

Article

Two-Stage Stochastic Optimization of Renewable-Integrated EV Charging Stations in Loop-Distribution Networks

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Abstract

The accelerating adoption of electric vehicles (EVs) alongside renewable distributed generators (RE-DGs), particularly solar photovoltaic (PV) and wind-based systems, is reshaping the operational and planning paradigms of modern power distribution networks. In this study, an optimal allocation framework is developed for the simultaneous integration of EV charging stations (EVCs) and RE-DGs within a looped configuration of the IEEE 33-bus distribution system. Two advanced metaheuristic techniques—Improved Grey Wolf Optimizer (IGWO) and Metaheuristic COOT-Based Optimization (MCBO)—are employed to determine the optimal siting and sizing of these resources. The optimization objectives focus on minimizing active power losses while enhancing voltage stability and reducing overall voltage deviation across the network. Simulation results reveal that the MCBO algorithm demonstrates superior performance, yielding a maximum reduction of 82.49% in active power losses with the integration of standalone PV, and 78.14% when PV is deployed in conjunction with EVCs. Similarly, wind turbine generator (WTG) integration resulted in a loss reduction of 85.74% without EVCs and 81.57% with EVC integration using the same approach. The findings further indicate that looped network configurations consistently outperform traditional radial systems in both loss reduction and voltage profile enhancement, underscoring their suitability for accommodating future EV and renewable energy penetrations in smart distribution grids.

Keywords: electric vehicle charging stations; renewable energy; Loop Networks



Academic Editor: José Matas

Received: 13 March 2026

Revised: 14 April 2026

Accepted: 22 April 2026

Published: 27 April 2026

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1. Introduction

The significant surge in power demand has led to voltage drops and line losses at the distribution level [1,2]. Current distribution networks (DNs) face numerous financial, environmental, and technical challenges, making it difficult to meet growing demand [3]. Radial distribution networks, in particular, are increasingly burdened by the integration of EVs, which introduces complexities in energy management. Renewable energy sources (RESs) offer a promising solution to meet rising demand by integrating with the utility grid [4–6]. EVs significantly reduce carbon emissions from fossil-fuel-based transportation. The development of electricity and carbon markets further promotes renewable energy adoption, energy efficiency, and decentralized power systems [7].

Prior work in this area has mainly focused on the allocation of conventional distributed generations (DGs) in radial networks, often without considering the uncertainty introduced

by EVCSs as loads. In contrast, this study investigates the integration of EVCS load (in grid-to-vehicle mode) and RE-DGs in an LCN, which offers superior reliability and operational flexibility compared to radial configurations.

This study is primarily concerned with mitigating power loss [8–11], minimizing voltage deviation [5,6,10], and maximizing the voltage stability index [2,9,12]. The core contributions of this paper are as follows:

1. A two-stage planning framework for transitioning from radial distribution networks (RDNs) to LCNs for the optimal placement of EVCSs and RE-DGs.
2. Seasonal stochastic modeling of PV, wind, EV load, and general load uncertainty.
3. A comparative evaluation of the MCBO and the IGWO under multi-objective constraints.
4. Quantitative results confirm that the LCN topology achieves substantially lower losses and enhanced voltage stability relative to radial networks.

Loop-configured network formulation explicitly incorporates bidirectional power flows and network reconfiguration capabilities, features that are increasingly adopted in modern distribution systems to enhance reliability and operational flexibility. This distinction constitutes a substantive methodological advancement over prior work.

2. Literature Review

In [2,13], the authors proposed novel hybrid techniques for the optimal allocation of DG in an IEEE 33-bus network at various power factors, achieving marginally lower power loss with minimum DG size. These studies did not analyze the EVCS load but assumed a fixed load model with conventional DGs without considering seasonal variation in RESs.

The study [12] found that incorporating DGs alongside EVs enhances the voltage profile and minimizes power losses in RDNs. However, it lags the seasonal variation for RERs and ignores the impact of voltage deviation on the system. All these mentioned studies were carried out in radial networks.

The growing penetration of EVs into power distribution networks often leads to higher system losses and compromised voltage stability. Hence, optimizing the positioning of EV charging points is vital to mitigate these adverse effects. The work presented in [12] employed both the bald eagle search algorithm (BESA) and the cuckoo search algorithm (CSA) to optimize an IEEE 33-bus radial distribution network for reduced losses. They also examined EV charging strategies in comparison with conventional approaches. However, the introduction of EV load into a RDN can negatively affect voltage levels and power quality, as well as elevate total system losses.

In [3], the authors optimized DG allocation in a mesh-configured network. Similarly, in [13], optimal DG placement was explored in an IEEE 33-bus mesh distribution network. However, these studies did not account for seasonal load variations or the integration of RESs.

Recent studies have explored spatio-temporal coordinated operation under uncertainty using distributionally robust optimization (DRO). The authors of [14] proposed a two-stage DRO framework that flexibly adjusts conservativeness through uncertainty regulation parameters to manage load and temperature uncertainties. Furthermore, researchers in [15] presented an asynchronous decentralized strategy that leverages the spatial–temporal flexibility of electric buses (E-Buses) for resilient restoration in coupled electricity–transportation networks. However, these studies do not address the optimal joint placement of RE-DGs and EV charging stations (EVCSs) in loop-configured distribution networks under seasonal load uncertainties.

In contrast, this study optimizes EV charging station locations in an IEEE 33-bus LCN using the MCBO and IGWO algorithms. Existing research has not jointly addressed the placement of EVCSs and RE-DGs in loop-configured networks under seasonal uncertainty—a

gap this work aims to fill. The validity of the proposed approach is established by comparing its results with those from related studies. The multi-objective optimization achieved through comparative evaluation of different algorithms for optimal allocation of RESs and EVCSs is summarized in Table 1.

Table 1. Comparative analysis of the proposed optimization methods.

Ref. Paper	Optimization Methods	Objectives			Seasonal Variation	Modeling of RER	EVCS	Power System	
		Power Loss	Voltage Deviation	Voltage Stability				Radial	Loop
[1]	GWO, WOA, DO	✓	✓	✓	✓	✓	✓	✓	x
[2]	IGWO, IGWO_PSO	✓	✓	✓	x	x	x	✓	x
[12]	BESA & CSA	✓	x	✓	x	x	✓	✓	x
[13]	COOT, GWO	✓	✓	✓	x	x	x	x	✓
[16]	ALO, MVO	✓	✓	✓	x	x	x	✓	x
[17]	VSI	✓	x	✓	x	x	✓	✓	x
[18]	NSGA-II	✓	x	x	✓	✓	x	✓	x
[19]	SHOA, CSA	✓	✓	✓	x	x	✓	✓	x
[20]	mPDO	✓	✓	✓	x	✓	x	✓	x
[21]	MEWOA	✓	x	✓	x	✓	✓	✓	x
[P]	MCBO, IGWO	✓	✓	✓	✓	✓	✓	✓	✓

3. Problem Formulation

This section includes the optimal allocation of DGs in an LCN.

3.1. Load Flow in Loop Configuration Network

Radial distribution networks typically offer the lowest service reliability. To enhance reliability and achieve better voltage regulation, meshed distribution networks are deployed by activating interconnector switches. These switches create loops within certain distribution feeders, particularly in areas serving highly dense load zones.

Given the load currents expressed in Equation (1), the currents flowing in each branch can be calculated. Figure 1 illustrates the branch currents for a six-bus radial network, which correspond to the equivalent current injections IL_{1-2} , IL_{2-3} , IL_{3-4} , IL_{4-5} , and IL_{3-6} and are given by

$$\begin{cases} IL_{1-2} = I_2 + I_3 + I_4 + I_5 + I_6 \\ IL_{2-3} = I_3 + I_4 + I_5 + I_6 \\ IL_{3-4} = I_4 + I_5 \\ IL_{4-5} = I_5 \\ IL_{3-6} = I_6 \end{cases} \quad (1)$$

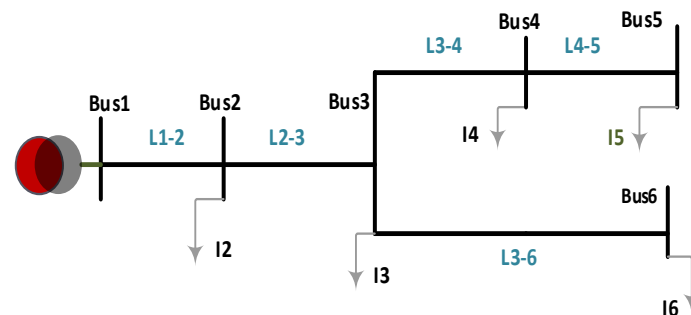


Figure 1. A typical radial distribution network (RDN).

In this configuration, the meshed network is formed by incorporating three loops into a basic radial system, as illustrated in Figure 2. The mathematical modeling for load flow analysis in meshed networks is presented below.

$$\begin{cases} IL'_{1-2} = IL_{1-2} \\ IL'_{2-3} = IL_{2-3} - I_{Loop3} \\ IL'_{3-4} = IL_{3-4} + I_{Loop1} - I_{Loop2} \\ IL'_{4-5} = IL_{4-5} + I_{Loop1} - I_{Loop2} \\ IL'_{3-6} = IL_{3-6} - I_{Loop1} - I_{Loop3} \end{cases} \quad (2)$$

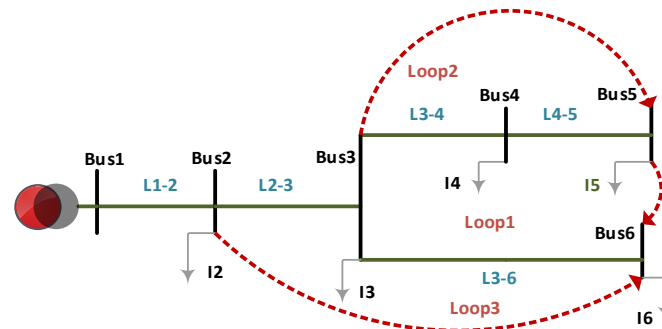


Figure 2. A typical loop-configured network (LCN) with three loops.

