75.61	64.16	0.0033	0.9372
IGWOPSO [50]	13 24 30	930.0 929.0 1450	76.65	63.67	0.0035	0.9354
CO [P]	14 24 30	869.0 1133 1444	70.73	**66.47**	0.0066	0.9204

By investigating the voltage profiles in both single and multi-objective optimization, considering all three power factor modes, it becomes evident that the OPF mode in MOOP offers the most optimal voltage profile. In this mode, the voltage profile exhibits a remarkable performance with a minimum network voltage of 0.9940 p.u and a maximum voltage of 1.0090 p.u. Notably, the entire network's voltage profile remains within ±1% of the nominal system voltage, has the minimum TVD of 0.0015 p.u and maximum voltage stability with VSI equal to 0.951 p.u compared to other modes.

5.1.3 | Economic optimization

This section evaluates the economic advantages of accommodating DER units into the IEEE 33 bus benchmark RDN,

TABLE 11 ODERA results for 0.95PF based MOOP.

Method	DER bus	DER size (kW)	DER size (kVar)	PF	APL (kW)	LR %	TVD (p.u)	VSI (p.u)
SIMBO-Q [5]	13	943.0	309	0.95	32.4	84.64	0.0003	0.977
	24	1327	436	0.95				
	30	1443	474	0.95				
QOSIMBO-Q [5]	13	898.0	295	0.95	31.7	84.97	0.0003	0.977
	24	1392	458	0.95				
	30	1419	467	0.95				
MOHHO [42]	13	1008	331	0.95	31.4	85.12	0.0005	0.976
	25	910.0	299	0.95				
	30	1334	439	0.95				
MOIHHO [42]	13	924.0	304	0.95	30.6	85.50	0.0004	0.979
	24	1312	431	0.95				
	30	1356	446	0.95				
IGWO [50]	13	948.0	311	0.95	30.4	85.57	0.0003	0.972
	24	1197	391	0.95				
	30	1411	463	0.95				
IGWOPSO [50]	13	930.0	306	0.95	30.0	85.77	0.0003	0.970
	24	1179	387	0.95				
	30	1412	464	0.95				
CO [P]	13	1451	477	0.95	27.7	**86.86**	0.0017	0.951
	24	1076	354	0.95				
	30	858.0	282	0.95				

TABLE 12 ODERA results for OPF based MOOP.

Method	DER bus	DER size (kW)	DER size (kVar)	PF	APL (kW)	LR %	TVD (p.u)	VSI (p.u)
MO HHO [42]	12	951.0	516.0	0.88	18.8	91.09	0.0005	0.978
	25	786.0	436.0	0.87				
	30	1381	809.0	0.86				
MO-IHHO [42]	12	916.0	576.0	0.85	15.0	92.89	0.0003	0.978
	24	1088	386.0	0.94				
	30	1171	830.0	0.82				
IGWO [50]	13	867.0	408.0	0.90	12.9	93.87	0.0003	0.9766
	24	1124	539.0	0.83				
	30	1130	1085	0.71				
IGWO-PSO [50]	13	863.0	432	0.90	12.9	93.88	0.0003	0.9767
	24	1116	517.0	0.83				
	30	1137	1057	0.72				
CO [P]	14	769.0	367	0.90	12.2	**94.20**	0.0015	0.951
	24	1165	550.0	0.90				
	30	1097	1059	0.71				

emphasizing the importance of early return on investment for electricity distribution companies. The economic analysis of ODERA involves 3 units operating on various power factor modes and positioned at respective buses within the RDN, as determined by the optimization results for both SOOP and MOOP.

This analysis is presented comprehensively in Table 13. As the DER operating mode changes from UPF to 0.95 lag PF and eventually to OPF, the AEL_{wDER} exhibits a consistent decrease from \$39,704 at UPF to \$14,452 at OPF for SOOP, and from \$41,317 at UPF to \$14,436 at OPF for MOOP. There is a

TABLE 13 Economic analysis of ODERA in RDN.

