

Article

Enhanced Grey Wolf Optimisation for Sustainable PV-DG Allocation Under Seasonal Uncertainty

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Abstract

Improving energy efficiency and renewable-energy hosting capacity in distribution networks is essential for sustainable power-system development. Conventional networks face power losses, voltage deviations, thermal stress, and limited flexibility to accommodate increasing renewable penetration. Accordingly, optimal placement and sizing of photovoltaic-based distributed generation (PV-DG) has become an effective approach for enhancing network performance. This study applies the Grey Wolf Optimiser (GWO) to PV-DG allocation considering three objectives: minimisation of active power loss and total voltage deviation, and maximisation of the voltage stability index. To mitigate the premature convergence of standard GWO, Opposition-Based Learning (OBL) is integrated to enhance exploration through opposite candidate solutions. The proposed OBL-GWO framework is evaluated on the IEEE 33-bus system under three PV-DG penetration scenarios using five-year irradiance and load data from Riyadh, including seasonal uncertainty and long-term load growth. Compared with standard GWO, it achieves average additional gains of 11.24, 10.0, 6.79, and 2.74 percentage points in power-loss reduction, TVD reduction, VSI improvement, and minimum-bus-voltage improvement, respectively. Sensitivity analysis confirms limited dependence on moderate changes in objective weights. A persistent cloudy-week case demonstrates robust performance against GWO, PSO, and GA under adverse irradiance. Scalability tests on IEEE 69- and 118-bus systems confirm that OBL-GWO retains its solution-quality and convergence advantages on larger networks.

Keywords: sustainable distribution networks; photovoltaic distributed generation; renewable-energy integration; energy efficiency; multi-objective optimisation; seasonal uncertainty; Opposition-Based Learning; Grey Wolf Optimiser



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1. Introduction

Traditional power distribution networks are increasingly challenged by rising power losses, voltage variations, grid strain and limited flexibility in delivering the growing demands and variability of renewable energy generation (REG). Mitigating these demands and alleviating the resulting strain on the grid require an efficient integration of grid-connected renewable energy sources (RESs). However, these sustainable technologies experience challenges arising from weather variability, including voltage instability, grid unreliability and increased energy losses [1]. The pressing need for more efficient and reliable distribution networks (DNs) underscores the importance of strategically allocating RES-based distributed generation (DG) units, as their sizes and locations notably influence

power losses, voltage regulation and system reliability. Effective planning is essential to meet technical targets while maintaining grid compliance and minimising power loss. In this study, five years of hourly solar radiation data were collected for Riyadh [2]; these data were then cleaned, analysed, and modelled to account for both seasonal and inter-annual variability. Recent advances in PV power forecasting have employed deep-learning models to capture complex spatial and temporal dependencies in solar-generation data. A Bayesian-optimised deep-learning model was developed to capture spatial and temporal variations in PV power generation under different weather and seasonal conditions [3]. Such forecasting methods are particularly valuable for short-term system operation, whereas the present study focuses on long-term PV-DG allocation planning through probabilistic seasonal irradiance modelling.

Identifying optimal locations and sizes for DG units constitutes a complex optimisation problem that has been addressed using diverse methodologies in recent studies. In these studies, numerous methods and algorithms have been developed to optimise the placement and sizing of RESs in active DNs, primarily aiming to minimise voltage instability and reduce total system losses. Among the various metaheuristic techniques adopted for this purpose, the Grey Wolf Optimiser (GWO) stands out for its simplicity; minimal control parameters; and capability to navigate complex, multi-objective search spaces. The GWO simulates the leadership hierarchy and hunting strategies of grey wolves [4], effectively balancing the exploration and exploitation phases. Nevertheless, despite these strengths, the conventional GWO is prone to premature convergence, particularly in multi-modal optimisation problems, prompting the introduction of enhancements such as Opposition-Based Learning (OBL) to improve its performance. The following discussion analyses the latest developments in this domain, focusing specifically on metaheuristic algorithms for DG allocation, their associated limitations and potential areas for improvement.

The GWO mimics the leadership hierarchy and cooperative hunting strategies of grey wolves. Its simplicity, adaptability and small number of control parameters make it a powerful metaheuristic optimiser with the most rapidly growing adoption in optimisation contexts.

The competitive performance of GWO was demonstrated in [4], which compared it with well-established heuristics, including particle swarm optimisation (PSO), gravitational search algorithm (GSA), differential evolution (DE), expectation propagation (EP) and envelope strategy (ES), and demonstrated its highly competitive performance. The algorithm also requires fewer parameters than many alternatives, is highly adaptable to both continuous and discrete problems and remains one of the most efficient metaheuristic approaches for navigating complex, multi-objective search spaces. GWO can accommodate optimisation problems with different dimensions; however, the practical scalability of a specific implementation must be established through validation on networks of increasing size and complexity [5]. However, when addressing multi-modal functions, the traditional GWO tends to become trapped in local optima, resulting in a notable reduction in convergence speed during the later stages of evolution. Various enhancements have therefore been introduced to address these limitations: refraction learning for global optimisation [6] and a stochastic walk strategy for further augmenting global search performance [7]. As summarised in Table 1, recent studies have employed various metaheuristic algorithms for DG allocation in DNs; however, they suffer from two critical limitations: premature convergence in complex multi-modal optimisation landscapes and lack of stochastic real-world data modelling of renewable variability resulting in suboptimal placement decisions that fail to maximise grid performance under real-world operating conditions. This study addresses these limitations by integrating OBL with GWO to improve convergence behaviour

and incorporating seasonal probabilistic models of solar irradiance and load variation derived from real-world multi-year data.

Table 1. Comparison of the proposed method with existing metaheuristic approaches for DG allocation.

Ref/Year	Method Used	Objectives	Limitations	Key Features
[8] 2023	Stochastic optimisation using graph-theory search and modular coordination of NR, DR and VVO	Determine optimal siting of solar PV-DG using GIS and electrical analysis to reduce losses and improve voltage profile	High computational complexity in full co-optimisation; problem partitioned into sub-problems; seasonal variation not considered	Applied to IEEE 123-node system; includes uncertainty modelling for PV/EV; captures spatio-temporal variation
[9] 2022	Multi-objective optimisation in GAMS (version not reported) via MINLP	Optimise positioning and sizing of wind/solar DGs, BESS and CBs with DR to minimise losses, maximise voltage stability and increase economic benefit	Lacks GIS spatial feasibility; high BESS cost affects feasibility; no scalability or seasonal variation analysis	Uses Beta and Weibull PDFs for wind/solar; incorporates uncertainty and curtailment; integrates DR; tested on IEEE 33-bus
[10] 2022	Integrated GIS and AHP for site selection	Select solar PV sites and assess DG impact on Algerian grid	Omits uncertainty and seasonal variation; emphasises location over operational and variability analysis	Based on Algerian DN; strong GIS and MCDM-based spatial analysis
[11] 2021	Genetic algorithm	Determine optimal DG siting/sizing to reduce losses and improve voltage profile	Does not model uncertainty; excludes real-world data; assumes static load/generation without seasonal variation	Uses IEEE 33-bus; multi-objective optimisation with PLRI, VDI and MORI indices
[12] 2020	GWO	Optimise DG siting/sizing to reduce power losses and enhance voltage stability	Lacks consideration of seasonal effects and uncertainty; assumes fixed load/generation; no real-world validation	Applied on IEEE systems; fast convergence; outperforms other optimisation methods
[13] 2020	Chaotic sine cosine algorithm	Determine optimal DG allocation to reduce losses, minimise voltage deviations and improve voltage stability	Focused on speed; includes basic PV variability via PDF; does not use real-world data	Uses Beta PDF for solar irradiance; reflects seasonal and diurnal variation; proposes PV-BES coordination

OBL-GWO was selected because PV-DG allocation involves a multidimensional search space containing both discrete bus locations and continuous DG capacities, in which conventional GWO may experience premature convergence. The OBL mechanism increases population diversity by evaluating opposite candidate solutions and therefore improves exploration while retaining the relatively simple structure and limited parameter requirements of GWO. To verify that this improvement is not limited to comparison with conventional GWO alone, the proposed method is also benchmarked against GA and PSO under identical computational conditions.

In previous research, OBL-GWO has been developed and applied to several optimisation problems, including the optimal allocation of wind-based distributed generation.

Therefore, the algorithmic mechanism of OBL-GWO is not claimed as a new contribution of the present study. Instead, this work extends its application through a PV-specific distribution-network planning framework that incorporates the distinct seasonal and diurnal characteristics of solar generation.

Unlike the previous wind-based study in [14], which represented wind uncertainty using a Weibull distribution, the present framework models PV-resource uncertainty using season-specific Beta probability distributions derived from five years of measured solar irradiance data. The PV uncertainty model is integrated with stochastic seasonal demand profiles obtained from five years of measured load data, thereby allowing both generation-side and demand-side variability to be considered within the same planning framework. The study also expands the application scenario by evaluating the optimal siting and sizing of one, two, and three PV-DG units under different penetration levels. In addition to comparing the optimisation results with conventional GWO and methods reported in the literature, the robustness and repeatability of the proposed planning framework are evaluated through 30 independent optimisation runs. However, the contribution of this study is not the introduction of a new OBL-GWO operator, but its integration into a reproducible, seasonal, and data-driven PV-DG planning framework for active distribution networks.

OBL is a search-enhancement strategy derived from opposing relationships between entities. It simultaneously evaluates a candidate solution and its opposite to more effectively identify the optimal result. The OBL approach enhances the convergence behaviour of metaheuristic algorithms by exploring opposite positions for each agent in the population. This mechanism is used not only during the initial population generation but also iteratively throughout the optimisation process. During the iterative optimisation process, opposite solutions are generated probabilistically according to the predefined jumping rate.

At each iteration, when the jumping criterion is satisfied, opposite solutions are generated for the current population and combined with the existing candidates and the best solution subset is retained. So far, OBL has been employed to enhance various metaheuristic optimisation algorithms, including genetic algorithms, ant colony system [15] and simulated annealing (SA) [16]. Given its capacity to improve the GWO search mechanism, it has also been integrated into advanced variants such as opposition-based GWO [17], which combines OBL with a jumping rate to help the algorithm avoid local optima without incurring additional computational complexity. Additionally, a nonlinear function automatically adjusts the parameter $\vec{a}$, which originally decreases linearly from 2 to 0, to control how much the wolves (candidate solutions) explore new areas or exploit around the best-known solution, thereby balancing exploration and exploitation based on specific constraints and objectives. Consequently, OBL demonstrates strong potential in addressing the local stagnation problem that can limit GWO performance. In this study, we adopted OBL to augment GWO for DG allocation, based on its demonstrated ability to enhance algorithmic efficiency.