The loop impedance matrix, derived by applying Kirchhoff's voltage law (KVL) equations for an LCN, is expressed in matrix form as follows:

$$\begin{bmatrix} (Z_{34} + Z_{36} + Z_{45} + Z_{56}) & -(Z_{34} + Z_{45}) & Z_{36} \\ -(Z_{34} + Z_{45}) & (Z_{34} + Z_{35} + Z_{45}) & 0 \\ Z_{36} & 0 & (Z_{23} + Z_{26} + Z_{36}) \end{bmatrix} \begin{bmatrix} I_{Loop1} \\ I_{Loop2} \\ I_{Loop3} \end{bmatrix} = - \begin{bmatrix} (Z_{34} \times IL_{3-4} - Z_{36} \times IL_{3-6} + Z_{45} \times IL_{4-5}) \\ (-Z_{34} \times IL_{3-4} - Z_{45} \times IL_{4-5}) \\ (-Z_{23} \times IL_{2-3} - Z_{36} \times IL_{3-6}) \end{bmatrix} \quad (3)$$

$$[Z_{Loop}] \times I_{Loop} = -[V_{D,Loop}] \quad (4)$$

The diagonal terms of the loop impedance matrix can be calculated as follows:

$$Z_{Loop}(i,i) = Z_{p.u.}(j) \times abs(C(j,i)) + Z_{Loop}(i,i) \quad (5)$$

for $i = 1$: number of links, $j = 1$: number of elements

The off-diagonal elements of the loop impedance matrix are given by

$$Z_{Loop}(i,j) = Z_{p.u.}(m) \times C(n,i) \times C(n,j) + Z_{Loop}(i,i) \quad (6)$$

for $i = 1$: number of links, $j = 1$: number of element, and $n = 1$: branches

The current in each loop can be computed as

$$I_{Loop} = [Z_{Loop}]^{-1} \times [-V_{D,Loop}] \quad (7)$$

3.2. Objective Functions

This study aims to determine the optimal allocation of RESs in LCNs to minimize real power losses through a multi-objective optimization framework. This is achieved by simultaneously addressing three critical performance criteria: minimizing real power

loss, minimizing voltage deviation, and maximizing the voltage stability index (VSI). The fundamental mathematical formulations for these objectives are presented in the following subsections.

3.2.1. Real Power Loss Reduction

The real power loss in an LCN can be calculated using the following formula [22]:

$$Power_{Loss} = \sum_{k=1}^{M_{br}} |I_k|^2 R_k \quad (8)$$

The distribution network experiences real power losses, which must be minimized. The first objective function ($objective_{F1}$) is formulated as

$$objective_{F1} = \min(Power_{Loss}) \quad (9)$$

3.2.2. Total Voltage Deviation (TVD)

Voltage fluctuations at the busbars are reduced by improving the voltage profile for consumers whose equipment is voltage-sensitive. The objective function ($objective_F$) for total voltage deviation is expressed as follows [23,24].

$$TVD = \sum_{i=1}^{m_{bus}} (V_{ref} - V_i) \quad (10)$$

where the reference voltage (V_{ref}) is typically taken as 1.00 p.u. Henceforth, the second objective function ($objective_{F2}$) is defined as

$$objective_{F2} = \min(TVD) \quad (11)$$

3.2.3. Maximization of VSI

The voltage stability index is an important parameter to consider alongside voltage deviation and power loss in distribution networks. The VSI is commonly used to assess voltage instability. For stable operation, the VSI must remain within acceptable limits across all network buses. The VSI for a distribution network is formulated as follows [25]

$$VSI_i = |v_j|^4 - 4(P_i x_{ij} - Q_i r_{ij})^2 - 4|v_j|^2 (P_i r_{ij} - Q_i x_{ij}) \quad (12)$$

where r_{ij} and x_{ij} represent the resistance and inductive reactance of the line, respectively. This equation serves as a criterion for evaluating voltage stability in LCNs; provided that the VSI_i is greater than zero, the network operation remains stable. If the voltage at a bus drops below a critical threshold, the system may experience instability [26]. To enhance voltage stability, the VSI_i should be maximized. The third $objective_{F3}$ is therefore defined as

$$objective_{F3} = \max(\min(VSI_i)) \quad (13)$$

3.2.4. Annual Cost of Power Loss (A_{CPL})

The annual cost of power loss reflects the economic efficiency of the proposed approach. The objective is to minimize the yearly cost associated with energy losses [16].

$$objective_{F4} = \min(A_{CPL}) \quad (14)$$

The annual cost of power loss is calculated using Equation (15):

$$A_{CPL} = Power_{Loss} \times \mu_{ER} \times t \quad (15)$$

where $Power_{Loss}$ is the real power loss, μ_{ER} is the energy rate (taken as 0.06 PKR/kWh), and t is the time in hours per year (taken as 8760 h).

3.3. Multi-Objective Functions

Each individual objective possesses its unique functional form and characteristics. In the unified measured expression of all individual objectives, an individually single $objective_F$ is fractioned through its base value then summed altogether with its weights. The multi-objective function $objective_F$ combines three key metrics—voltage deviation, active power loss, and the voltage stability index—into a single weighted sum. The weighted-sum approach provides a straightforward and practical formulation [27]. Using weighting coefficients, the three individual objective functions are transformed into a single cumulative objective function as follows:

$$objective_F = minimize(w_1 \times \frac{Power_{Loss}}{Power_{Loss (Base)}} + w_2 \times \frac{TVD}{TVD_{(Base)}} + w_3 \times \frac{VSI_{(Base)}}{VSI}) \quad (16)$$

Subject to:

$$w_1 + w_2 + w_3 = 1$$

In this study, equal weights are assigned to each objective, i.e., 1/3 (0.3334) to maintain neutrality and avoid subjective bias in the multi-objective optimization problem (MOOP).

3.4. Problem Constraints

In the LCN, several constraints are imposed to address the DG allocation problem. These constraints are formulated as follows.

3.4.1. Equality Constraints

Equality constraints maintain a steady equilibrium between power generation, demand, and losses. This equilibrium helps avoid reverse power flow and potential system damage. These constraints are formulated as

$$\sum_{j=1}^{M_{DG}} P_{Gen} = P_{demand} + Power_{Loss}; j = 1, \dots, No_DG \quad (17)$$

$$\sum_{j=1}^{M_{DG}} Q_{Gen} = Q_{demand} + QPower_{Loss}; j = 1, \dots, No_DG \quad (18)$$

Here, No DG represents the number of distributed generators that have been integrated, P_{Gen} signifies the generation power, which is supplied via the installed DG, and P_{demand} indicates the power required by the loads.

3.4.2. Inequality Constraints

To ensure efficient system operation, two sets of inequality constraints must be satisfied. The first set pertains to voltage limits, while the second encompasses technical constraints related to DG size limits and the power factor. These constraints are essential for the integration of DGs while maintaining system stability.

- Voltage Limits

The voltage magnitude at each bus must remain within the permissible range specified below [28,29]:

$$0.95 \text{ p.u.} \leq V_j \leq 1.05 \text{ p.u.} \quad (19)$$

- Thermal Limits

The current flowing through each branch must not exceed its maximum rated capacity [28,29]:

$$I_{j,i} \leq I_{j,i}^{max} \quad (20)$$

where, $I_{j,i}^{max}$ is the maximum current allowable between the j th and i th bus.

- **DG Size Limits**

The output power of each DG unit is constrained within the following ranges [28,30]:

$$\text{Real power Range : } P_{Gen}^{min} \leq P_{Gen} \leq P_{Gen}^{max} \quad (21)$$

$$\text{Reactive Power Range : } Q_{Gen}^{min} \leq Q_{Gen} \leq Q_{Gen}^{max} \quad (22)$$

- **DG Power Factor Limits**

The power factor of each DG unit must operate within the following range:

$$p.f_{DG,j}^{min} \leq p.f_{DG,j} \leq p.f_{DG,j}^{max} = 1, M_{DG} \quad (23)$$

For effective utilization of electrical energy, the power factor of distributed generators must remain within the permissible limits of [0.7, 1] [31–33]. The power factor is calculated as

$$p.f_{DG,j} = P_{DG,j}^2 / \sqrt{P_{DG,j}^2 + Q_{DG,j}^2} \quad (24)$$

4. Uncertainty Problem

This study investigates four key uncertainty parameters: PV power, wind power, EV demand, and general load demand. The model captures the stochastic nature of the yearly dataset by dividing it into four seasons and analyzing it using a 24 h timeframe. This approach generated four distinct probability distribution functions (PDFs), one for each season, resulting in a total of 96 time intervals (24 h $\times$ 4 seasons). The methodology for developing the probabilistic framework for these parameters is discussed in the following sections.

4.1. Solar Modeling

The output power of the solar PV system, P_{output} (in kW), for a given time interval is given by Equation (25) [34].

$$P_{Output} = \begin{cases} p_r \left(\frac{G_s^2}{G_{stand} \times X_c} \right) & \text{for } 0 < G_s \leq X_c \\ p_r \left(\frac{G_s}{G_{stand}} \right) & \text{for } X_c < G_s \leq G_{stand} \\ p_r & G_{stand} \leq G_s \end{cases} \quad (25)$$

In the preceding equation, X_c denotes the reference irradiance value, G_s represents the solar irradiance in W/m^2 , and G_{std} refers to the standard solar irradiance, which is fixed at $1000 W/m^2$.

Solar Irradiance Modeling

To build a Beta PDF for a given hour based on available data [1], solar irradiance is modeled using the following equation.

$$f_b(pd_s) = \begin{cases} \frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha) \Gamma(\beta)} pd_s^{\alpha-1} (1 - pd_s)^{\beta-1}, & 0 < pd_s \leq 1; \alpha, \beta \geq 0 \\ 0, & \text{otherwise} \end{cases} \quad (26)$$

Here, $f_b(pds)$ represents the Beta PDF of the normalized solar irradiance. The shape parameters α and β are determined using Equations (27) and (28) [35].

$$\alpha = \frac{\mu \times \beta}{1 - \mu} \quad (27)$$

$$\beta = (1 - \mu) \times \left(\frac{\mu \times (1 + \mu)}{\sigma^2} - 1 \right) \quad (28)$$

Representative seasonal mean values μ are adopted for the four periods. These values reflect typical normalized solar irradiance statistics commonly used in stochastic distribution system planning studies [34]. For each period, the standard deviation of solar irradiance is taken as $\sigma = 0.2$.