Objectives	PF	AEL_{woDER} (\$)	AEL_{wDER} (\$)	ACS (\$)
Single	UPF	92,369	39,704	52,665
	0.95 lag	92,369	22,185	70,184
	OPF	92,369	14,452	77,917
Multiple	UPF	92,369	41,317	51,052
	0.95 lag	92,369	22,287	70,082
	OPF	92,369	14,436	77,933

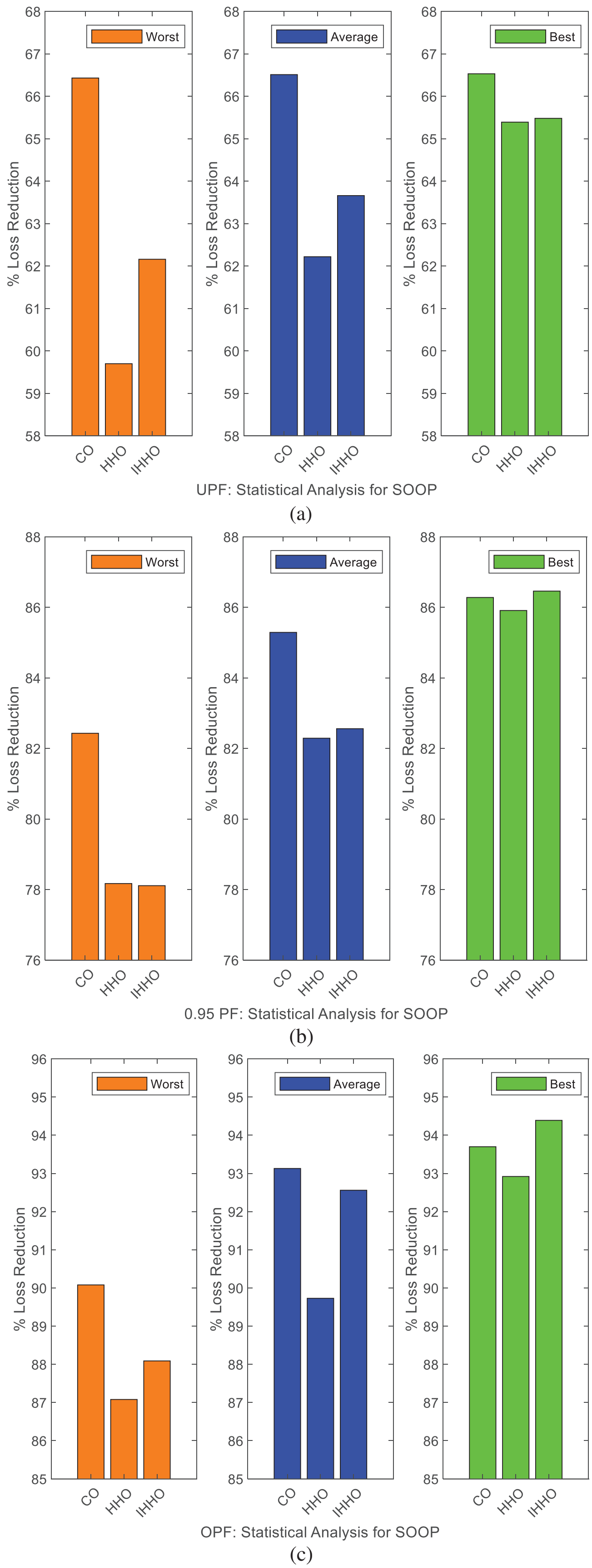

FIGURE 8 Graphs for SOOP statistical analysis.