This study extends OBL-GWO to PV-based DG planning under seasonal uncertainty using real-world irradiance and load data and demonstrates improved performance over conventional optimisation methods. Previous models overlook seasonal variation, stochasticity, and uncertainties in both generation and demand. This study focuses on three technical objectives: minimising active power loss (P_{Loss}), minimising total voltage deviation (TVD), and maximising the voltage stability index (VSI), while maintaining bus voltages within the standard $\pm 5\%$ tolerance. Figure 1 illustrates the primary phases of the proposed framework and optimisation procedure. From a sustainability perspective, inefficient PV-DG allocation can increase network losses and weaken voltage performance, thereby limiting the efficient utilisation of renewable generation. Conversely, coordinated

PV-DG siting and sizing can improve energy efficiency, support reliable solar-energy integration, and strengthen the technical resilience of distribution networks. Accordingly, the present study addresses the technical dimension of sustainability by quantifying reductions in power losses and voltage deviation and improvements in voltage stability under seasonal generation and demand uncertainty. Economic, environmental life-cycle, and social sustainability indicators remain outside the present scope.

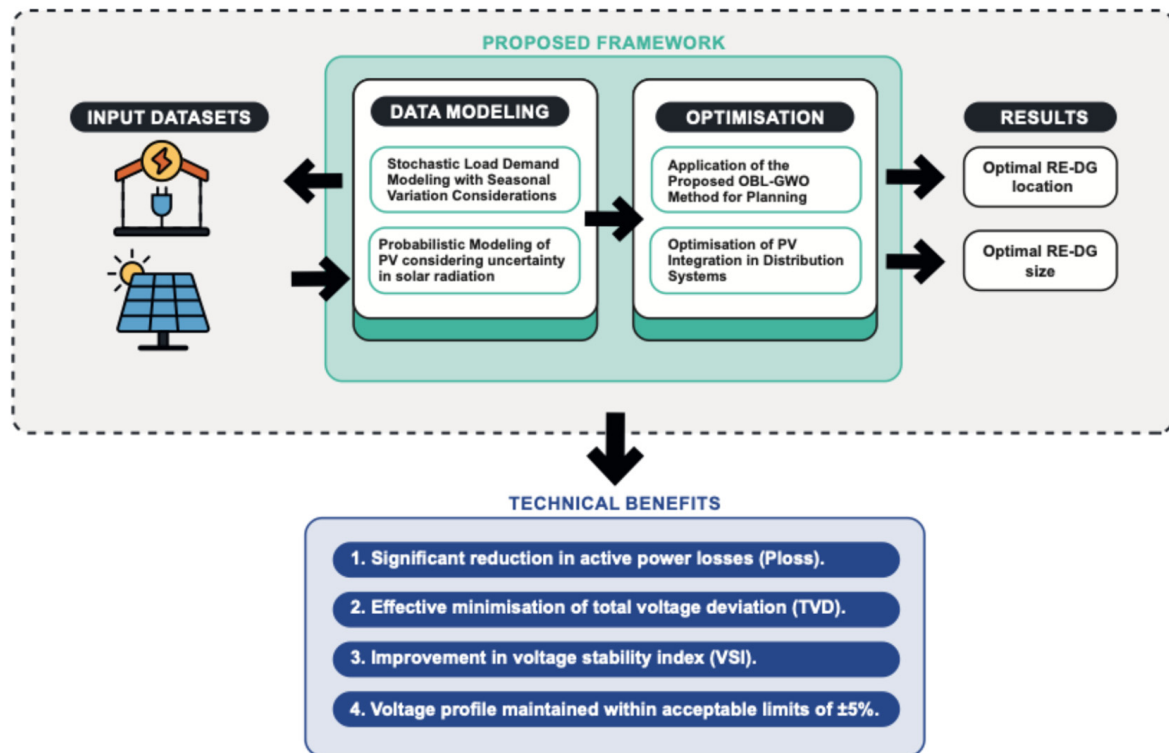


Figure 1. Block diagram illustrating the steps of the proposed research framework.

The primary contributions of this study are as follows:

- Development of an OBL-GWO-based planning framework for the optimal siting and sizing of PV-DG under seasonal generation and demand uncertainty.
- Development of a PV uncertainty model using season-specific Beta probability distributions derived from five years of measured solar irradiance data to capture seasonal and diurnal variability.
- Integration of stochastic PV generation and load-demand models, both derived from five-year real-world datasets from Riyadh, within a unified distribution-network planning framework.
- Performance benchmarking of the proposed approach against conventional GWO and other existing optimisation methods using the IEEE 33-bus test distribution system across multiple PV-DG penetration scenarios.
- Quantification of the technical sustainability benefits of optimised PV-DG allocation through reduced network losses, improved voltage performance, and more reliable integration of seasonally variable solar generation.

2. Uncertainty Modelling of the Stochastic Behaviour of Renewable Energy Generation (REG) and Load

In this study, probabilistic methods were employed to model seasonal variability in solar radiation and load profiles, aiming to improve planning accuracy. Riyadh, Saudi Arabia, was selected due to its desert climate, pronounced seasonal irradiance variation and

extended sunshine duration, making it ideal for simulating PV generation across seasons. Seasonal stochasticity is represented through probabilistic profile construction based on historical data rather than through Monte Carlo sampling.

2.1. Solar Radiation Modelling

Five years of hourly solar irradiance measurements were classified into spring, summer, autumn, and winter. For each season, measurements corresponding to the same hour of the day were averaged across the five-year dataset to obtain a representative 24 h seasonal irradiance profile. For the statistical modelling, nighttime hourly means with negligible irradiance were excluded, and the remaining daylight values were normalised by the maximum measured irradiance of 1076 W/m². The Beta-distribution shape parameters were then estimated using the method of moments based on the mean (μ_s) and variance (σ_s^2) of the normalised irradiance profile. Accordingly, the shape parameters α_s and β_s were calculated using Equations (1) and (2).

$$\alpha_s = \mu_s \left[\frac{\mu_s(1-\mu_s)}{\sigma_s^2} - 1 \right], \quad (1)$$

$$\beta_s = (1 - \mu_s) \left[\frac{\mu_s(1-\mu_s)}{\sigma_s^2} - 1 \right]. \quad (2)$$

The derived seasonal Beta distributions were subsequently used to construct representative 24 h irradiance profiles for the four seasons, with zero irradiance assigned to nighttime hours, as illustrated in Figure 2.

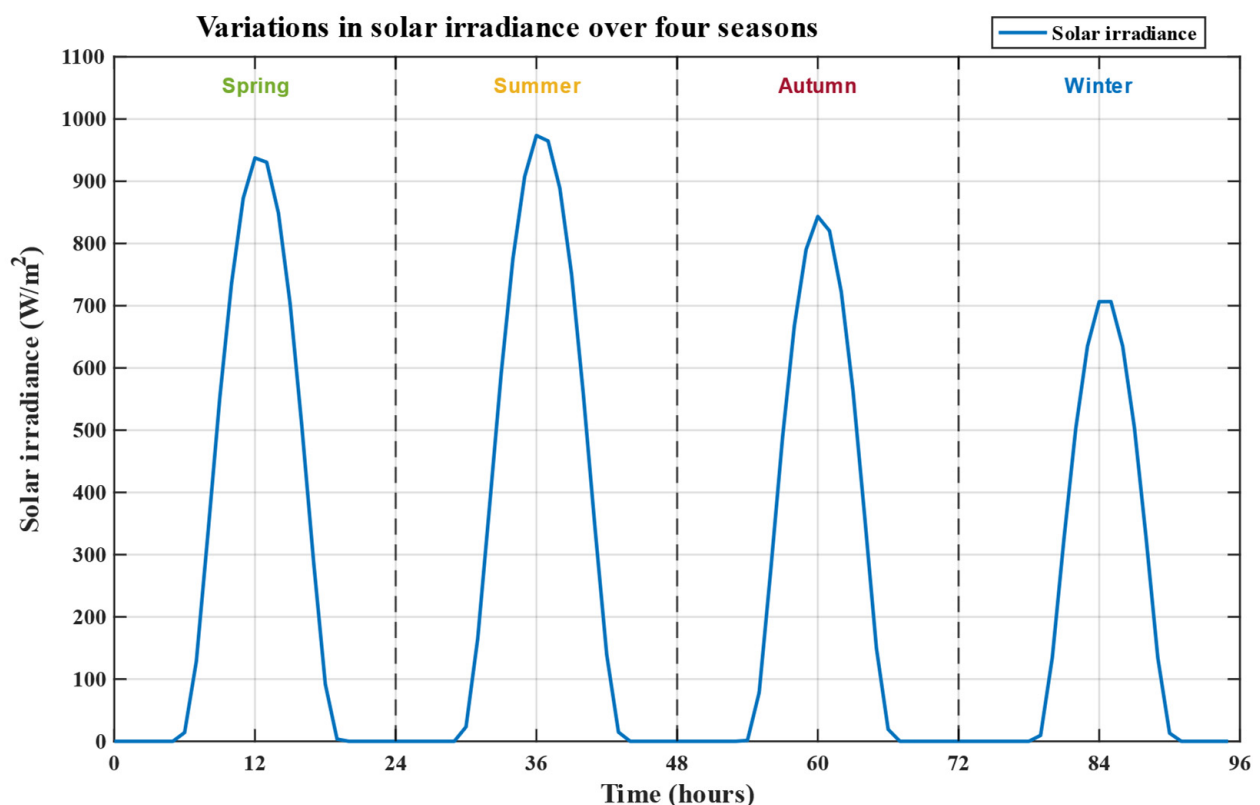


Figure 2. Seasonal variation in solar irradiance based on five-year data.

The resulting seasonal Beta distributions were subsequently evaluated using the Kolmogorov–Smirnov (K–S) goodness-of-fit test. The K–S statistic D represents the maximum absolute difference between the empirical and fitted cumulative distribution functions. The null hypothesis that the observations follow the fitted Beta distribution was evaluated at a significance level of 0.05, where a p -value greater than 0.05 indicates that the fitted distribution is not rejected. The resulting seasonal parameters, K–S statistics and p -values are presented in Table 2.

Table 2. Seasonal Beta-distribution parameters and K–S goodness-of-fit results.