4.2. Wind Modeling

To address the uncertainty of wind energy, the wind speed is modeled using the Weibull PDF [36], which is widely recognized for its excellent fit to wind speed data due to its flexibility in representing skewed distributions with varying shapes:

$$PDF(v) = \frac{\beta}{\alpha} \left(\frac{v}{\alpha} \right)^{\beta-1} \exp\left(-\left(\frac{v}{\alpha}\right)^\beta\right) \quad 0 \leq v \leq \infty \quad (29)$$

Here, α represents the scale parameter, while β denotes the shape parameter. These parameters are estimated for each of the four representative periods based on typical seasonal wind resource characteristics. The power output from the wind turbine, expressed as $\rho_\omega(v)$, was established as a function of the prevailing wind speed.

$$\rho_\omega(v) = \begin{cases} 0 & \text{if } V \leq V_{cut-in} \text{ or } V > V_{cut-out} \\ \partial + \sigma V & \text{if } V_{cut-in} \leq V \leq V_{normal} \\ \rho_{\omega\epsilon} & \text{if } V_{normal} \leq V \leq V_{cut-out} \end{cases} \quad (30)$$

In this equation, $\rho_\omega(v)$ is equal to the injected power, while V represents the actual wind speed. $\rho_{\omega\epsilon}$ is identified as the wind turbine's maximum output power, and $\partial + \sigma$ are the linear parameters. The parameters V_{cut-in} , $V_{cut-out}$, and V_{normal} are defined as the cut-in wind speed, cut-out wind speed, and rated wind speed, respectively.

These seasonal wind speed profiles and Weibull parameters are derived from typical wind resource data to reflect realistic seasonal variations, which is a common practice in stochastic planning of wind-integrated distribution networks with EV charging stations [21,37].

4.3. EV Modeling

Electric vehicles are modeled as grid-to-vehicle (G2V) loads in the distribution system [38]. The EV charging demand is treated as an additional stochastic load, with uncertainty incorporated through time-varying probabilistic profiles across the 96 seasonal time blocks.

Two representative EV models are considered: the Nissan Leaf 2018 (40 kWh battery, 220 km range) and the MG ZS EV (44.5 kWh battery, 220 km range). The charging infrastructure consists of Level-2 (19.2 kW) and Level-3 (50 kW) chargers. Five EV charging stations (EVCSs) were optimally placed to serve a total of 100 EVs. The detailed charger specifications and EV allocation are presented in Table 2.

Table 2. Electric vehicle model with charger types and specifications.

EV Model	EV Provisions	Charging Port _{Level 2}		Charging Port _{Level 3}	
		(19.2 kW)		(50 kW)	
		Charging _{Time}	EVs No.	Charging _{Time}	EVs No.
MGZSEV	44.5 kWh, 220 km	2 h 19 m	18	53 m	32
Nissan Leaf 2018	40 kWh, 220 km	2 h 5 m	16	48 m	34
Total No. of EVs			34	66	

EVCS Characteristics

Five EVCSs were added at optimal locations in the system by tapping into the existing distribution network to serve 100 EVs. Two EVCSs were equipped with Level-2 chargers and three EVCSs with Level-3 chargers, each with different numbers of charging points (CP), as shown in Table 3 [1].

Table 3. Charging port ratings and EV charging stations [1].

Charger	No. CP Per EVCS	Rating of CP (kW)	Rating of EVCS (kW)	No. of EVCS	Total Rating (kW)
Level 3	10	50	500	3	1500
Level 2	15	19.2	288	2	576
Total:				5	2076

4.4. Load Modeling

A load with fluctuating characteristics is one that experiences varying power requirements each hour. To model this uncertainty, the load demand for each bus is estimated using a normal (Gaussian) PDF. The probability density function of the uncertain load demand is given by Equation (31) [34]:

$$fn(l) = \frac{1}{\sigma\sqrt{2\pi}} \times \exp\left[-\left(\frac{1-ul}{2\sigma^2_i}\right)\right] \quad (31)$$

where $fn(l)$ is the probability density of load demand, l is the load value, ul is the mean load and σ is the standard deviation of the load demand over each time interval. This normal distribution is applied independently to each of the 96 time blocks to capture realistic hourly and seasonal fluctuations around the base demand profile. The Gaussian model is chosen because it effectively represents aggregated load uncertainty arising from a large number of independent consumers.

The load characteristics and power demand associated with the IEEE 33-bus test network [39] is tabulated in Table 4.

Table 4. Institutional load and power demand of the IEEE 33-bus system.

P_{Demand}	P_{Active} (kW)	$P_{Reactive}$ (kVAR)	$P_{Apparent}$ (kVA)
Institutional Load (EV)	2289.56	3231.19	3960.13
IEEE 33-bus Test System	2300	3715	4369.35

5. Proposed Optimization Algorithms

In this research, two metaheuristic optimization methods are used to generate the results: the Improved Grey Wolf Optimizer (IGWO) and the Metaheuristic COOT-Based Optimization (MCBO). The details are as follows.

5.1. Improved Grey Wolf Optimizer Technique (IGWO)

The Grey Wolf Optimizer (GWO), developed by Mirjalili et al. (2014) [40], is a population-based optimization technique. In this method, the top three solutions, called α , β , and δ , act as leaders that guide the rest of the group in searching for the optimal solution [41].

5.1.1. Encircling

The encircling behavior during hunting [42] can be modeled by Equations (32) and (33):

$$d(t) = \left| \partial \times X_{prey}(t) - X_{wolf}(t) \right| \quad (32)$$

$$X_{wolf}(t+1) = X_{prey}(t) - \omega \times d(t) \quad (33)$$

In the above equations, X_{prey} is the position vector of the prey, X_{wolf} represents the position vector of a grey wolf, and t represents the present iteration. As described in [40], the coefficient vectors ∂ and ω are computed using Equations (34) and (35), respectively:

$$\omega = 2 \times \omega \times r_1 - \vartheta(t) \quad (34)$$

$$\partial = 2 \times rand_2 \quad (35)$$

Throughout the iterative process, the vector ϑ is linearly reduced from 2 to 0, with r_1 and r_2 representing random vectors in the range of [0, 1]. This is shown in Equation (36):

$$\vartheta(t) = 2(1 - t/iter_{max}) \quad (36)$$

5.1.2. Hunting

Hunting is described here as a mathematical analysis following the hunting attitude of wolves. It is assumed as α , β , and δ , and these can find the prey from its position. Hence, these parameters will give the top best locations, which will be followed by other wolves. The hunting skills of these wolves are mentioned in Equations (37)–(39).

$$\begin{aligned} d_\alpha &= \left| \partial_1 \times X_\alpha - X_{wolf}(t) \right| \\ d_\beta &= \left| \partial_2 \times X_\beta - X_{wolf}(t) \right| \\ d_\delta &= \left| \partial_3 \times X_\delta - X_{wolf}(t) \right| \end{aligned} \quad (37)$$

where ∂_1 , ∂_2 , and ∂_3 , are found by Equations (34) and (35).

$$\begin{aligned} X_{j1}(t) &= X_\alpha(t) - \omega_{j1}(t)d_\alpha(t) \\ X_{j2}(t) &= X_\beta(t) - \omega_{j2}(t)d_\beta(t) \\ X_{j3}(t) &= X_\delta(t) - \omega_{j3}(t)d_\delta(t) \end{aligned} \quad (38)$$

$$X_{wolf}(t+1) = (X_{j1}(t) + X_{j2}(t) + X_{j3}(t))/3 \quad (39)$$

5.1.3. Attacking

The attack phase begins when the prey stops moving. This is mathematically modeled by decreasing the value of ϑ in Equation (36), which in turn decreases the fluctuation range of a within the interval (2, 0) as shown in Equation (36).

IGWO improves the exploration–exploitation balance through three major stages.

5.1.4. Initializing Phase

In this phase, N number wolves are randomly positioned within the quantified search range $[l_j, u_i]$ using Equation (40):

$$V_{ji} = l_j + r_{\text{andi}}[0, 1] \times (u_i - l_i), j \in [1, \tau], i \in [1, d] \quad (40)$$

The location of the j -th wolf in the t -th iteration is a real-valued vector $X_j(t) = \{X_{j1}, X_{j2}, \dots, X_{jd}\}$, where d is the dimension of the problem. A matrix comprises τ rows and d columns, representing the population of wolves. The fitness function ($\text{fit}(X_j(t))$) defines the optimal value of $X_j(t)$.

5.1.5. Movement Phase

IGWO incorporates a dimension-learning-based hunting (DLH) method. Based on Equation (44) discussed later in this section, the new positions of each dimensional X_j wolf will result from the DLH probing procedure. Based on equations discussed later, a new candidate position for the j -th wolf $X_{j_DLH}(t+1)$ is produced alongside the candidate from the original GWO, $X_{j_GWO}(t+1)$.

To generate the new position $X_j(t)$, a radius $R_j(t)$ is calculated as the Euclidean distance between the candidate position $X_{j_GWO}(t+1)$ and the current position $X_j(t)$, as in Equation (41). This radius defines the neighborhood:

$$R_j(t) = \|X_j(t) - X_{j_GWO}(t+1)\| \quad (41)$$

The neighbors of $X_j(t)$, denoted by $N_j(t)$, are determined in Equation (42) based on the radius $R_j(t)$, with d_j representing the Euclidean distance between $X_j(t)$ and $X_i(t)$.

$$N_j(t) = \{ (X_i(t) | d_j(X_j(t), X_i(t)) \leq R_j(t), X_i(t) \in \text{Population} \} \quad (42)$$

After establishing the neighborhood of $X_j(t)$'s, the position is updated during the multi-neighbor learning phase according to Equation (43).

$$X_{j_DLH,m}(t+1) = X_{j,m}(t) + r_{\text{and}} \times (X_{n,m}(t) - X_{r,m}(t)) \quad (43)$$

a. Selecting And Updating Phase

This phase comprises three steps. To begin, the fitness values of the two candidate solutions, $X_{j_GWO}(t+1)$ and $X_{j_DLH}(t+1)$, are compared to identify the superior one, as described in Equation (44).

$$X_j(t+1) = \begin{cases} X_{j_GWO}(t+1), & \text{if } f(X_{j_GWO}) < f(X_{j_DLH}) \\ X_{j_DLH}(t+1), & \text{otherwise} \end{cases} \quad (44)$$

The second step is to update the position of the wolf to $X_j(t+1)$ if its fitness is better than that of $X_j(t)$. This cycle is repeated iteratively until the maximum iteration count is met. Algorithm 1 represents the pseudocode for the IGWO algorithm.