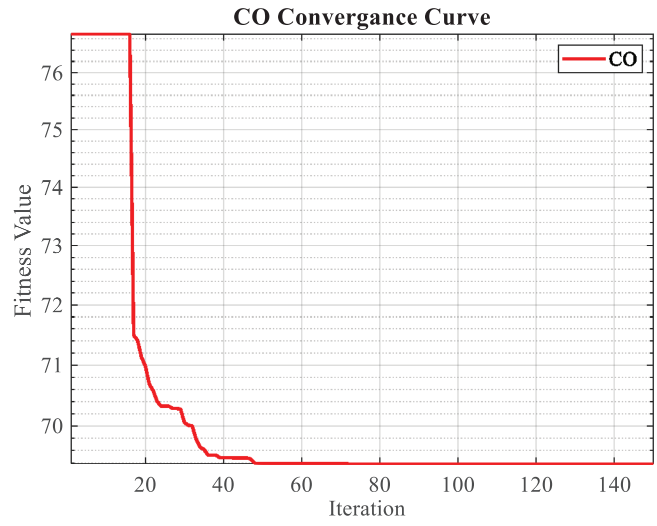

FIGURE 9 Convergence characteristic of CO.

proportional increase in ACS from $52,665 at UPF to $77,917 at OPF for SOOP and for MOOP from $51,052 at UPF to $77,933 at OPF. While SOOP typically performs better in terms of loss reduction and savings due to ODERA across UPF and 0.95PF lag modes, the OPF mode for MOOP demonstrates superior performance with the minimum value of AEL_{wDER} and the maximum ACS. The economic analysis results are visually depicted in Figures 13 and 14 for SOOP and MOOP respectively. In following diagrams, ACS is represented by a line plot, while AEL_{wDER} is represented by the bar chart.

5.2 | Reliability analysis

After the preliminary study of optimal DER accommodation in IEEE 33 bus DN, it is extended to include the reliability aspect by employing ETAP software 19.0.1 version to ensure that the expectations of customers are met, and the amount spent on maintenance is managed efficiently. In the following sections, reliability indices for two cases of PV and WT will be determined with each having three scenarios and compared with the indices for base case. It is an important aspect of power system planning to analyze these indices and obtain information to ensure higher quality electrical power delivery to the customers. This is made sure by making assessments such as customer satisfaction, which is based on continuity and stability of supply, the economic impact of power interruptions on the consumers, reliability standards that the utility must meet, the ability of the network to recover from disasters, energy efficiency and evaluating the environmental footprint of the network. Data required for network reliability analysis is presented in Table 14 and taken from [57].

5.2.1 | Base case study

The base case represents IEEE 33 bus benchmark RDN without DER integration. Five commonly used reliability indices

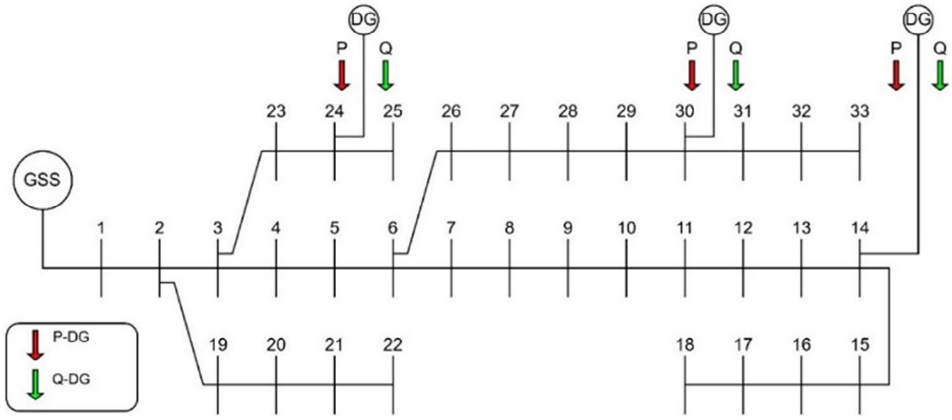

FIGURE 10 SLD of RDN with ODERA.

TABLE 14 Reliability data for DN components.