Season	α	β	K–S Statistic (D)	p -Value
Spring	0.6202	0.7241	0.1565	0.8324
Summer	0.6442	0.6544	0.1553	0.8385
Autumn	0.7512	1.0654	0.1497	0.8915
Winter	1.0045	1.7958	0.1750	0.7967

The fitted Beta parameters vary across the four seasons, indicating distinct seasonal irradiance distributions. Summer exhibits nearly equal α and β values, indicating a relatively symmetric distribution, whereas autumn and winter exhibit larger β values relative to α , reflecting greater weighting toward lower normalised irradiance levels. The K–S statistics range from 0.1497 to 0.1750, with autumn showing the smallest deviation between the empirical and fitted distributions. Moreover, all p -values exceed 0.05, indicating that the fitted seasonal Beta distributions are not rejected at the 5% significance level.

To investigate whether seasonal averaging masks short-term irradiance variability, the historical data within each season were further classified into normal and cloudy conditions using the season-specific 25th percentile of daily irradiation as the threshold. Separate representative profiles and condition-specific α and β parameters were then estimated using the same method-of-moments procedure and evaluated using the K–S test. Extended cloudy conditions were additionally assessed using a representative seven-day period consisting entirely of cloudy days, selected based on seasonal normalised daily irradiation. The corresponding condition-dependent and cloudy-week validation results are presented in Section 5.6.

2.2. Load Modelling

Electricity demand in Riyadh is strongly influenced by seasonal variations in temperature and daylight. Hourly consumption data spanning five years were categorised into four seasons and normalised relative to peak load to generate representative 24 h seasonal demand profiles.

2.3. Seasonal Profiles and Uncertainty Modelling

To reflect variability and uncertainty in load modelling, Gaussian noise was generated separately for each season to reproduce realistic fluctuations around the representative demand profile and account for variations in consumer behaviour within Riyadh’s electricity demand. The parameters of each seasonal noise distribution were derived by comparing every historical hourly load observation with the corresponding hourly value of the seasonal average profile. Accordingly, the residual noise at time t was calculated as:

$$\text{Noise}(t) = L_{\text{hist}}(t) - \bar{L}_s(h), \quad (3)$$

where $L_{\text{hist}}(t)$ denotes the historical load at time t , and $\bar{L}_s(h)$ represents the average load for hour h in season s . The mean and standard deviation of the resulting residuals were

calculated independently for spring, summer, autumn, and winter and subsequently used to define the corresponding Gaussian distributions. The probability density function of the seasonal noise is expressed as:

$$f_n(l) = \frac{1}{\sigma_n \sqrt{2\pi}} \exp \left[-\frac{(l - \mu_n)^2}{2\sigma_n^2} \right] \quad (4)$$

where $f_n(l)$ is the probability density of the noise, l is the random load variable, μ_n is the mean of the noise distribution, σ_n is its standard deviation, and σ_n^2 is the corresponding variance [18]. The generated seasonal noise was then incorporated into the representative load profiles to capture stochastic demand variations. As illustrated in Figure 3, the resulting 96 h profile comprises four consecutive 24 h periods representing spring, summer, autumn, and winter, respectively. The adopted uncertainty model captures seasonal and random variations in irradiance and demand but does not explicitly consider spatial correlations, extreme weather events, or multivariate dependencies between generation and load. These aspects are reserved for future research.

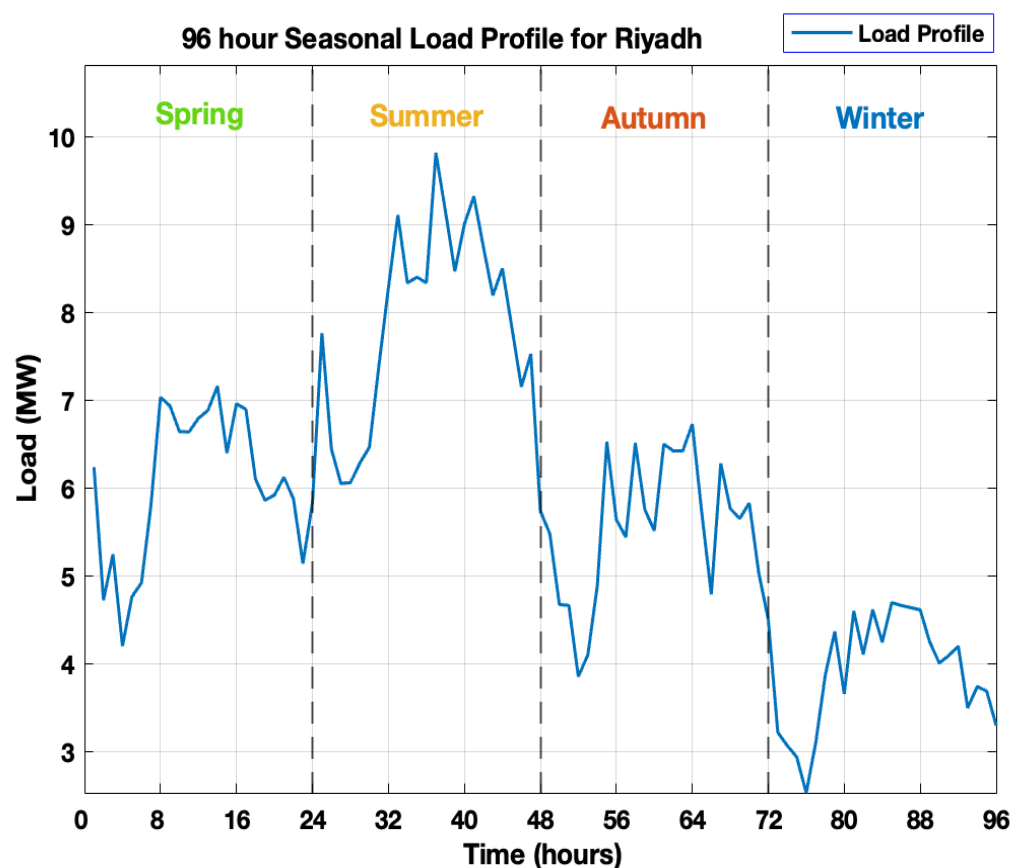


Figure 3. Seasonal load profile over 96 h for Riyadh after modelling.

To account for long-term demand growth, the seasonal load baseline was projected over a 20-year planning horizon using an annual growth rate of 5.48%, following the load-growth model adopted in [14]. The projected load at year y was calculated as $L_y = L_0(1 + g)^y$, where L_0 is the base load and g is the annual load-growth rate.

3. Problem Formulation

The proposed framework considers three technical objectives: active power-loss minimisation, total voltage-deviation minimisation, and voltage-stability improvement. These

objectives are closely associated with the principal technical effects of DG integration on radial distribution networks [19]. Active power loss reflects network operating efficiency, as DG placement and sizing directly influence feeder currents and associated losses. Total voltage deviation evaluates the overall voltage-profile quality by quantifying departures of bus voltages from the nominal value, whereas the voltage stability index provides an indication of the stability margin, particularly at weak buses [20]. Their simultaneous consideration therefore enables DG allocation to account for network efficiency, voltage regulation, and voltage-stability performance.

3.1. Objective Functions

Allocating DG units involves addressing multiple optimisation objectives aimed at improving system performance. The corresponding objective functions are formulated as follows.

1. Real power-loss minimisation

Real power loss (P_{Loss})—defined in Equation (5)—quantifies real power loss due to distribution inefficiencies [20]:

$$P_{\text{Loss}} = \sum_{k=1}^{N_{br}} PL_{(k,k+1)} \quad (5)$$

$$OF_1 = \min(P_{\text{Loss}}) \quad (6)$$

where k denotes the bus index while N_{br} corresponds to the overall number of branches in the network.

2. Total voltage deviation (TVD) minimisation

As expressed in Equation (7), TVD quantifies the variation in voltage levels from the nominal reference and indicates deviations that may impair system performance [19,21]:

$$\text{TVD} = \sum_{a=1}^n (V_a - V_{ref})^2 \quad (7)$$

$$OF_2 = \min(V_D) \quad (8)$$

where V_a represents the voltage magnitude at a given bus, V_{ref} is set to 1.0 pu, a indexes the bus number and n represents the total number of buses.

3. Voltage stability index (VSI) improvement

The objective here is to optimise the minimum VSI by maintaining $\text{VSI}_{(k,k+1)}$ as close as possible to one [20]. The objective function in Equation (9) was reformulated for minimisation to maximise the weakest bus voltage.

$$\text{VSI}_{(k,k+1)} = V_k^4 - 4(P_{k+1}R_{k,k+1} + Q_{k+1}X_{k,k+1})V_k^2 - 4(P_{k+1}X_{k,k+1} - Q_{k+1}R_{k,k+1})^2 \quad (9)$$

$$OF_3 = 1 - \min(\text{VSI}_{(k,k+1)}) \quad (10)$$

3.2. Multi-Objective Functions Formulation and Weight Selection

Equation (11) represents the mathematical formulation of the multi-objective function using the weighted sum method:

$$OF_T = w_1 \left(\frac{OF_1}{P_L^{\text{no DG}}} \right) + w_2 \left(\frac{OF_2}{\text{TVD}^{\text{no DG}}} \right) + w_3 \left(\frac{OF_3}{1 - \text{VSI}^{\text{no DG}}} \right) \quad (11)$$

In the formulation, OF_T represents the overall multi-objective function, while w_1 , w_2 , and w_3 denote the weights assigned to the individual optimisation criteria. These coefficients are normalised such that the sum of their absolute values is equal to unity.

Equal weighting is commonly adopted in weighted-sum-based validation studies to avoid assigning a priori preference to any objective. Accordingly, each weight was set to 1/3 in the principal analysis, although these values may be adjusted in practice to reflect the priorities of network planners or decision-makers.

In the weighted-sum formulation, w_1 , w_2 , and w_3 represent the relative importance assigned to active power loss, total voltage deviation, and voltage stability, respectively, with $w_1 + w_2 + w_3 = 1$ where $w_i \geq 0$. Since the individual objective terms in Equation (11) are normalised using their corresponding no-DG reference values, they are expressed on comparable dimensionless scales before weighting. In the absence of an a priori preference for a particular technical objective, equal weights ($w_1 = w_2 = w_3 = 1/3$) were therefore adopted for the principal analysis to provide a neutral compromise among network loss, voltage regulation, and voltage stability. In practical planning applications, the weights may be selected according to the operational priorities of the network operator. A larger w_1 is appropriate when loss reduction and energy efficiency are prioritised, whereas a larger w_2 gives greater emphasis to maintaining bus voltages close to the nominal value. Increasing w_3 places greater emphasis on the voltage-stability margin. Where no explicit preference is specified, equal weighting provides the default balanced configuration.