The dimension-learning-based hunting (DLH) strategy integrated in IGWO strengthens local exploitation by allowing wolves to learn from feasible neighboring solutions. This helps achieve faster and more stable convergence in network reconfiguration and DG allocation problems, which involve highly constrained and nonlinear search spaces. Furthermore, the modified position update mechanism in IGWO enhances population diversification, enabling the algorithm to effectively escape local optima in loss minimization tasks characterized by high penetration of PV, WTG, and EVCS units.

Algorithm 1: Pseudocode for IGWO.

Input: Search Agent (SA), Dimension, Max_{iter} , α , β , and δ Pos.

Output: Global Optima

```

1: Start
2: Initialize(In each space to find  $r_{and}$  [0,1]
    distributed  $N$  wolves and their fitness)
3: For iteration = 2 to  $iter_{max}$ 
4:   Determine  $X_\alpha$ ,  $X_\beta$ , and  $X_\delta$ 
5:   For  $j = 1$  to  $N$ 
6:     Calculating objective fitness function for
        each Search Agent
7:     Evaluating  $x_{j1}$ ,  $x_{j2}$ , and  $x_{j3}$  by using Eq. (38)
8:     Evaluating  $X_{j\_GWO}(t + 1)$  by using Eq. (39)
9:     Determining  $R_j(t)$  by Eq. (41)
10:    Determining Neighborhood  $N_j(t)$  using Eq. (42)
11:      For  $m = 1$  to  $d$ 
12:         $X_{j\_DLH,m}(t + 1) = X_{j,m}(t) + r_{and}(0,1) \times$ 
         $(X_{n,m}(t) - X_{r,m}(t))$ 
13:      End
14:      Choosing Superior ( $X_{j\_GWO}(t + 1)$ ,
         $X_{j\_DLH}(t + 1)$ )
15:      Upgrading Pop.
16:    End
17:  End
18:  Return to Global optima
19: End

```

5.2. Procedure of MCBO Algorithm

Coots exhibit movement in both two and three dimensions, linked to two main types of behavior. As seen in Figure 3a, they start in a disordered state with low density and random directions. They then move into a coordinated state, as shown in Figure 3b, where their direction, density, and speed become stable. They can also move long distances in three dimensions [43], as seen in Figure 3c.

Coots display a variety of collective actions, which form the basis of the MCBO algorithm—a combination of orderly patterns and random movements on the water's surface. Coots located at either end of the group act as guides (leaders) to encourage the others toward the goal (food).

The transition between these states happens through two main strategies. The first increases the speed of certain followers to catch up with nearby coots and updates the leaders' positions. The second allows high-performing followers to become leaders, either replacing underperforming leaders or reinforcing the best followers.



Figure 3. Stages and behavior of coot birds [44].

Leaders constitute a proportion of the entire coot population, N_{pop} , while the rest are followers. Both leaders ($\mathcal{G}_{Leader}$) and followers ($\mathcal{G}_{COOT}$) are assigned random starting positions within specific limits, as in Equations (45) and (46):

$$\mathcal{G}_{Leader} = Lower_b + random_{Leader} \cdot (Upper_b - Lower_b) \quad (45)$$

$$\mathcal{G}_{Coots} = Lower_b + random_{Coot} \cdot (Upper_b - Lower_b) \quad (46)$$

where $Upper_b$ and $Lower_b$ denote the upper and lower boundaries of the search space, respectively. A follower's performance, fit_{Coot} , is evaluated using the objective function,

as in Equation (47). The best overall performance ($\delta\beta est_{score}$) and its position ($\delta\beta est_{\rho}$) are tracked throughout the process using Equation (48):

$$fit_{Coot}(1, j) = OF_{obj}(g_{Coot}(j)), \quad j = 1 \text{ to } N_{Coot} \quad (47)$$

$$\begin{cases} \text{if } \delta\beta est_{score} > fit_{Coot}(1, j) \\ \delta\beta est_{score} = fit_{Coot}(1, j) \\ g_{Coot}(j) = \delta\beta est_{\rho} \end{cases} \quad (48)$$

Similarly, leaders are assigned a fitness value by Equation (49). The $\delta\beta est_{score}$ and its $\delta\beta est_{\rho}$ are updated as in (50):

$$fit_{Leader}(1, j) = OF_{obj}(g_{Leader}(j)), \quad j = 1 \in N_{Leader} \quad (49)$$

$$\begin{cases} \text{if } \delta\beta est_{score} > fit_{Leader}(1, j) \\ \delta\beta est_{score} = fit_{Leader}(1, j) \\ g_{Leader}(j) = \delta\beta est_{\rho} \end{cases} \quad (50)$$

In flocking behavior, the leaders are a few birds at the front, and the rest adjust their positions relative to them. Using the average position of the leaders can lead to premature convergence, so a different method is used to select leaders, as in Equation (51).

$$iN = 1 + \text{Mod}(j, N_{Leader}) \quad (51)$$

Here, j represents the index of the current coot, N_{Leader} denotes the total number of leaders, and iN corresponds to the index of the chosen leader. This process is illustrated in Figure 4.

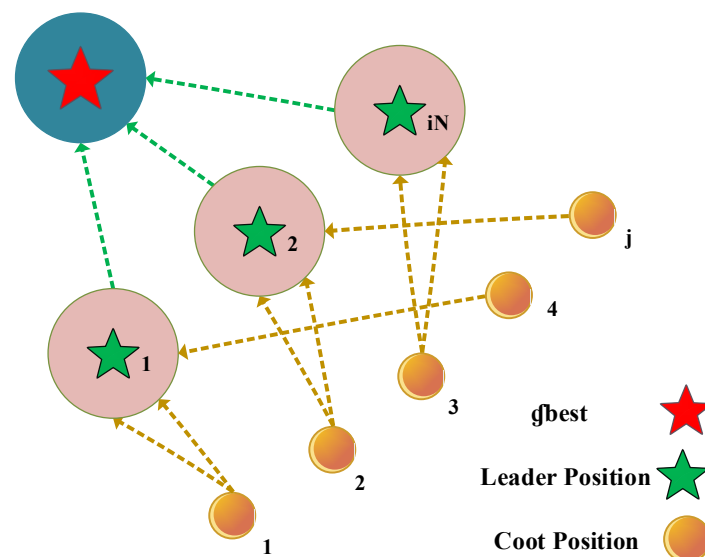


Figure 4. Coot's mechanism for selecting a leader.

According to the leader's index iN , the position of coot (j) is updated using Equation (52). The updated positions are then verified to stay within the limits defined in Equation (53):

$$g_{Coot}(j) = g_{Leader}(iN) + 2 \cdot rand1 \cdot \cos(2 \cdot \pi \cdot R) \cdot [g_{Leader}(iN) - g_{Coot}(j)] \quad (52)$$

$$\begin{cases} \text{if } g_{Coot}(j) > Upper_b, & \text{then, } g_{Coot}(j) = Upper_b \\ \text{if } g_{Coot}(j) < Lower_b, & \text{then, } g_{Coot}(j) = Lower_b \end{cases} \quad (53)$$

Here, $g_{Coot}(j)$ represents current position of the coot, $g_{Leader}(iN)$ indicates the position of the selected leader, $rand1$ is a randomly generated number within the range $[0, 1]$, and R is a random number between -1 and 1 .

If a follower performs better than a leader, the follower takes over the leader's role, and the previous leader becomes a follower, as in Equation (54).

$$\begin{cases} \text{if } fit_{Coot}(1, j) < fit_{Leader}(1, iN), \text{ then} \\ fit_{Leader}(1, iN) = fit_{Coot}(1, j) \text{ and} \\ g_{Leader}(iN) = g_{Coot}(j) \end{cases} \quad (54)$$

The leaders always progress toward the area with the best overall solution (global optima). Equation (55) shows how a leader updates its position within the search space. Once the maximum number of iterations is complete, the best-known solution is identified:

$$g_{Leader} = \delta\beta\epsilon\tau_{\rho} + A \cdot rand2 \cdot \cos(2 \cdot \pi \cdot R) \cdot [\delta\beta\epsilon\tau_{\rho} - g_{Leader}(j)] \quad (55)$$

where $\delta\beta\epsilon\tau_{\rho}$ is the best position found so far, $rand2$ is an arbitrary number between 0 and 1 , and A is calculated using Equation (56).

$$A = 2 - \frac{C}{iter_{max}} \quad (56)$$

Equation (57) is used to determine the overall best location and its corresponding value.

$$\begin{cases} \text{if } \delta\beta\epsilon\tau_{score} > fit_{Leader}(1, j) \text{ then} \\ fit_{Leader}(1, iN) = \delta\beta\epsilon\tau_{score} \\ g_{Leader}(j) = \delta\beta\epsilon\tau_{\rho} \end{cases} \quad (57)$$

The term $2 \times rand2$ encourages more random steps to avoid the algorithm getting trapped in local optima. The cosine function $\cos(2 \cdot \pi \cdot R)$ helps leaders explore different areas of the solution space. Figure 5 shows how leaders update their positions based on the best result found so far, and Figure 6 provides a full overview of the MCBO in a flowchart.

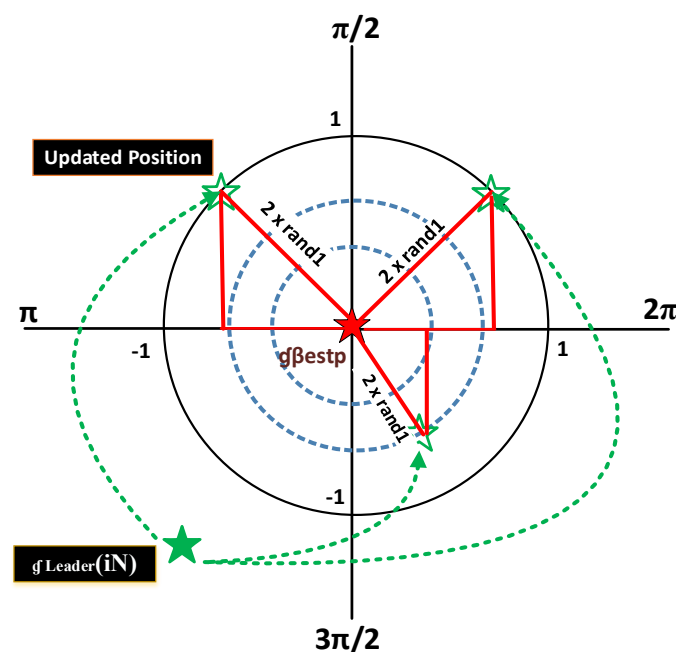


Figure 5. Positioning of leaders in relation to the ideal position.