Component	Active failure rate	Passive failure rate	MTTR (h)	Switching time (h)
Transmission lines	0.065	0.065	5.0	1
Bus bars	0.001		2.0	1
Utility grid	0.643		12	1
PV DER	1.250		5.0	2
WT DER	0.020		60	1

TABLE 15 Reliability indices value for base case.

Number	Indices	Base case
1	SAIDI	60.68
2	CAIDI	11.04
3	SAIFI	5.496
4	ASAI	0.993
5	ASUI	0.007

by the utility are calculated based on input data provided for each component involving active failure rate, passive failure rate, MTTR and switching time. Table 15 presents these indices calculated for the base case.

5.2.2 | Reliability indices for PV & WT der units

Table 16 displays reliability index outcomes for the two cases of PV and WT DER for accommodation into the IEEE 33 bus RDN, including three scenarios corresponding to OPF based MOOP results, where scenarios 1, 2, and 3 represent single, double, and triple DER units accommodated.

Moreover, the charts in Figure 15 depict the index values using bar graphs, enhancing the visual comparison between reliability indices of different DER types and scenarios.

TABLE 16 Reliability indices for PV and WT units.

Indices	Base case	Scenario 1	Scenario 2	Scenario 3
Case 1: PV DER				
SAIDI	60.680	60.660	63.717	66.362
CAIDI	11.040	9.9130	8.6610	7.7950
SAIFI	5.4960	6.1190	7.3570	8.5130
ASAI	0.9930	0.9930	0.9927	0.9924
ASUI	0.0069	0.0070	0.0073	0.0076
Case 2: WT DER				
SAIDI	60.680	58.729	59.847	60.557
CAIDI	11.040	12.021	12.241	12.587
SAIFI	5.4960	4.8854	4.8890	4.8910
ASAI	0.9930	0.9933	0.9932	0.9931
ASUI	0.0069	0.0067	0.0068	0.0069

- SAIDI: In the PV case, only scenario 1 displays a value lower than the base case; however, it rises with an increased number of DER units. In the WT case, scenario 1 records the lowest value among all scenarios, but it increases with the number of DER units, although it consistently stays below the base case. This indicates improved reliability for WT across all scenarios and superior performance compared to the base and PV case. SAIDI should decrease to signify enhanced reliability, shorter interruption durations, and improved consumer service continuity.
- CAIDI: In the PV case, the value improves over the base case, decreasing with increased DER integration and reaching its lowest point in scenario 3. In contrast, for the WT case, all values deteriorate compared to the base case, exhibiting an upward trend with higher DER integration, with scenario 3 registering the highest value. A reduced CAIDI value signifies enhanced reliability, indicating a prompt utility response to equipment failure. This improvement is notably attributed to the considerably shorter MTTR for PV systems compared to WT.
- SAIFI: The PV case exhibits lowest value in scenario 1, still higher than the base case, showing an increase with additional DER integration. In the WT case, SAIFI maintains a lower value than the base case across all scenarios,