To examine the sensitivity of the optimisation results to these preferences, three weighting configurations were considered. Equal weighting (0.3333, 0.3333, 0.3333) assigns identical importance to all three objectives and is adopted as the baseline configuration. A loss-oriented weighting (0.50, 0.25, 0.25) gives greater priority to active power-loss minimisation, whereas a voltage-oriented configuration (0.20, 0.40, 0.40) gives greater combined emphasis to total voltage deviation and voltage stability. These configurations were selected to represent balanced, loss-prioritised, and voltage-prioritised planning preferences, as summarised in Table 3. The corresponding sensitivity results are presented in Section 5.2.

Table 3. Weighting configurations adopted for sensitivity analysis.

Weight Configuration	(w_1, w_2, w_3)	Planning Priority
Equal	(0.3333, 0.3333, 0.3333)	Balanced
Loss-oriented	(0.50, 0.25, 0.25)	Loss reduction
Voltage-oriented	(0.20, 0.40, 0.40)	Voltage performance

3.3. Power Flow Analysis

At each iteration of the optimisation process, the electrical performance of the distribution network was evaluated using a backward/forward sweep (BFS) load-flow algorithm, which is particularly suitable for radial distribution systems due to its numerical stability and low computational complexity. The network was assumed to be balanced and operated under steady-state conditions. Real power losses, bus voltage magnitudes, total voltage deviation, and voltage stability indices were calculated based on the BFS load-flow results for each candidate solution. The implementation follows the conventional formulation reported in [14].

3.4. System Constraints

This section presents the voltage, branch-current, DG-capacity, and placement constraints, together with the unity-power-factor operating condition adopted for all PV-DG units.

$$V_{\min} \leq V_{i,i+1} \leq V_{\max} \quad (12)$$

$$I_{i,j} \leq I_{i,j}^{\max} \quad (13)$$

$$P_{DG,i}^{min} \leq P_{DG,i} \leq P_{DG,i}^{max} \quad (14)$$

$$Q_{DG,i} = 0 \quad (15)$$

$$PF_i = 1 \quad (16)$$

4. Proposed Optimisation Method

In the developed model, the standard GWO algorithm was implemented to establish optimal DG allocation. The equations corresponding to each phase of the algorithm were coded in MATLAB R2024b, following the approach adopted in [4]. Heuristic algorithms typically generate initial solutions randomly when seeking the optimal solution to a given problem. The goal of optimisation is to minimise the gap between these initial solutions and the optimal solution. If initial predictions are close to the optimum, convergence occurs more quickly. The proposed OBL-GWO method enhances the exploration and exploitation capabilities of the standard GWO by incorporating opposite solutions not only during optimisation but also in the population initialisation phase. During initialisation, opposite solutions are generated for all wolves and combined with the original population, from which the best candidates are selected. During the main optimisation process, opposition-based generation jumping is controlled by a predefined jumping rate J_r . At each iteration, a uniformly distributed random number r is generated. If $r < J_r$, an opposite population is generated from the current population, evaluated, and combined with the current wolves, after which the best candidates are retained for the subsequent iteration. Thus, J_r controls the frequency with which the OBL mechanism is activated during the optimisation process. In this study, the jumping rate was set to $J_r = 0.35$, such that opposition-based generation jumping is activated with a probability of 35% at each iteration.

The OBL mechanism incorporates two core approaches. The opposite number method computes the opposite value of a scalar value within a defined range using Equation (17) and replaces the original value if the opposite yields a better fitness. Meanwhile, the opposite point method extends this concept to multidimensional points by computing the opposite of each component within its bounds. A candidate solution can be represented as a vector $X_i = [x_1, x_2, \dots, x_D]$, where each x_j remains within its limits $[a_j, b_j]$. The corresponding opposite vector is $\bar{X}_i = [\bar{x}_1, \bar{x}_2, \dots, \bar{x}_D]$, computed using Equation (18), as described in [22].

$$\bar{x} = a + b - x \quad (17)$$

$$\bar{x}_j = a_j + b_j - x_j \quad (18)$$

where $j = 1, 2, \dots, D$ denotes the dimension of the search space.

In this study, the standard GWO algorithm is augmented with the opposite point method, as defined in Equation (18) and illustrated in Figure 4 to accommodate the multi-dimensional nature of DG allocation, where each candidate comprises multiple decision variables. Each wolf or candidate solution is represented as a vector comprising multiple decision variables, rather than a single scalar value. The corresponding opposite vector, $\bar{X}$, is evaluated against X using the fitness function. If $\bar{X}$ outperforms X , it replaces the original solution.

Each candidate solution therefore comprises the active-power capacity and bus location of each PV-DG unit. The power factor is fixed at unity and is not included as an optimisation variable.

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Initialise the grey wolf population randomly within bounds [lb, ub]
Set jumping rate  $J_r = 0.35$ 
Generate opposite vector  $\bar{X}_i$  for each wolf using Equation (18)
Combine positions into All_Positions = [ $X_i$ ; Opposite_Positions]
Initialise a, A, C
Define the jump rate  $J_r$ 

Calculate the fitness of all wolves in All_Positions
Identify  $X_\alpha, X_\beta, X_\delta$ :

 $X_\alpha$  = Best search agent
 $X_\beta$  = Second-best search agent
 $X_\delta$  = Third-best search agent

while (t < Max number of iterations):

    for each search agent  $X_i$ :
        Generate a uniformly distributed random number (r in [0, 1])
        Update the position of the current search agent using the standard GWO mechanism

        if (r <  $J_r$ )
            Generate opposite positions for the current wolf using Equation (18)
            Combine  $X_i$  and Opposite_Positions into All_Positions
            Evaluate the fitness of All_Positions and update  $X_\alpha, X_\beta, X_\delta$ 
        else
            Evaluate the fitness of the updated  $X_i$  and update  $X_\alpha, X_\beta, X_\delta$ 
        end if