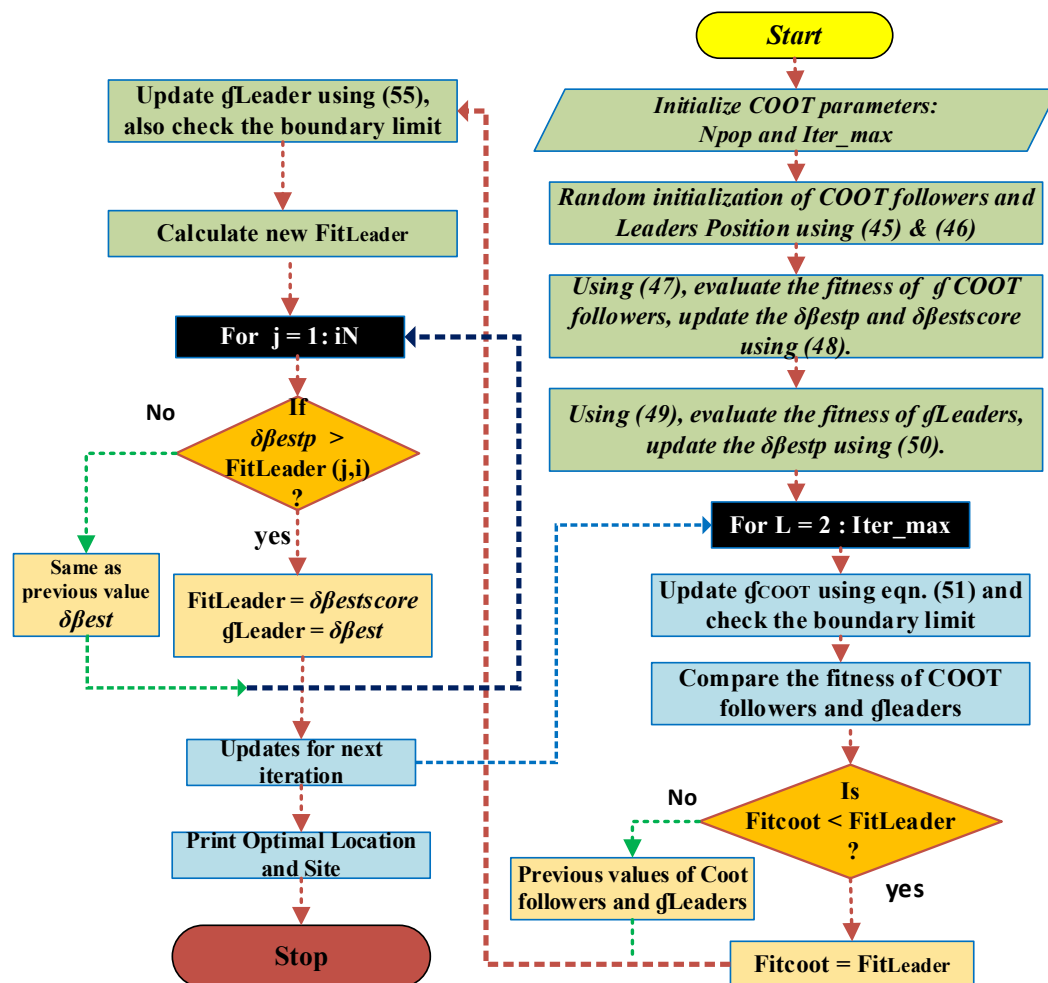


Figure 6. MCBO Flowchart.

The proposed MCBO is well suited to manage the complex and varying nature of the search space in both coordinated and uncoordinated operating conditions. It dynamically tunes its main parameters based on established performance indicators, which supports a smooth shift from exploration to exploitation. As a result, MCBO converges faster and consistently finds better solutions close to the global optimum without getting stuck in local minima. These features make it highly effective for the optimal allocation of EVCS, PV, and WTG units under seasonal load variations.

6. Results and Discussion

In this work, IGWO and MCBO were applied to an IEEE 33-bus system modeled in a looped configuration. The population size was 50 for both IGWO and MCBO. The simulations were terminated upon reaching a maximum of 150 iterations. Table 5 provides the control parameter settings for both methods.

Table 5. Control parameters of proposed optimization techniques.

Algorithms	Parameters
IGWO [P]	Max-iter 150, PF = 0.9, Size of Population = 30, Size of RE (MVA) = 0–2000
MCBO [P]	Max-iter 150, PF = 0.9, Size of Population = 30, Size of RE (MVA) = 0–2000

Single and multiple DG allocation based on RES was carried out to minimize real power loss (P_{Loss}) and total voltage deviation (TVD) while simultaneously maximizing

the voltage stability index (VSI). These goals were incorporated into a multi-objective optimization framework. The effectiveness of the proposed algorithms was benchmarked against other existing methods. All simulations were conducted using MATLAB 2020a (MathWorks) on an HP ProBook 840 G9 laptop equipped with an Intel Core i5 processor and 8 GB of RAM.

In the IEEE 33-bus LCN, PV systems, wind turbine generators (WTGs), and EVCSs were integrated as multiple distributed generators, all operating at a 0.9 lagging power factor.

6.1. IEEE-33 Bus Radial Configured Network

The performance of the optimization techniques examined in this study was assessed using the IEEE 33-bus RDN as the test platform.

EVCS in IEEE 33-Bus Test System

EVCSs are connected to the existing IEEE 33-bus system, drawing power from the grid to charge EVs, thus functioning as loads on the RDN. In this process, the charging stations operate in grid-to-vehicle (G2V) mode. Table 5 shows the optimal locations for EVCSs, with a load power factor of 0.9 lagging. Using IGWO, the optimal locations were buses 2, 23, 4, 10, and 13, while using MCBO, the identified buses were 2, 3, 4, 9, and 13. Figure 7 shows these EVCS locations in the RDN.

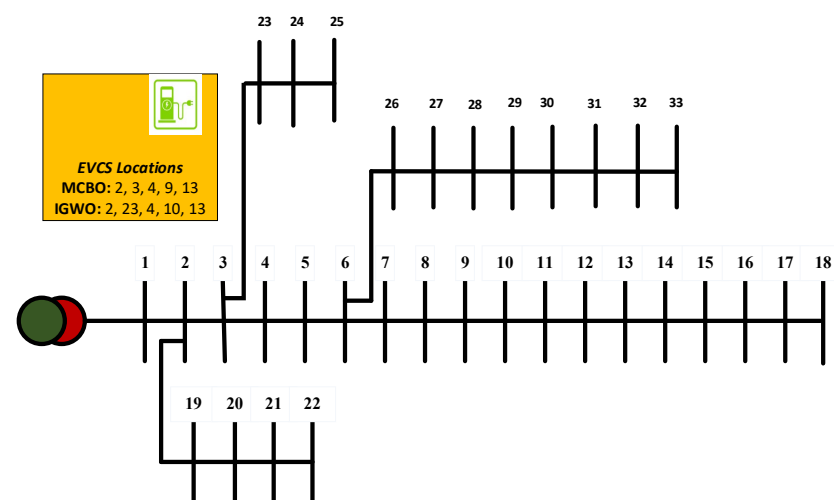


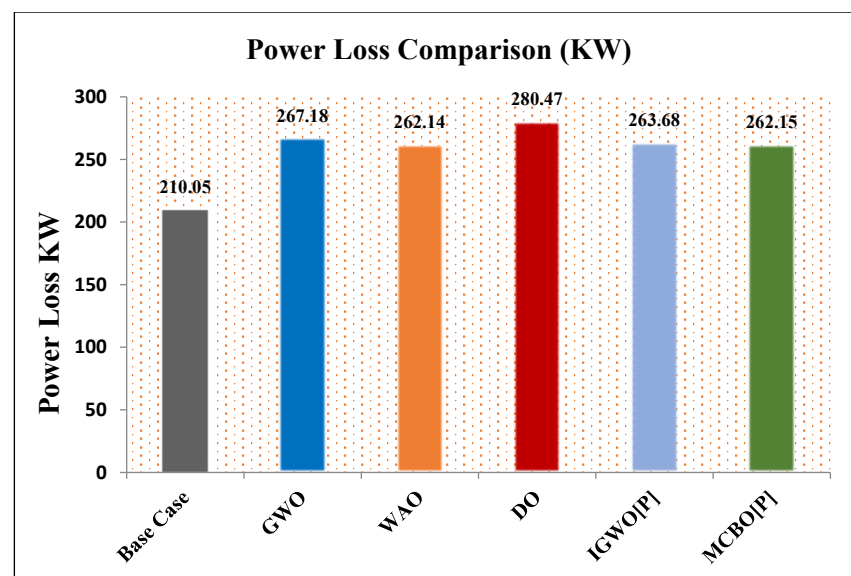
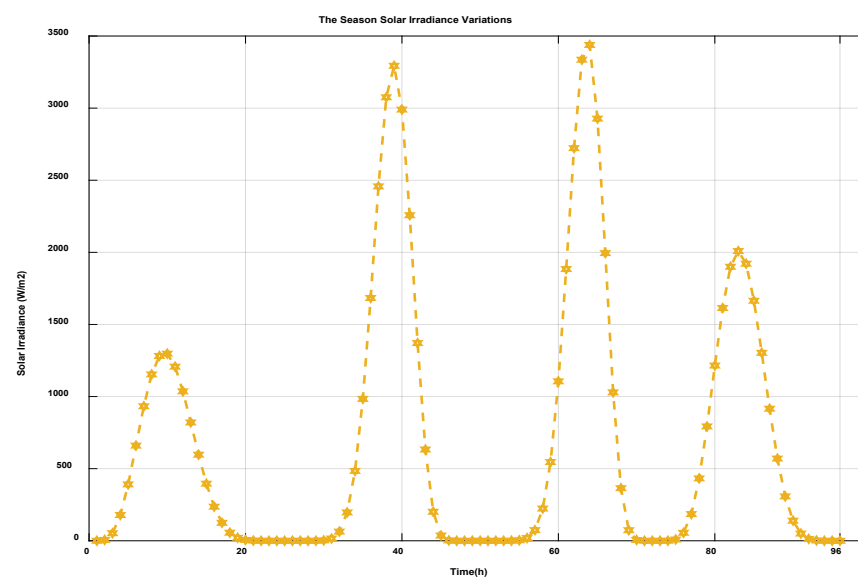
Figure 7. EVCS locations in RDN.