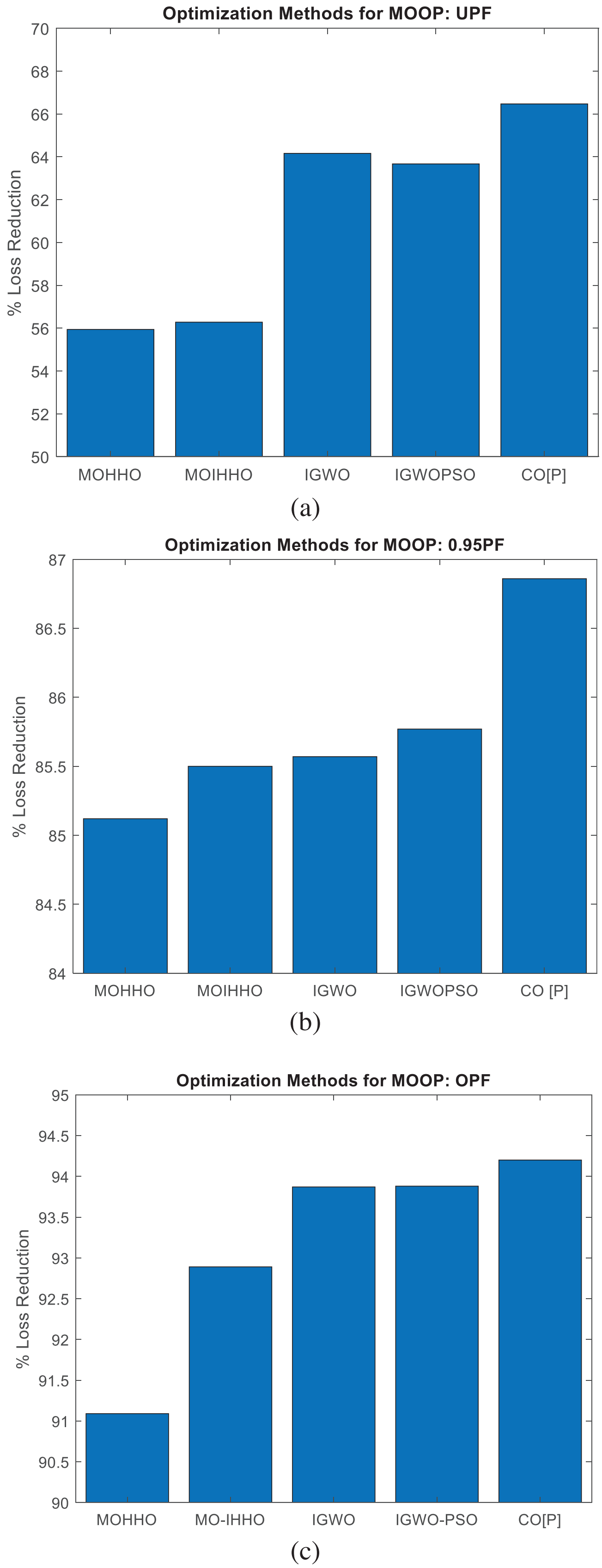

FIGURE 11 %LR for DER PF modes in MOOP.

remaining relatively stable with minor fluctuations and achieving its lowest value in scenario 1. A decline in SAIFI indicates enhanced reliability and a decrease in the average frequency of interruptions in the network.

- ASAI: It is a crucial metric for assessing reliability, particularly in indicating system improvements over the base case. In the PV scenario, the value remains similar to the base case in scenario 1, decreasing as the number of DER units increases, reaching its lowest in scenario 3. Regarding the WT scenario, it consistently exhibits higher values than the base case, peaking in scenario 1 and displaying a decreasing trend with additional DER units. An increased ASAI signifies enhanced reliability and an overall increase in system availability.
- ASUI: It is employed as an additional metric for comprehensive reliability evaluation. In the PV scenario, the lowest value is observed in scenario 1, higher than the base case, and it rises with more DER units. Conversely, for WT, the lowest value is also in scenario 1, increasing with additional DER units and reaching a maximum value which is slightly lower than the base case. A decrease in ASUI signifies improved reliability and reduced system unavailability, aligning with the objective.

Despite the increasing CAIDI values for WT systems, the distinction between interruption affecting customers and outage affecting equipment significantly influences the ASAI results. For WT, the ASAI value is improved from the base case, while for PV systems, it deteriorated, apparently conflicting with the CAIDI trend. This suggests that the impact of equipment outage on overall reliability is comparatively less than the effect of interruption.

In conclusion, scenario 1 generally exhibits higher reliability for respective cases. The WT DER shows improvement in overall reliability compared to the base case by enhanced service continuity, reduced interruption frequency and duration, and increased system availability.