    end for
Update a, A, C
t = t + 1
end while
return Alpha_score,  $X_\alpha$ (Alpha_pos)

```

Figure 4. Pseudocode for the proposed OBL-GWO method.

5. Results and Discussion

The results obtained using the adopted OBL-GWO algorithm for optimal DG allocation in a radial distribution network are presented here, along with a comparison against those from the conventional GWO method. The analysis includes four scenarios representing different levels of PV penetration.

5.1. Distributed Generation (DG) Allocation Scenarios

Four DG allocation scenarios with progressively increasing PV penetration were analysed to assess the performance of the proposed algorithm. All DG units operate at a unity power factor, injecting only real power, to ensure consistency with related studies and enable fair comparison. The scenarios are defined as follows:

- Base Case: Network operates normally without DGs;
- Scenario 1: One PV unit operating at a unity power factor (UPF);

- Scenario 2: Two PV units operating at a UPF;
- Scenario 3: Three PV units operating at a UPF.

5.2. Multi-Objective Optimisation Results

The standard GWO and the proposed OBL-GWO method were applied to the pre-defined scenarios with varying PV penetration levels of feeder capacity. For each method, the scenarios were evaluated based on optimal DG locations, optimal sizing, real power losses (P_{Loss}) and TVD and VSI values. A detailed comparison of the GWO and OBL-GWO simulation outputs is provided in Table 4. For a fair comparison, the number of PV-DG units was fixed identically for both algorithms within each scenario. Scenario 1 contains one DG, Scenario 2 contains two DGs, and Scenario 3 contains three DGs. Only the DG locations and capacities were optimised.

Table 4. Multi-objective optimisation results for the GWO and proposed OBL-GWO across three scenarios.

Method	Scenario	Optimal Locations	Optimal Sizing		Real Power Losses		TVD		VSI	V_{min}
			P (kW)	% Penetration	P_{Loss} (kW)	% Improvement	Pu	% Improvement	Pu	
-	Base Case	-	-	-	210.07	-	0.1328	-	0.705	0.9072 (18)
GWO	Scenario 1	6	2145.3	57.70%	105.23	49.91%	0.0427	67.85%	0.8231	0.9344 (18)
	Scenario 2	30	1232	58.80%	72.83	65.33%	0.0132	90.06%	0.9013	0.9698 (33)
		10	952							
	Scenario 3	25	793	84.60%	65.7	68.72%	0.0084	93.67%	0.9251	0.9743 (33)
		14	653							
		33	1700							
OBL-GWO	Scenario 1	8	1821.2	49.00%	77.35	63.18%	0.0155	88.40%	0.8823	0.9741 (18)
	Scenario 2	30	1378.2	61.10%	55.79	73.44%	0.0052	96.08%	0.9327	0.9859 (18)
		6	893							
	Scenario 3	30	1615	96.50%	39.8	81.05%	0.0038	97.14%	0.9781	0.9932 (18)
		14	444							
		6	1526							

A comparison between the base case and the optimisation scenarios, presented in Table 4, demonstrates that DG integration notably reduces power losses and enhances the overall voltage profile. The optimisation results from the conventional GWO approach demonstrates substantial reductions in power losses along with notable enhancements in voltage profiles across all scenarios. In Scenario 1, 57.7% PV penetration resulted in a 49.9% reduction in power loss. Scenarios 2 and 3, which involved higher PV penetration levels, achieved even greater improvements, with power-loss reductions of up to 68.7% and TVD improvements of up to 93.67% relative to the base case.

The results in Table 4 also indicate that the proposed OBL-GWO method yields further enhancements across all DG integration scenarios when compared with the base case. In Scenario 1, with 49% PV penetration, power losses decreased by 63.2% and TVD improved by 88.33%, accompanied by an increase of nearly 25% in VSI. Under Scenario 2, a 12% increase in PV penetration, achieved by placing PV units at two different buses, led to a 96.1% improvement in TVD and a 73.44% reduction in power losses. Scenario 3 featured approximately 97% PV penetration with installations at buses 30, 14 and 6, resulting in an 81.05% reduction in power losses and a 97.14% improvement in voltage profile compared to the base case.

Figure 5 illustrates the basic IEEE 33-bus distribution network configuration, with DGs integrated under the three defined scenarios using the proposed OBL-GWO approach. To represent the various DG placements, each scenario is shown using a distinct colour. The medium-voltage substation marks the starting point of the network, while solar panel icons indicate the locations of DG placements.

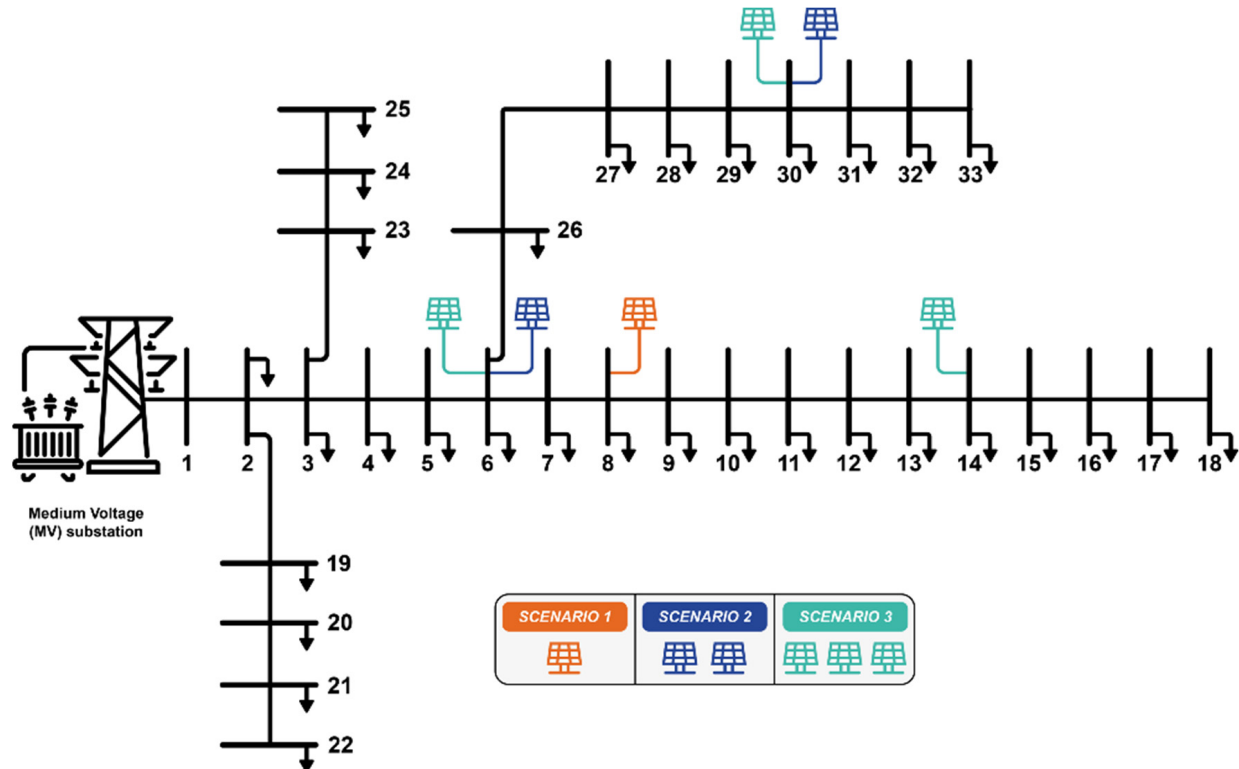


Figure 5. Basic DN configuration with DG unit placement based on the proposed OBL-GWO method.

The OBL-GWO results for Scenarios 1, 2 and 3 are illustrated as seasonal DN voltage profiles in Figure 6a–c, respectively. For each scenario, voltage profiles at all buses are depicted across seasons, with the vertical axis representing voltage magnitude (p.u.) and the horizontal axis indicating bus numbers. Across all scenarios, the profiles obtained using the proposed OBL-GWO method exhibit seasonal variations, with the lowest voltage observed at bus 18 at approximately 0.9741 p.u., 0.9859 p.u., and 0.9932 p.u. for Scenarios 1, 2, and 3, respectively. Although solar radiation peaks during summer, all three scenarios recorded a voltage drop during this season owing to the extremely high load demand. Nevertheless, the voltages remained within acceptable limits ($\pm 5\%$) and showed considerable improvement compared to the base-case test system conditions. The most favourable voltage profiles across all scenarios occurred during autumn and spring, which feature moderate load demands and relatively high solar radiation levels. The following section presents a comparative analysis of the standard GWO and the enhanced OBL-GWO algorithms.

To assess the influence of the weighting factors on the final PV-DG allocation, Scenario 3, comprising three PV-DG units, was selected as the representative sensitivity-analysis case because it represents the highest-dimensional allocation problem considered in this study. The proposed OBL-GWO was re-executed using the three weighting configurations defined in Section 3.2, while all other optimisation parameters, constraints, and operating conditions were maintained unchanged. The resulting changes in total PV capacity, active power loss, total voltage deviation, and voltage stability index are summarised in Table 5.

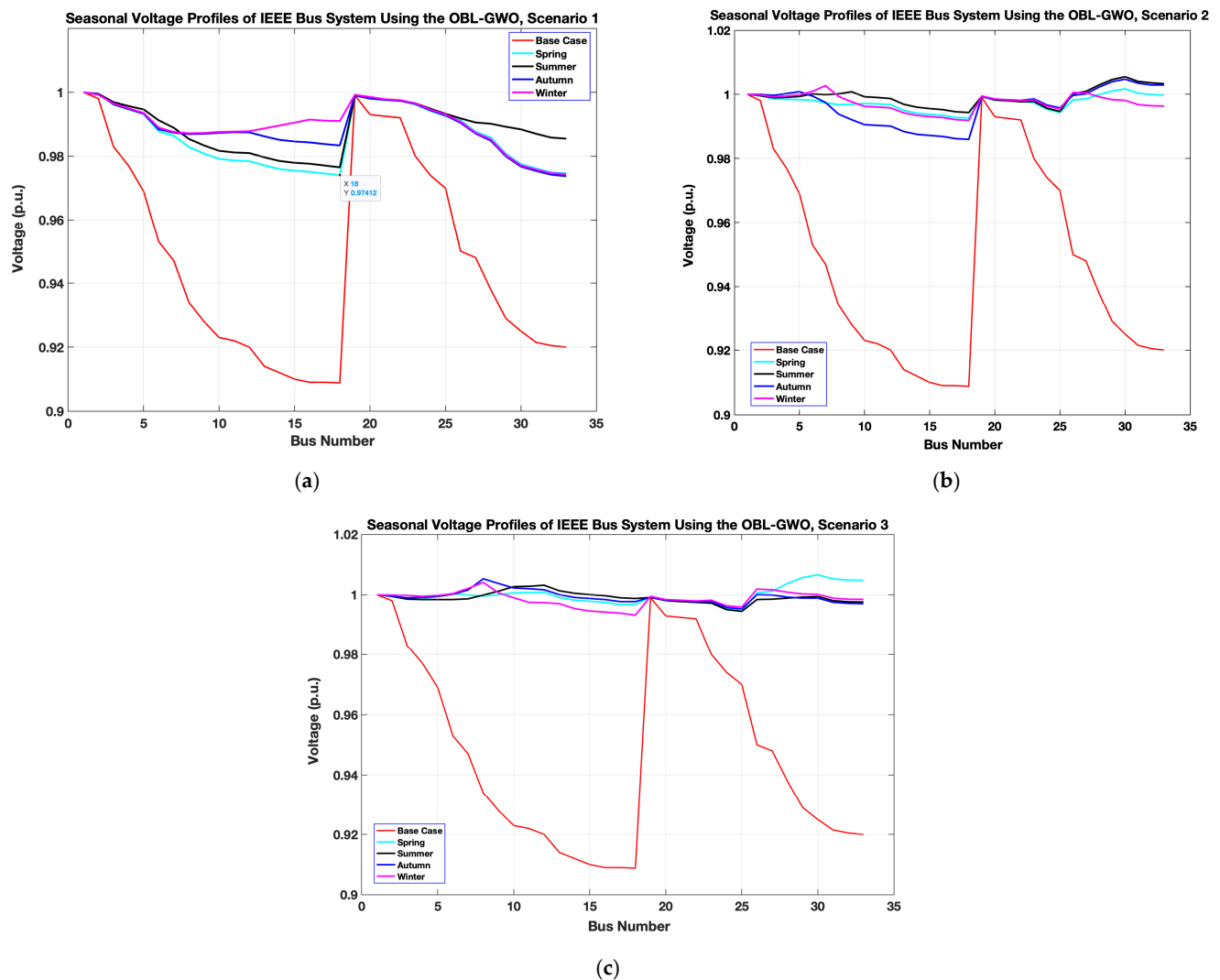


Figure 6. Seasonal voltage profiles for the IEEE 33-bus system under the proposed OBL-GWO method: (a) Scenarios 1, (b) 2 and (c) 3.

Table 5. Sensitivity of the OBL-GWO results to different weighting configurations.

Weight Configuration	(w_1, w_2, w_3)	Bus/Size (kW)	P_{Loss} (kW)	TVD	VSI
Equal	(1/3, 1/3, 1/3)	30/1615, 14/444, 6/1526	39.8	0.0038	0.9781
Loss-oriented	(0.50, 0.25, 0.25)	30/1590, 14/425, 6/1465	37.6	0.0045	0.974
Voltage-oriented	(0.20, 0.40, 0.40)	30/1652, 14/473, 6/1580	42.3	0.0028	0.984