The resulting real power losses were 263.68 kW for IGWO and 262.15 kW for MCBO. Although both optimization techniques for EVCS placement resulted in higher losses compared to the base case (no EVCS integration), the MCBO method drew slightly less real power from the system, indicating a more efficient placement strategy. Further comparisons with other techniques are provided in Table 6. Figure 8 illustrates the increase in active power losses associated with EVCS integration using the IGWO and MCBO algorithms.

As shown in Figures 9–11, solar irradiance, wind speed, and load demand exhibit significant seasonal variation. To model this, average hourly values for each season—spring, summer, autumn, and winter—were calculated to create representative 24 h profiles for the simulation. In the simulation, hours 0–24 correspond to spring, hours 24–48 to summer, hours 48–72 to autumn, and hours 72–96 to winter.

Table 6. Electric vehicle charging station integration in IEEE 33-Bus network results.

Method	Location	P(MW)	Q (MVAR)	Power _{Loss} (KW) (PLR %)	VD (p.u.)	Min. VSI (p.u.)	A_{CPL} 10^3 PKR
Base Case	-	-	-	210.05	0.1328	0.6697	110.402
GWO	4, 12, 13, 22, 25			267.1758 (27.196%)	-	-	140.428
WOA	2, 3, 4, 9, 13			262.1438 (24.80%)	-	-	137.783
DO	6, 12, 17, 22, 25	1.332, 0.546, 1.497, 0.546, 1.299	0.841, 0.345, 0.945, 0.345, 0.82	280.4705 (33.525%)	-	-	147.415
IGWO [P]	2, 23, 4, 10, 13			263.68 (25.53%)	-	-	138.590
MCBO [P]	2, 3, 4, 9, 13			262.15 (24.80%)	-	-	137.786

**Figure 8.** EVCS active power losses in 33-bus network using various techniques.**Figure 9.** Profile of seasonal variation for solar irradiance.

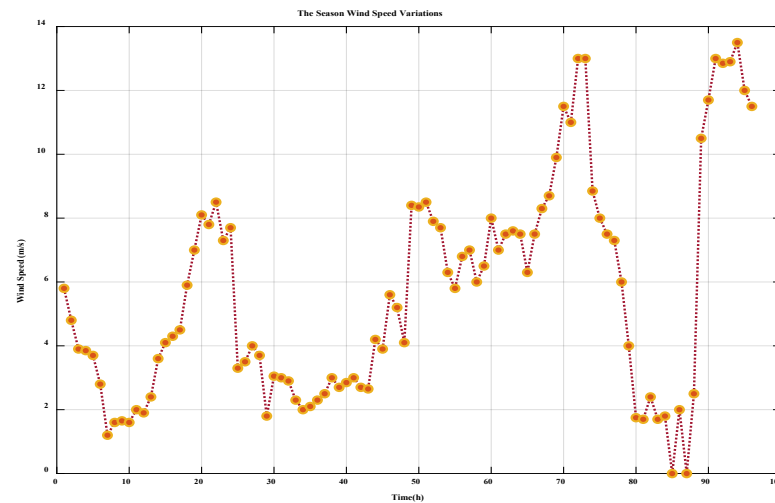


Figure 10. Profile of seasonal variation for wind speed.

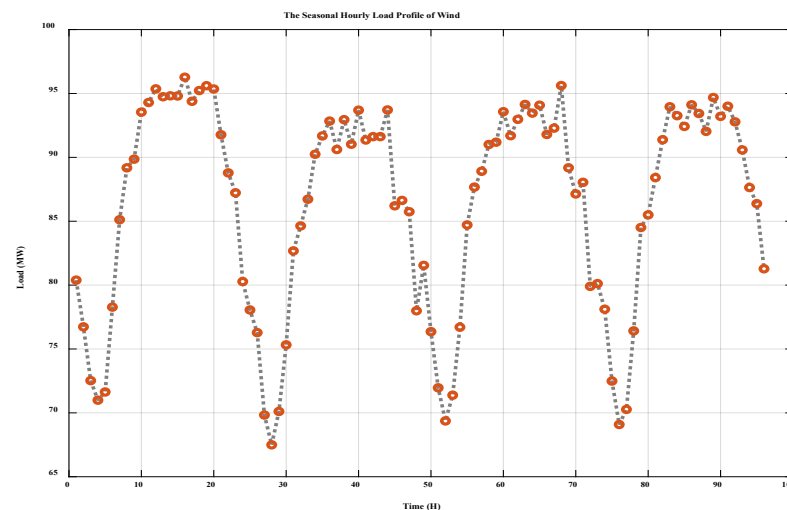


Figure 11. Seasonal load variation profile.

6.2. Multi-Objective Assessment of the 33-Bus Loop-Configured Network

The IEEE 33-bus LCN was subjected to an MOOP to determine the best RE-DG and EVCS placement. The optimal allocation aims to minimize P_{Loss} and TVD while maximizing the VSI. The power flow analysis for the baseline case (without RE-DGs and EVCSs) revealed a P_{Loss} of 210.05 kW, a TVD of 0.1328 p.u., and a minimum VSI of 0.6697 p.u. Figure 12 shows the LCN with optimized EVCS locations using MCBO.

Table 7 presents the various case scenarios considered in this study for evaluating the multi-objective optimization performance of metaheuristic algorithms applied to the optimal placement and sizing of RE-DGs and EVCSs in the IEEE 33-bus LCN.

Table 7. Four cases implemented for analysis.

Cases	EVCS	SPV	WTG
Case 1	x	✓	x
Case 2	x	X	✓
Case 3	✓	✓	x
Case 4	✓	X	✓

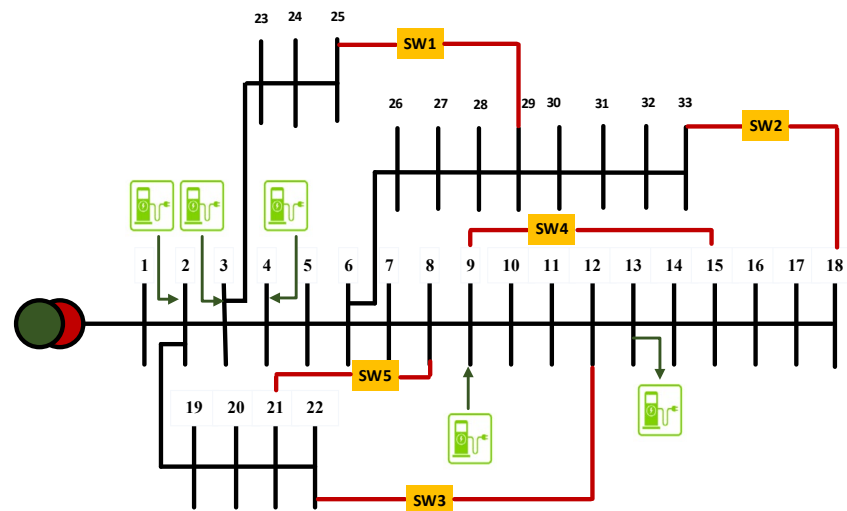


Figure 12. EVCS integration using MCBO in 33-bus LCN.

6.2.1. Case 1: Only SPV

Table 8 illustrates the optimal placement of SPV-based DGs. The IGWO algorithm identified optimal locations at buses 6, 25, and 2, resulting in a power loss of 37.12 kW. The MCBO technique identified optimal locations at buses 27, 31, and 8, achieving a slightly lower power loss of 36.77 kW. MCBO achieved a power loss reduction of 82.49% from the baseline, slightly outperforming IGWO's 82.33% reduction. IGWO yielded a lower voltage deviation (0.0018477 p.u.) compared to MCBO (0.002813 p.u.), while IGWO's minimum VSI (0.92973 p.u.) was higher than MCBO's (0.91127 p.u.).

Table 8. Solar integration without EVCS in IEEE 33-bus network results.

Method	Location	P (MW)	Q (MVAR)	Power _{Loss} (KW) (PLR%)	VD (p.u.)	Min. VSI (p.u.)	A _{CPL} 10 ³ PKR
Radial Configuration							
Base Case (R)	-	-	-	210.0	0.132	0.66	110.4
GWO [1]	14, 25, 32	0.688, 0.793, 1.306	0.246, 0.334, 0.503	65.50 (68.813%)	0.003824	0.92513	34.430
WOA [1]	12, 24, 31	0.81, 0.95, 1.08	0.297, 0.303, 0.398	56.88 (72.913%)	0.002839	0.94655	29.901
DO [1]	14, 24, 30	0.80, 0.83, 1.07	0.213, 0.253, 0.477	61.59 (70.674%)	0.004336	0.92127	32.376
Loop-Configured Network [25-29, 18-33, 12-22, 9-15, 8-21]							
IGWO [P]	6, 25, 2	1.809, 1.014, 0.110	0.592, 0.483, 0.053	37.12 (82.33%)	0.0018477	0.92973	19.510
MCBO [P]	27, 31, 8	1.173, 0.854, 0.855	0.08, 0.280, 0.280	36.77 (82.49%)	0.002813	0.91127	19.326

Active Power Loss Profile

Figure 13 compares the active power loss with other techniques from [1]. It clearly shows that active power loss is significantly reduced in the LCN using IGWO and MCBO with SPV-based DGs.