6 | CONCLUSION AND RECOMMENDATIONS

This research demonstrates the successful application of CO algorithm for the optimal accommodation of RER based DER for multiple PF cases in IEEE 33 bus RDN. The study formulates APL reduction as the single-objective optimization problem with maximum reduction of 66.55% for UPF mode and surpasses other techniques. In the context of multi-objective optimization, CO aims for APL reduction, TVD reduction and VSI enhancement through WSM, an MCDM technique. It exhibits the highest reduction in APL across all three DER AC operation modes surpassing the mentioned literature with maximum value of 94.20% loss reduction in OPF mode. Among all modes, for the OPF, CO achieves a minimal TVD of 0.0015 p.u and maximum VSI of 0.951 p.u. The economic analysis of ODERA in RDN indicates that in the context of SOOP, it demonstrates better economic performance for UPF and 0.95PF lag scenarios. However, in the MOOP for OPF

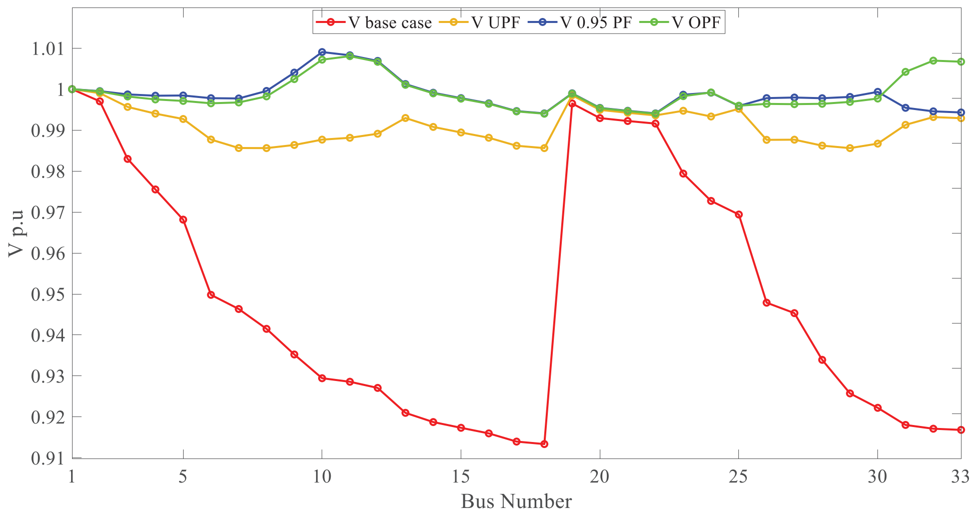

FIGURE 12 Voltage profile of IEEE RDN for MOOP.

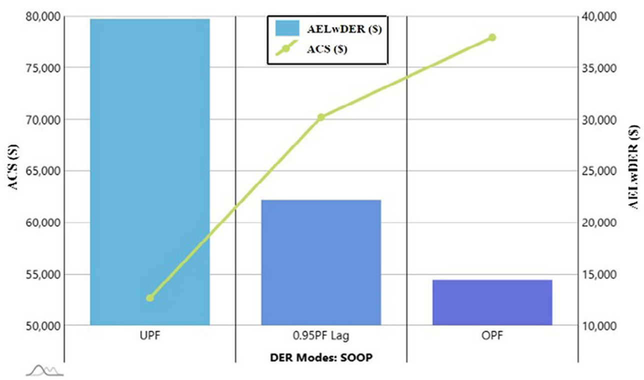

FIGURE 13 Economic analysis of ODERA for SOOP.