The sensitivity analysis demonstrates the expected trade-off among the three technical objectives. Increasing the weight assigned to active power loss reduced P_{Loss} from 39.8 to 37.6 kW, although this was accompanied by a higher TVD and a slightly lower VSI. Conversely, the voltage-oriented configuration reduced TVD from 0.0038 to 0.0028 and increased VSI from 0.9781 to 0.984, at the expense of higher active power loss. The total PV capacity varied only moderately across the three configurations, from 3480 to 3705 kW. However, the resulting variations in the objective components and PV-DG capacities remain relatively small, while the optimal bus locations and the overall ranking of the investigated scenarios are preserved. This consistency indicates that the principal conclusions are not highly sensitive to the selected weight combination and supports the use of equal weighting as a balanced baseline when no specific operational preference is imposed.

5.3. Comparative Performance of OBL-GWO and GWO

The simulation results for P_{Loss} , TVD, VSI and V_{min} obtained using the conventional GWO were compared with those generated by the proposed OBL-GWO method under identical conditions, as reported in Table 4. The corresponding percentage improvements achieved by OBL-GWO over conventional GWO are summarised in Table 6.

Table 6. Comparison of performance improvements using standard GWO and OBL-GWO.

Scenario	GWO		OBL-GWO		Additional % Improvement with OBL-GWO
	Parameter	% Improvement	Parameter	% Improvement	
Scenario 1	P_{Loss}	49.91%	P_{Loss}	63.18%	13.27%
	TVD	67.85%	TVD	88.33%	20.5%
	VSI	16.75%	VSI	25.15%	8.4%
	V_{min}	2.99%	V_{min}	7.37%	4.38%
Scenario 2	P_{Loss}	65.33%	P_{Loss}	73.44%	8.11%
	TVD	90.06%	TVD	96.08%	6.02%
	VSI	27.84%	VSI	32.29%	4.45%
	V_{min}	6.90%	V_{min}	8.68%	1.77%
Scenario 3	P_{Loss}	68.72%	P_{Loss}	81.05%	12.33%
	TVD	93.67%	TVD	97.14%	3.46%
	VSI	31.21%	VSI	38.73%	7.52%
	V_{min}	7.39%	V_{min}	9.48%	2.08%

As indicated in Table 6 and illustrated in Figure 7a, the proposed method provides greater reductions in real power losses of 13.27%, 8.11% and 12.33% for Scenarios 1, 2 and 3, respectively, compared to the conventional GWO. Additionally, the proposed method achieves superior TVD minimisation: 20.5%, 6.02% and 3.46% for Scenarios 1, 2 and 3, respectively, as depicted in Figure 7b. Figure 7c displays a modest improvement in VSI across the three scenarios. The final metric, V_{min} any bus (Figure 7d), is notably better in Scenario 1 under the OBL-GWO method, with a value of approximately 0.9741 p.u. at bus 18 compared to 0.9344 p.u. at bus 18 under the conventional GWO. In Scenario 1, the proposed method improves V_{min} by nearly 4.38%. However, with increased PV penetration in Scenarios 2 and 3, the improvement becomes marginal, at only around 1.77% and 2.08% respectively. Across all three scenarios, the average additional improvements with the OBL-GWO method are approximately 11.24% for P_{Loss} , 10% for TVD, 6.8% for VSI and ~2.74% for V_{min} .

From a sustainability perspective, the reduction in active power loss indicates more efficient utilisation of generated electrical energy, while the improvements in TVD, VSI, and V_{min} demonstrate the ability of the network to accommodate variable PV generation while maintaining acceptable voltage performance. These outcomes represent technical sustainability benefits through enhanced energy efficiency, renewable-energy utilisation, and network reliability.

To evaluate the robustness and repeatability of the optimisation results, the standard GWO and the proposed OBL-GWO-based planning framework were executed independently over 30 runs for all three scenarios using identical parameter settings. Table 7 reports the mean and standard deviation of P_{Loss} , TVD, and VSI. Across all scenarios, OBL-GWO achieved lower average power losses and voltage deviations, higher average VSI values, and smaller standard deviations than conventional GWO. These results demonstrate that OBL-GWO provides more stable and repeatable performance and is less sensitive to random initialisation than the standard GWO.

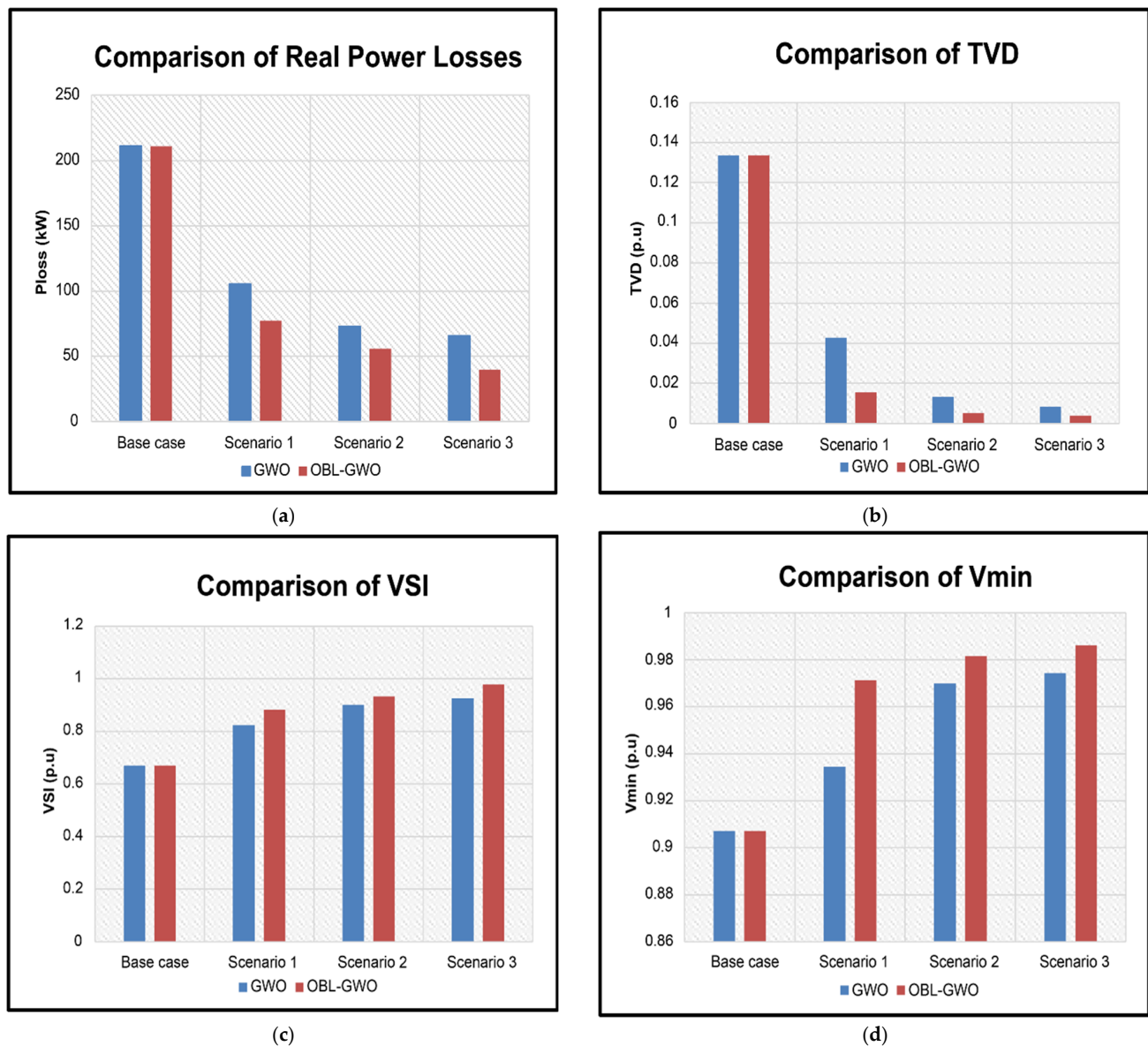


Figure 7. Comparison of results obtained using the proposed OBL-GWO method versus the conventional GWO in terms of: (a) real power losses, (b) TVD, (c) VSI and (d) minimum voltage at any bus (V_{min}).

Table 7. Statistical performance comparison of GWO and OBL-GWO over 30 independent runs.

Scenario	Method	P_{Loss} (kW)	TVD (p.u.)	VSI (p.u.)
1	GWO	106.31 ± 0.70	0.0439 ± 0.0015	0.8224 ± 0.00045
	OBL-GWO	77.78 ± 0.31	0.0160 ± 0.0005	0.8819 ± 0.00038
2	GWO	73.22 ± 0.53	0.0154 ± 0.0011	0.9006 ± 0.00054
	OBL-GWO	56.27 ± 0.24	0.0057 ± 0.0003	0.9314 ± 0.00033
3	GWO	66.36 ± 0.38	0.0093 ± 0.0008	0.9232 ± 0.00062
	OBL-GWO	40.42 ± 0.19	0.0041 ± 0.0002	0.9775 ± 0.00030

5.4. Convergence Behaviour and Computational Performance

To further illustrate the performance differences, the convergence behaviour of the standard GWO and the adopted OBL-GWO algorithm is depicted in Figure 8. In all

cases, OBL-GWO exhibits faster convergence and achieves a lower normalised objective-function value. For Scenario 1, OBL-GWO stabilises at approximately 0.29, whereas GWO converges to about 0.47. Similarly, the final objective values in Scenario 2 are approximately 0.18 for OBL-GWO and 0.26 for GWO. The best performance is observed in Scenario 3, where OBL-GWO reaches nearly 0.10, compared with approximately 0.21 for GWO. The convergence curves also show that OBL-GWO produces substantial objective-value reductions during the early iterations. Furthermore, the nearly constant OBL-GWO curves during the later iterations indicate stable convergence after reaching high-quality solutions. Overall, the results demonstrate that OBL-GWO consistently provides better convergence performance as the number of PVs increases, indicating its effectiveness in addressing the increasing complexity of the allocation problem. The convergence curves present the best objective-function value obtained at each iteration for GWO and OBL-GWO across the three scenarios.

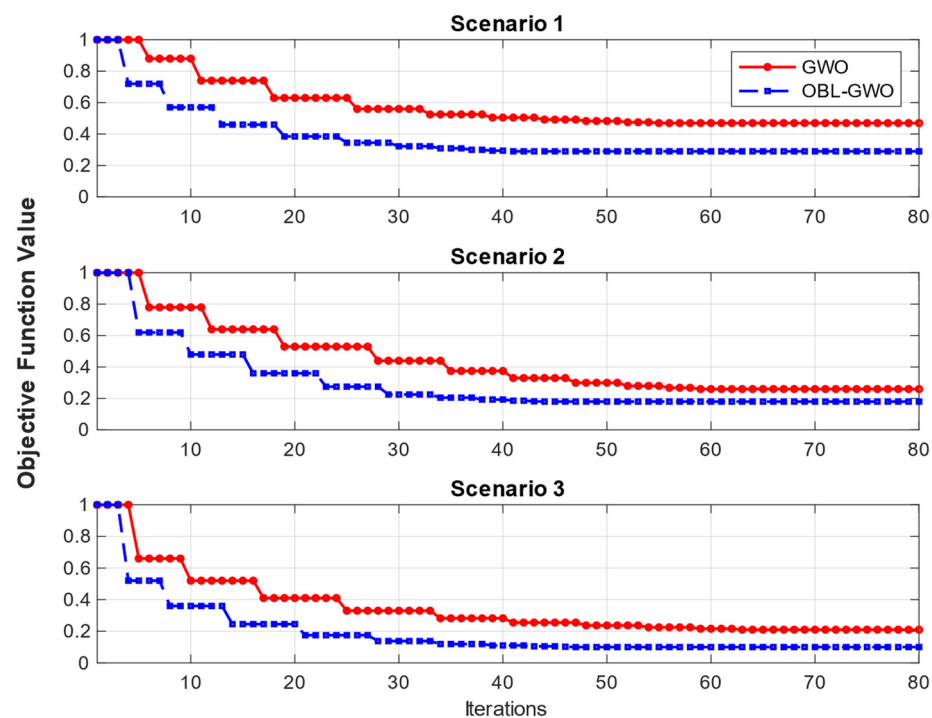


Figure 8. Convergence characteristics of the standard GWO and the proposed OBL-GWO across all scenarios.

To further assess computational efficiency and convergence performance, GWO and OBL-GWO were evaluated under identical computational conditions for all three scenarios, using 100 search agents, 200 maximum iterations, and the same hardware and software environment. The results over 30 independent runs are summarised in Table 8. In terms of computational cost, OBL-GWO increased the average runtime by approximately 6.3–7.0% across the three scenarios due to the additional evaluation of opposite solutions. Similarly, the function evaluations required to reach convergence ranged from 5700–6400 for GWO and 5735 to 6545 for OBL-GWO.

As presented in Table 8, OBL-GWO consistently converged in fewer iterations and achieved lower final objective-function values across all scenarios. Specifically, convergence was reached at iterations 41, 44, and 47 for S1–S3, respectively, compared with iterations 56, 59, and 63 for conventional GWO. The corresponding final objective values decreased from 0.47 to 0.29 in S1, from 0.26 to 0.18 in S2, and from 0.21 to 0.10 in S3. These results demonstrate a consistent trade-off between computational cost and optimisation performance: although OBL-GWO requires additional function evaluations and moderately