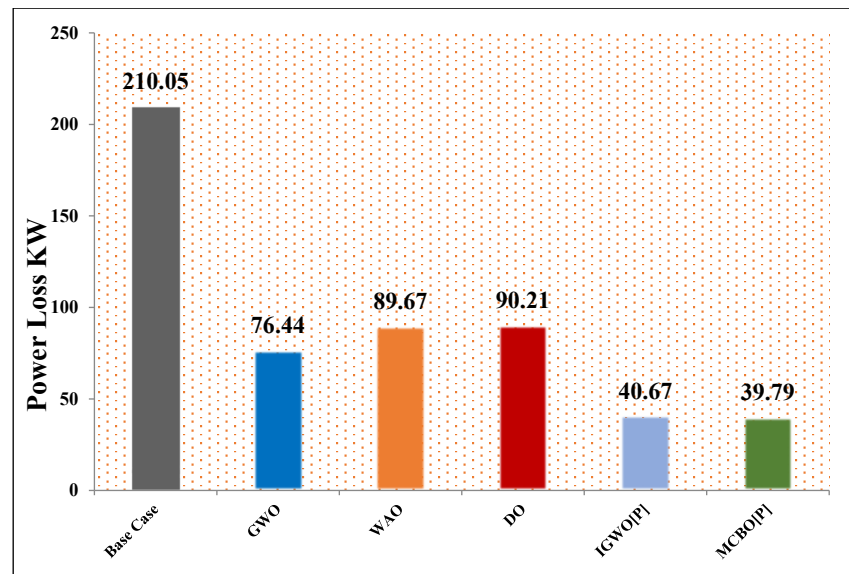


Figure 13. Active power loss profile for SPV.

Voltage Profile of 33-Bus LCN for SPV

By optimizing the location of SPV-based DGs for both TVD and the VSI, the voltage profile of the LCN was enhanced. The voltage profile achieved by the MCBO algorithm for this multi-objective problem is illustrated in Figure 14.

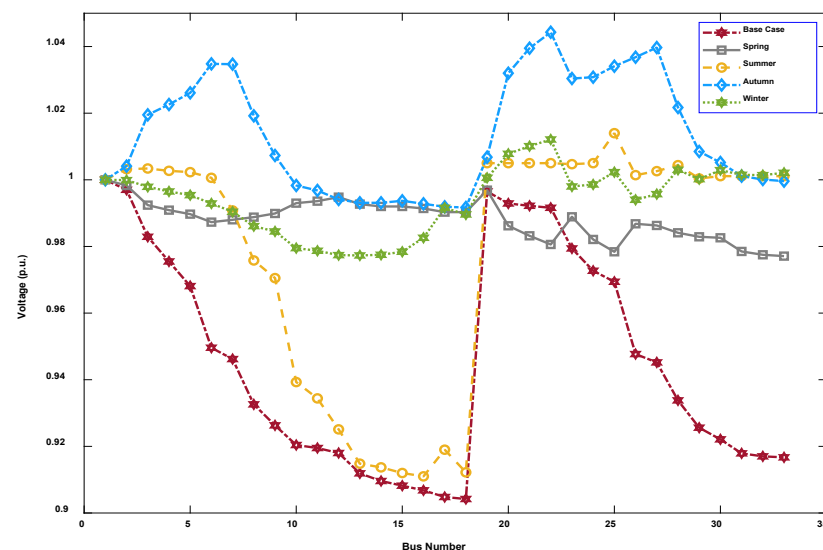


Figure 14. Seasonal voltage profile of the 33-bus LCN with SPV using MCBO.

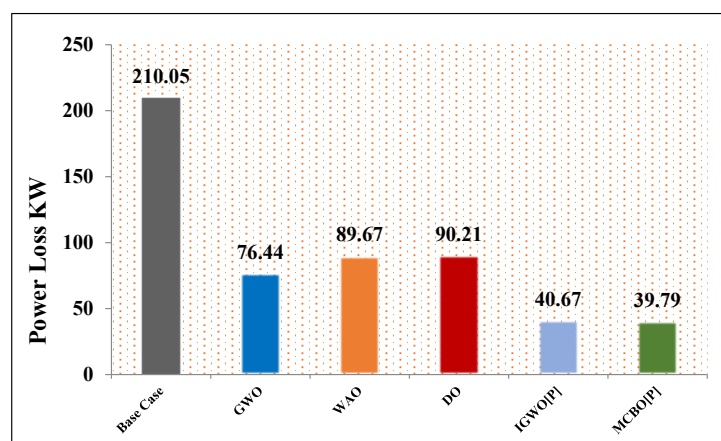
6.2.2. Case 2: Only WTG

Table 9 illustrates the optimal placement of wind-based DGs operating at a 0.9 power factor. IGWO identified optimal locations at buses 25, 10, and 3, resulting in a power loss of 34.516 kW. MCBO identified locations at 25, 10, and 30, achieving a lower power loss of 29.958 kW. MCBO demonstrated superior performance with an 85.74% reduction from the baseline, outperforming IGWO's 83.57% reduction. MCBO also yielded a lower voltage deviation (0.0039444 p.u.) compared to IGWO (0.008398 p.u.) and a higher minimum VSI (0.93084 p.u.) compared to IGWO (0.86835 p.u.). This indicates MCBO's greater effectiveness for wind DG integration.

Table 9. Wind integration without EVCS in IEEE 33-bus network results.

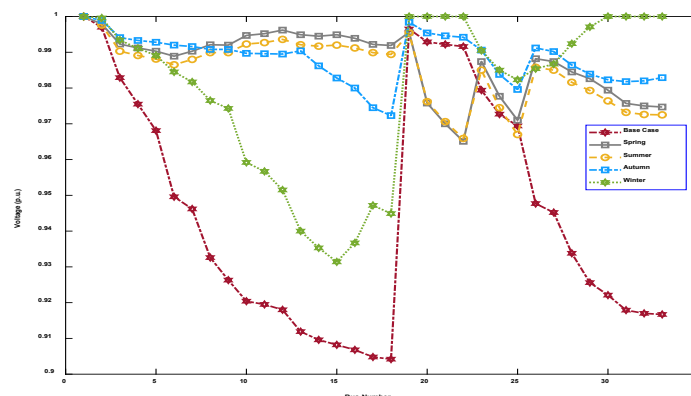
Method	Location	P (MW)	Q (MVAR)	Power _{Loss} (KW) (PLR%)	VD (p.u.)	Min. VSI (p.u.)	A _{CPL} 10 ³ PKR
Radial Configuration							
Base Case (R)	-	-	-	210.05	0.1328	0.6697	110.402
GWO [1]	13, 24, 30	0.772, 0.922, 1.348	0.258, 0.324, 0.584	49.482 (76.44%)	0.004624	0.6697	26.008
WOA [1]	13, 24, 30	0.765, 0.88, 1.452	0.372, 0.381, 0.643	54.04 (74.269%)	0.009322	0.84611	28.408
DO [1]	13, 24, 30	0.853, 1.006, 1.266	0.425, 0.457, 0.510	54.08 (74.148%)	0.005671	0.97896	28.426
Loop-Configured Network [25-29, 18-33, 12-22, 9-15, 8-21]							
IGWO [P]	25, 10, 3	0.614, 1.292, 1.37	0.248, 0.541, 0.561	34.51 (83.57%)	0.008398	0.86835	18.142
MCBO [P]	25, 10, 30	0.474, 1.06, 0.935	0.098, 0.383, 0.171	29.95 (85.74%)	0.0039444	0.93084	15.746

Figure 15 compares the active power loss with other methods from [1]. It shows that losses are significantly reduced in the LCN using IGWO and MCBO with WTG-based DGs.

**Figure 15.** Active power loss profile for WTG.

Voltage Profile of 33-Bus LCN for WTG

Considering both the VSI and TVD objectives has resulted in better location selection for WTG-based DGs, thus improving voltage levels throughout the 33-bus loop, as illustrated in Figure 16.

**Figure 16.** Seasonal voltage profile of 33-bus LCN with WTG using MCBO.

6.2.3. Case 3: SPV with Integration EVCS

Table 10 presents the optimal placements for EVCSs and SPV-based DGs, both at a 0.9 power factor. The optimal SPV locations for IGWO were buses 28, 32, and 3. The resulting P_{Loss} was 47.248 kW for IGWO and 45.927 kW for MCBO. MCBO achieved a power loss reduction of 78.14% from the baseline, outperforming IGWO's 77.51% reduction. IGWO yielded a lower voltage deviation (0.003116 p.u.) compared to MCBO (0.004631 p.u.), while IGWO's minimum VSI (0.9256 p.u.) was higher than MCBO's (0.91724 p.u.). The active power losses for both algorithms are plotted in Figure 17.

Table 10. Solar integration with EVCS in IEEE 33-bus network results.

Method	Location	P (MW)	Q (MVAR)	Power _{Loss} (KW) (PLR%)	VD (p.u.)	Min. VSI (p.u.)	A _{CPL} 10 ³ PKR
Radial Configuration							
Base Case (R)	-	-	-	210.05	0.1328	0.6697	110.402
GWO [1]	9, 23, 29	0.725, 0.939, 1.159	0.281, 0.292, 0.491	79.4624 (62.170%)	0.005726	0.94724	41.765
WOA [1]	8, 22, 29	0.690, 0.973, 1.099	0.231, 0.392, 0.495	54.0478 (74.269%)	0.009322	0.84611	28.408
DO [1]	13, 22, 29	0.768, 0.977, 1.330	0.331, 0.391, 0.571	63.8158 (69.619%)	0.005419	0.94821	33.542
Loop-Configured Network [25-29, 18-33, 12-22, 9-15, 8-21]							
IGWO [P]	28, 32, 3	1.504, 0.658, 0.649	0.674, 0.310, 0.247	47.2482 (77.51%)	0.003116	0.9256	24.834
MCBO [P]	33, 15, 10	1.113, 0.996, 0.620	0.411, 0.369, 0.182	45.9273 (78.14%)	0.0046312	0.91724	24.139

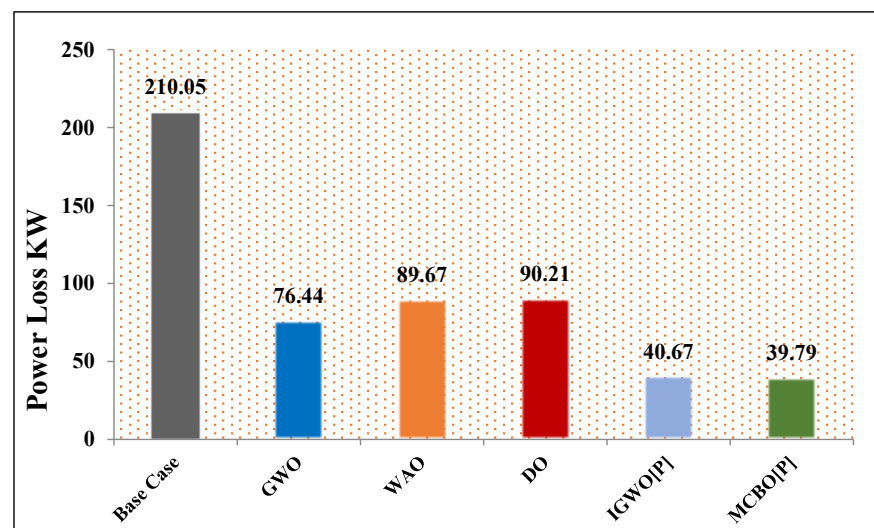


Figure 17. Active power loss profile.