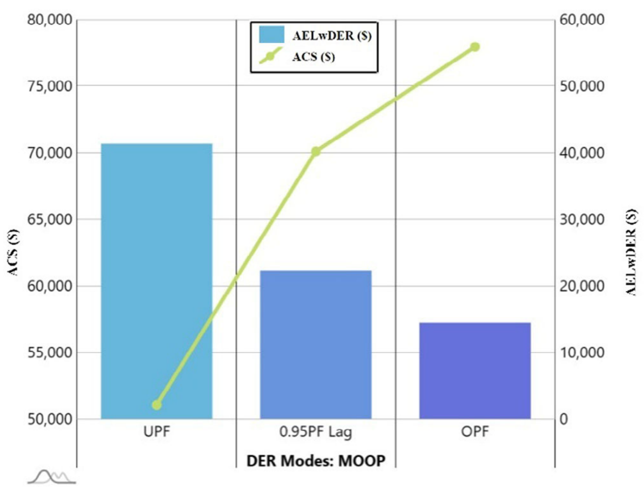

FIGURE 14 Economic analysis of ODERA for MOOP.

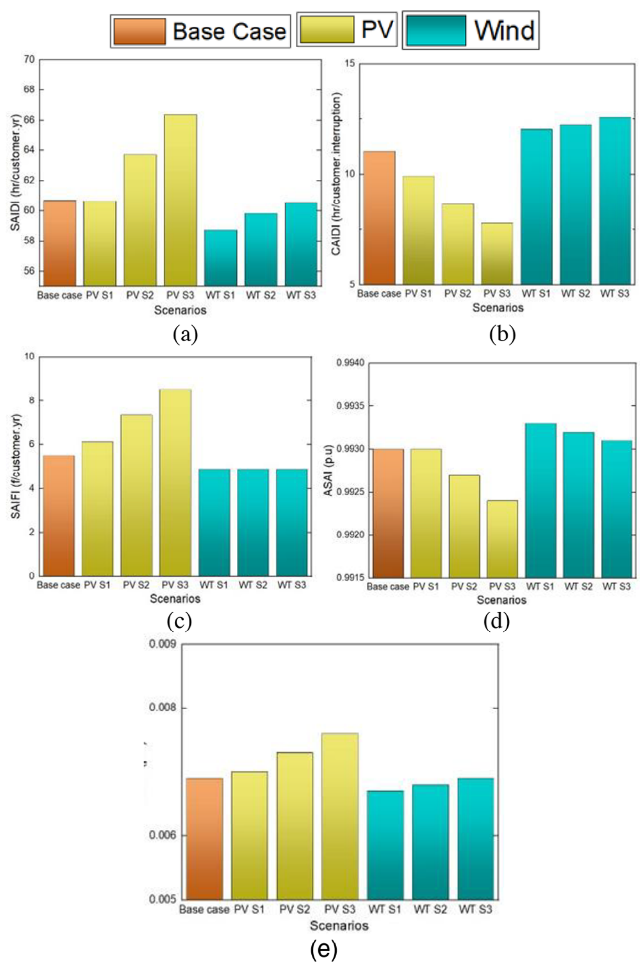

FIGURE 15 Evaluation of reliability for PV and WT.

mode, the ODERA exhibits minimum losses of $14,436, and maximum annual cost savings of $77,933. The reliability analysis of the network demonstrates that scenario one of PV or WT has higher reliability compared to other scenarios within the respective cases. It also highlights the superiority of WT DER systems over base case and PV systems with better service continuity, lower frequency and duration of interruptions and higher system availability. This is due to a lower active failure rate, which translates to fewer annual failures for WT. These observations solidify the superior capability of WT DER systems in enhancing overall system reliability.

The future work recommendations are optimizing DER unit accommodation in dynamic load modelling scenarios and investigate impact of network unbalance on RDN performance, considering larger network size.

AUTHOR CONTRIBUTIONS

Muhammad Shaarif: Conceptualization; formal analysis; investigation; methodology; software; writing—original draft; writing—review & editing. **Muhammad Yousif**: Investigation; methodology; supervision; validation. **Muhammad Numan**: Data curation; formal analysis; investigation; supervision. **Muhammad Zubair Iftikhar**: Conceptualization; methodology; resources; software. **Izhar Us Salam**: Conceptualization; methodology; software; writing—review & editing. **Thamer A. H. Alghamdi**: Funding acquisition; methodology; resources.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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