longer execution times, it reaches better-quality solutions in fewer optimisation iterations. The results therefore support the effectiveness of the OBL mechanism in improving the search performance of conventional GWO across the considered allocation scenarios.

Table 8. Statistical performance comparison of GWO and OBL-GWO over 30 independent runs for all scenarios.

Scenario	Method	Average Runtime (s)	Function Evaluations	Convergence Iteration	Final Objective Value
S1	GWO	381	5700	56	0.47
	OBL-GWO	405	5735	41	0.29
S2	GWO	401	6000	59	0.26
	OBL-GWO	429	6140	44	0.18
S3	GWO	428	6400	63	0.21
	OBL-GWO	458	6545	47	0.10

5.5. Benchmarking Against Alternative Optimisation Algorithms

To provide a controlled benchmark, OBL-GWO was compared for scenario 1 with conventional GWO, PSO, and GA on the IEEE 33-bus system under identical optimisation conditions. All algorithms employed the same objective function, operational constraints, PV-DG decision variables, population size of 100, and maximum of 200 iterations. Performance was assessed using the best objective value, mean $\pm$ standard deviation, convergence iteration, relative percentage deviation (RPD), active power loss, TVD, and VSI. The RPD was used to provide a normalised measure of solution quality by quantifying the relative deviation of each algorithm from the best-known objective value obtained in the comparison and was calculated as:

$$RPD_i(\%) = \frac{F_i - F_{\min}}{F_{\min}} \times 100 \quad (19)$$

where F_i is the best objective value obtained by algorithm i , and $F_{\min}$ is the lowest objective value obtained among all compared algorithms.

As shown in Table 9, OBL-GWO achieved the best overall performance, with the lowest objective value of 0.2946 and an RPD of 0%, compared with objective values of 0.4172, 0.4323, and 0.4740 for PSO, GA, and GWO, respectively. It also produced the lowest mean objective value and variability (0.2982 ± 0.002), indicating improved robustness. In terms of network performance, OBL-GWO achieved the lowest power loss (77.35 kW) and TVD (0.0155) while providing the highest VSI (0.8823). It also converged earlier at iteration 41 compared with GWO (56), PSO (68), and GA (82) showing better solution quality and convergence behaviour under the same computational settings.

Table 9. Performance comparison of metaheuristic algorithms for Scenario 1 under normal weather conditions.

Method	OF	Mean OF $\pm$ SD	P_{Loss} (kW)	TVD	VSI	Convergence Iteration	RPD (%)	Average Runtime (s)
GA	0.4323	0.4502 ± 0.014	116.12	0.0239	0.8336	82	46.74	560
PSO	0.4172	0.4342 ± 0.008	115.12	0.0238	0.8453	68	41.62	472
GWO	0.4740	0.4861 ± 0.012	105.23	0.0427	0.8231	56	60.90	381
OBL-GWO	0.2946	0.2982 ± 0.002	77.35	0.0155	0.8823	41	0.00	405

5.6. Robustness Under Cloudy Conditions

To investigate whether seasonal averaging masks short-term variations in solar irradiance, the historical data were further examined under cloudy conditions using the classification procedure described in Section 2.1. Separate Beta-distribution parameters were estimated for the cloudy observations of each season using the same method-of-moments procedure adopted for the original seasonal distributions. Table 10 compares the original seasonal parameters with the corresponding cloudy-condition parameters and presents the K–S goodness-of-fit results for the cloudy subsets.

Table 10. Comparison of seasonal and cloudy condition Beta-distribution parameters.

Season	α_{seasonal}	β_{seasonal}	α_C	β_C	D_C	p_C
Spring	0.6202	0.7241	0.9034	1.3217	0.1491	0.894
Summer	0.6442	0.6544	0.6535	0.7548	0.1497	0.8675
Autumn	0.7512	1.0654	1.3659	2.1854	0.1495	0.9368
Winter	1.0045	1.7958	1.1633	3.1568	0.1927	0.6967

As illustrated in Figure 9, the measured irradiance under cloudy conditions is consistently lower than the normal-condition profile and follows the general behaviour of the corresponding cloudy-condition profile. The persistent cloudy-week case further demonstrates that the reduction in irradiance is sustained over several consecutive days rather than being associated with a single isolated low-irradiance event. To quantify these differences, Table 10 compares the original seasonal Beta parameters with the parameters obtained after considering cloudy observations separately, where α_C and β_C denote the Beta-distribution parameters under cloudy conditions. The K–S statistic (D_C) and p -value (p_C) are also reported for each cloudy-condition distribution.

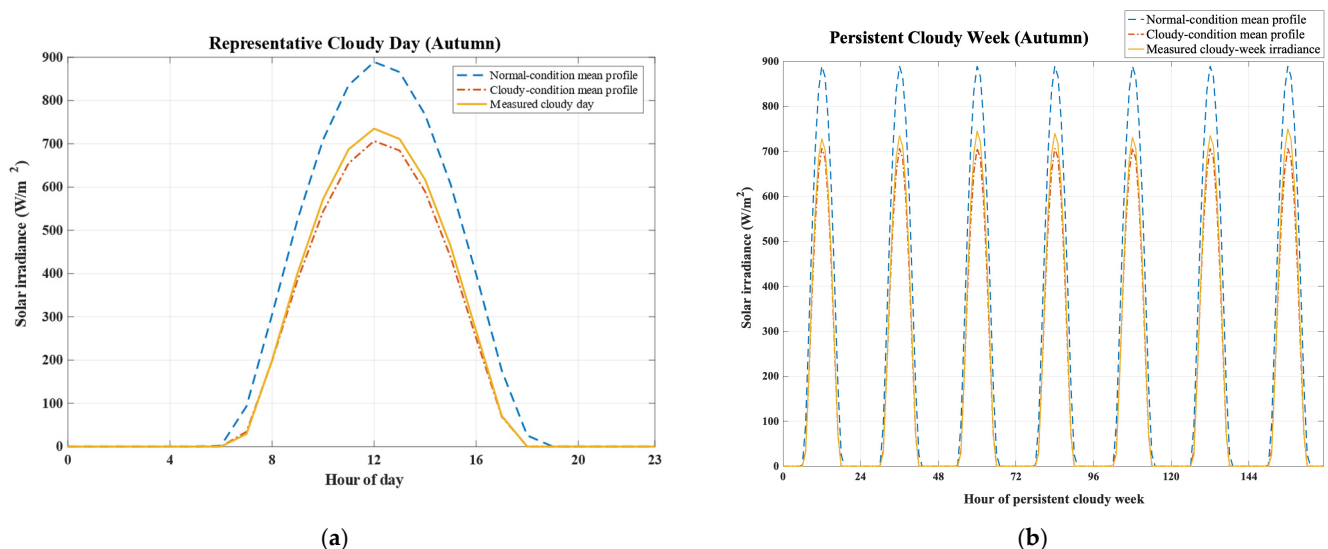


Figure 9. Irradiance behaviour under representative cloudy conditions in autumn: (a) representative cloudy day; and (b) persistent cloudy week.

The condition-specific results show that the fitted Beta parameters change under cloudy conditions, with the most noticeable differences occurring during autumn and winter. This indicates that seasonal averaging can attenuate weather-dependent irradiance characteristics. Nevertheless, all cloudy-condition distributions produced p -values greater than 0.05 and were therefore not rejected at the 5% significance level, confirming that

the Beta distribution remains suitable when its parameters are estimated specifically for cloudy conditions.

To further examine the validity of the irradiance model during prolonged cloudy conditions, a persistent seven-day period from 13 to 19 November 2019 was selected from the autumn dataset. When the complete cloudy-week observations were evaluated using the original autumn seasonal distribution ($\alpha = 0.7512$, $\beta = 1.0654$), the distribution was rejected at the 5% significance level ($D = 0.2377$, $p = 0.0003$). In contrast, the corresponding cloudy-condition distribution was not rejected ($D = 0.1457$, $p = 0.0684$). Furthermore, the same cloudy-condition parameters remained statistically acceptable for all seven individual days, with the daily K–S p -values ranging from 0.0626 to 0.9114 as presented in Table 11.

Table 11. K–S validation during the representative persistent cloudy week.

Day	K–S Statistic (D)	p -Value
Day 1	0.157	0.9114
Day 2	0.1881	0.7663
Day 3	0.2952	0.2411
Day 4	0.3792	0.0626
Day 5	0.2046	0.6748
Day 6	0.2677	0.3463
Day 7	0.3273	0.1502

Results indicate that while a single set of seasonally averaged parameters remains suitable for broader seasonal modelling, it may not be sufficient to reflect prolonged cloudy conditions. Therefore, the incorporation of condition-specific Beta parameters provides a more realistic representation of extended cloudy periods while preserving the original seasonal distributions for long-term seasonal planning.