Voltage Profile 33-Bus LCN for SPV with EVCS

The optimal placement of SPV-based DGs, based on TVD and VSI criteria, improved the voltage profile. The performance of this configuration under the MCBO approach is shown in Figure 18. The integration of EVCSs resulted in a slight voltage reduction compared to Case 1.

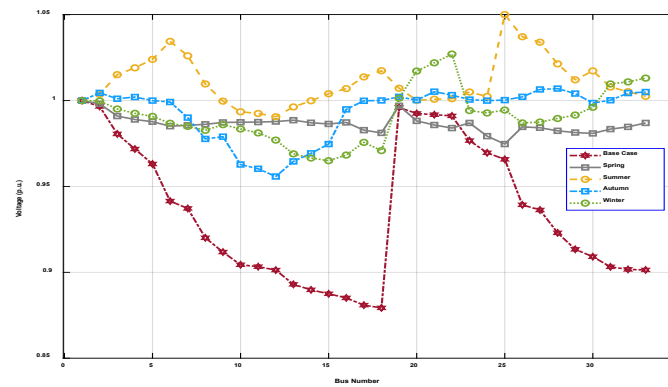


Figure 18. Seasonal voltage profile of the 33-bus LCN with SPV and EVCS using MCBO.

6.2.4. Case 4: WTG with Integration of EVCS

Table 11 presents the optimal placements for wind-based DGs and EVCSs. For IGWO, the optimal WTG locations were buses 10, 32, and 12. For MCBO, the optimal EVCS locations were buses 28, 9, and 20. The total power loss was 40.668 kW for IGWO and 39.790 kW for MCBO. MCBO achieved a power loss reduction of 81.57% from the baseline, outperforming IGWO's 80.64% reduction. MCBO also yielded a slightly lower voltage deviation (0.002144 p.u.) compared to IGWO (0.002187 p.u.). IGWO achieved a slightly higher minimum VSI (0.93056 p.u.) compared to MCBO (0.9175 p.u.). Figure 19 shows the active power loss for both algorithms.

Table 11. Wind integration with EVCS in IEEE 33-bus network results.

Method	Location	P (MW)	Q (MVAR)	Power _{Loss} (KW) (PLR %)	VD (p.u.)	Min. VSI (p.u.)	A _{CPL} 10 ³ PKR
Radial Configuration							
Base Case (R)	-	-	-	210.05	0.1328	0.6697	110.402
GWO [1]	6, 14, 28	0.604, 1.015, 1.324	0.235, 0.344, 0.507	76.440 (63.608%)	0.00982	0.92341	40.177
WOA [1]	11, 18, 29	0.577, 1.167, 1.173	0.166, 0.248, 0.543	89.6694 (57.310%)	0.00551	0.92139	47.130
DO [1]	9, 20, 28	0.746, 0.912, 0.951	0.228, 0.418, 0.426	90.207 (57.055%)	0.02631	0.79254	47.413
Loop-Configured Network [25-29, 18-33, 12-22, 9-15, 8-21]							
IGWO [P]	10, 32, 12	0.324, 1.221, 1.079	0.107, 0.54, 0.443	40.668 (80.64%)	0.00218	0.93056	21.375
MCBO [P]	28, 9, 20	1.339, 1.526, 0.608	0.243, 0.593, 0.240	39.7899 (81.57%)	0.00214	0.9175	20.914

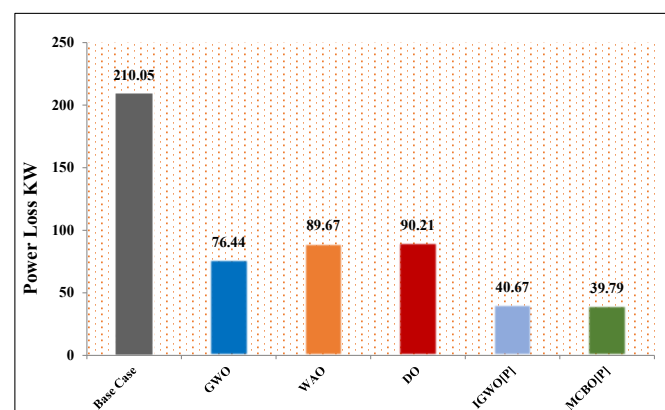


Figure 19. Active power loss.

Voltage Profile 33-Bus LCN for WTG with EVCS

The 33-bus system voltage profile was improved by the optimal placement of WTG-based DGs, with TVD and the VSI as the multi-objective criteria. Figure 20 shows the performance under the MCBO technique. A small voltage drop was observed due to the addition of EVCSs, similar to Case 2.

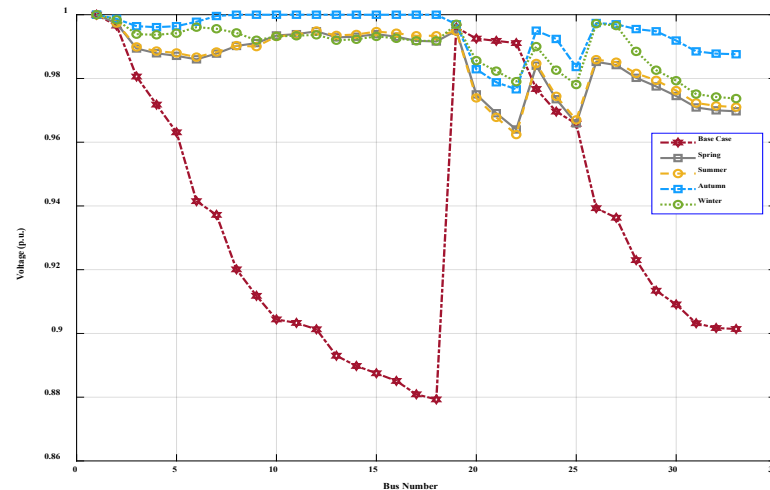


Figure 20. Seasonal voltage profile of the 33-bus LCN with WTG and EVCS using MCBO.

6.3. Statistical Analysis of 33-Bus LCN for IGWO and MCBO Under MOOP

To assess the robustness and consistency of the proposed algorithms, a statistical analysis was conducted over 20 independent runs for IGWO and MCBO. The performance is evaluated in terms of minimum, average, and maximum active power loss (kW) under four different cases. The statistical results are summarized in Table 12.

Table 12. Statistical analysis of active power loss (kW) over 20 independent runs.

Method	Case	Min.	Avg.	Max.
		Power _{Loss}		
IGWO	Only SPV	37.12	48.39541	60.7351
MCBO		36.77	40.8271	56.4678
IGWO	Only WTG	34.5161	47.26686	64.8092
MCBO		29.9583	44.20273	61.1486
IGWO	SPV with integration of EVCS	47.2482	62.21106	76.9828
MCBO		45.9273	60.61745	72.0353
IGWO	WTG with integration of EVCS	40.668	58.11827	75.1459
MCBO		39.7899	56.1748	71.2088

The results indicate that MCBO consistently outperforms IGWO in terms of average power loss while maintaining competitive stability across all cases.

7. Conclusions

This study employed two metaheuristic algorithms, IGWO and the MCBO, to optimally place EVCSs and RE-DGs within DNs. A two-stage methodology was adopted for determining optimal locations. In the first stage, suitable sites for EVCSs were identified in the RDN. The second stage involved reconfiguring the RDN into an LCN to optimally position SPV and WTG systems.

Both single-objective and multi-objective placement strategies were analyzed, focusing on minimizing power loss and voltage deviations, maximizing voltage stability, and reducing the annual cost associated with power losses. For the multi-objective framework, all objectives were given equal importance using the weighted-sum method. Uncertainties and seasonal variations were also taken into account. All simulations were conducted in MATLAB 2020a, and the performance was evaluated across multiple scenarios involving SPV units, WTGs, and EVCS integration.

The results demonstrate significant gains in network performance. For example, with the allocation of SPV alone, MCBO achieved an 82.49% reduction in real power loss, slightly surpassing IGWO's 82.33% reduction and outperforming other benchmark algorithms. In another instance, MCBO proved most effective for wind integration, achieving an 85.74% reduction in real power loss and a low voltage deviation of 0.003944 p.u. Both techniques also resulted in substantial savings in the annual cost of real power losses.

While the integration of EVCSs alone increased network demand and resulted in higher power losses compared to the base case, their integration alongside RE-DGs proved beneficial. For the combined allocation of SPV-DGs and EVCSs, MCBO achieved a 78.14% reduction in real power losses. For WTG-DGs with EVCSs, MCBO achieved an 81.57% reduction. These findings confirm that the proposed algorithms and optimization methods for placing RE-DGs and EVCSs yield beneficial effects in terms of loss reduction, improved voltage profiles, and enhanced network stability.

Future work can extend this research to dynamic charging optimization in real-time configurations, enabling seamless integration with renewable energy sources and grid load balancing. This scalability will enhance the efficiency and sustainability of EV charging infrastructure, supporting widespread adoption and grid resilience.

Author Contributions: Conceptualization, M.C. and M.N.; methodology, M.I.A.; software, M.C.; validation, M.I.A.; formal analysis, M.C.; investigation, M.C.; resources, A.Q.; data curation, M.C.; writing—original draft preparation, M.C. and M.N.; writing—review and editing, M.N. and A.Q.; visualization, M.C.; supervision, M.N.; project administration, A.Q.; funding acquisition, A.Q. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported and funded by the Deanship of Scientific Research at Imam Mohammad Ibn Saud Islamic University (IMSIU) (grant number IMSIU-DDRSP2603).

Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

Acknowledgments: During the preparation of this manuscript, the authors used ChatGPT-4o solely for grammatical correction and improvement of English language in the manuscript. The authors have reviewed and edited the output and take full responsibility for the content of this publication.

Conflicts of Interest: Author Muhammad Imran Akbar was employed by Multan Electric Power Company (MEPCO). Author Affaq Qamar was affiliated with Imam Mohammad Ibn Saud Islamic University at the time of this study. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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