To further evaluate the robustness of the proposed optimisation framework under adverse weather conditions, the representative persistent cloudy week was considered as a dedicated optimisation case study for Scenario 1. The measured 168 h irradiance profile of the selected cloudy week was directly incorporated into the PV-generation model, while the network data, objective-function formulation, weighting factors, operational constraints, and PV-DG limits were maintained unchanged. The proposed OBL-GWO was compared with conventional GWO, PSO, and GA under identical optimisation conditions using a population size of 100 and a maximum of 200 iterations. Each algorithm was independently executed 30 times to account for its stochastic behaviour. The comparative optimisation results under the adverse cloudy-weather condition are summarised in Table 12.

Table 12. Performance comparison of metaheuristic algorithms for Scenario 1 under adverse cloudy-weather conditions.

Method	OF	Mean OF $\pm$ SD	P_{Loss} (kW)	TVD	VSI	Convergence Iteration	RPD (%)	Average Runtime (s)
GA	0.4618	0.4825 $\pm$ 0.017	121.68	0.0267	0.825	86	49.06	565
PSO	0.4421	0.4603 $\pm$ 0.010	120.34	0.0261	0.8376	72	42.7	476
GWO	0.5096	0.5238 $\pm$ 0.015	111.74	0.0486	0.8137	61	64.49	386
OBL-GWO	0.3098	0.3136 $\pm$ 0.003	81.12	0.0172	0.8741	47	0.00	458

As shown in Table 12, the proposed OBL-GWO maintained effective optimisation performance under the persistent cloudy-week condition. Compared with the alternative

algorithms, it achieved the best overall objective value while maintaining acceptable network voltage, loss, and stability performance. Its lower mean objective value, statistical variability, and RPD further indicate that the proposed method retains its optimisation capability under the reduced and highly variable irradiance associated with prolonged cloudy weather.

These results demonstrate that the proposed OBL-GWO maintains its optimisation effectiveness under prolonged cloudy conditions and provides more robust and higher-quality solutions than the alternative metaheuristic methods considered under the same adverse-weather scenario.

5.7. Scalability Validation on Larger Benchmark Networks

To investigate the scalability and applicability of the proposed optimisation framework beyond the IEEE 33-bus system, additional simulations were conducted using the IEEE 69-bus and IEEE 118-bus radial distribution networks for scenario 3. The three-PV-DG allocation case was selected as the representative scalability scenario because it represents the highest-dimensional allocation problem considered in the present study. The same objective-function formulation, weighting factors, operational constraints, PV operating assumptions, population size, maximum number of iterations, and convergence criteria were maintained for all test systems. Only the network-specific electrical data, loading levels, DG capacity limits, and base-case normalisation values were modified.

The conventional GWO and proposed OBL-GWO were independently applied to both larger networks under identical computational conditions. Their performance was evaluated in terms of objective-function value, active power loss, total voltage deviation, voltage stability index, convergence iteration, and computational time. Table 13 summarises the resulting performance. For completeness and to provide a common reference for assessing scalability, the corresponding IEEE 33-bus results are reproduced alongside the IEEE 69- and 118-bus results for scenario 3.

Table 13. Scalability performance on the IEEE 33-, 69-, and 118-bus distribution systems.

Scenario	Method	Bus/Size (kW)	Best OF	P_{Loss} (kW)	TVD (p.u.)	VSI (p.u.)	Convergence Iteration	Average Runtime (s)
IEEE 33-bus	GWO	25/793, 14/653, 33/1700	0.21	65.7	0.0084	0.9251	63	428
	OBL-GWO	30/1615, 14/444, 6/1526	0.10	39.8	0.0038	0.9781	47	458
IEEE 69-bus	GWO	11/520, 18/430, 61/1710	0.24	72.4	0.0121	0.9452	78	905
	OBL-GWO	17/460, 61/1570, 65/620	0.14	61.2	0.0064	0.9763	57	968
IEEE 118-bus	GWO	50/2680, 71/3140, 108/2890	0.32	681.5	0.0272	0.9184	105	1560
	OBL-GWO	50/3210, 71/3480, 110/3160	0.19	542.8	0.0143	0.9608	76	1667

The scalability results confirm that the proposed OBL-GWO maintains its optimisation advantage as the distribution-network size increases. For the IEEE 69-bus

system, OBL-GWO reduced the best objective-function value from 0.24 to 0.14, while decreasing active power loss from 72.4 to 61.2 kW and TVD from 0.0121 to 0.0064 p.u. The VSI increased from 0.9452 to 0.9763 p.u., and convergence was achieved at iteration 57, compared with iteration 78 for conventional GWO. Similarly, for the IEEE 118-bus system, OBL-GWO reduced the objective value from 0.32 to 0.19, power loss from 681.5 to 542.8 kW, and TVD from 0.0272 to 0.0143 p.u., with an increase in VSI from 0.9184 to 0.9608 p.u. Moreover, OBL-GWO converged at iteration 76, compared with 105 for GWO. Although OBL-GWO required moderately higher runtimes of 968 and 1667 s for the IEEE 69- and 118-bus systems, respectively, compared with 905 and 1560 s for GWO because of the additional opposite-solution evaluations, its consistent improvements in solution quality and convergence across both larger networks demonstrate the scalability and computational feasibility of the proposed framework for radial distribution networks of increasing size and complexity.

5.8. Comparison with Existing Methods in the Literature

Compared with previously published techniques such as genetic algorithm, PSO and teaching-learning-based-optimisation (TLBO)-GWO, all applied under similar conditions, the proposed OBL-GWO approach demonstrates superior performance in Scenario 1. It achieves the highest reduction in power losses (63.18%) along with a substantial improvement in voltage profile, as shown in Table 14.

Table 14. Performance evaluation of the proposed OBL-GWO in Scenario 1 vs. existing techniques.

Technique	Ref.	Optimal Location	Optimal Sizing		Real Power Losses		TVD	$V_{\min}$
			P (kW)	% Penetration	P_{Loss} (kW)	% Improvement		
Base Case	-	-	-	-	210.07	-	0.1328	0.9072 (18)
GA	[23]	6	3117.9	83.9%	115.03	45.48%	0.02376	0.9557 (18)
PSO	[23]	6	3125	84.1%	115.12	45.44%	0.02363	0.9558 (18)
HHO-PSO	[24]	6	2574.31	69.3%	103.94	50.73%	-	0.9510 (18)
TLBO-GWO	[25]	30	1000	26.9%	127.28	39.67%	-	-
SCA	[26]	6	2590.21	69.7%	111.02	47.38%	-	0.9424 (18)
HA-SCA	[26]	6	2590.15	69.7%	111.02	47.38%	-	0.9424 (18)
GSA	[27]	6	2586.79	69.6%	111.02	47.38%	-	0.9423
CFA	[27]	6	2590.22	69.7%	111.02	47.38%	-	0.9424
MRFO	[28]	6	2590.22	69.7%	111.03	47.37%	-	-
GWO	[P]	6	2145.3	57.7%	105.23	49.91%	0.0427	0.9344 (18)
OBL GWO	[P]	8	1821.2	49.0%	77.35	63.18%	0.0155	0.9741 (18)

Figure 10 presents the real power-loss result of the proposed OBL-GWO alongside values reported in existing studies. Under the conditions considered in this study, OBL-GWO achieved the lowest reported power loss among the listed methods. However, differences in system assumptions, constraints, and optimisation settings mean that the comparison should be interpreted as a contextual benchmark rather than a statistically controlled ranking.

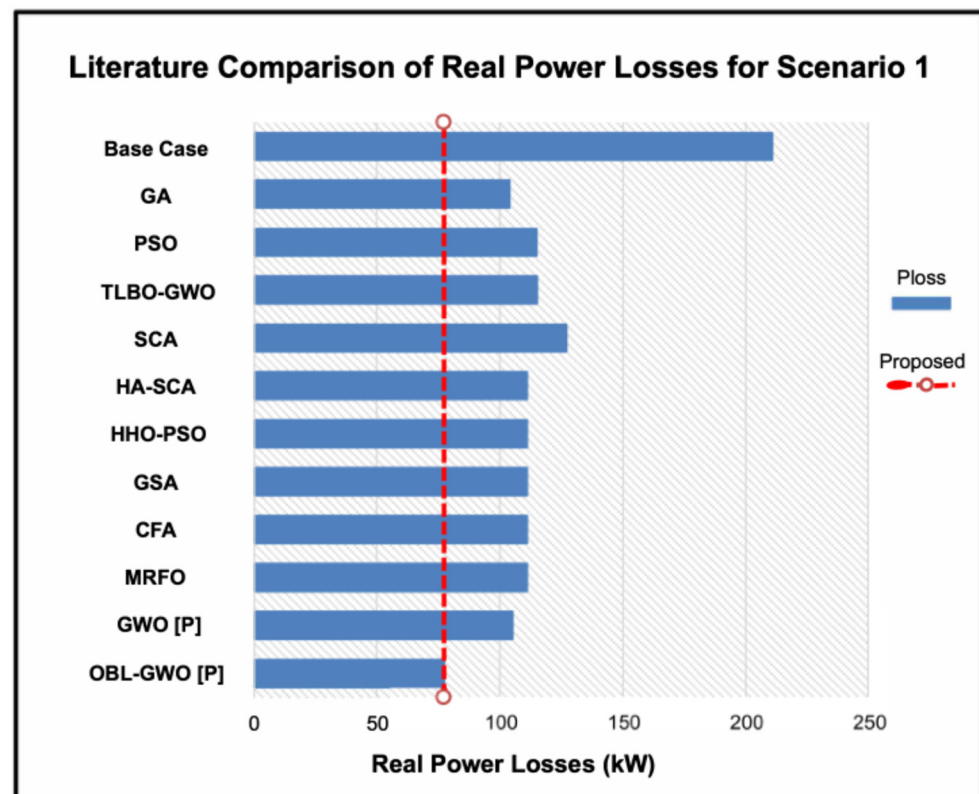


Figure 10. Real power loss comparison between the proposed OBL-GWO approach and existing literature-reported techniques for Scenario 1. GA and PSO results are from [23], HHO-PSO from [24], TLBO-GWO from [25], SCA and HA-SCA from [26], GSA and CFA from [27], and MRFO from [28].

6. Conclusions

Effective load planning must account for the variability of weather-dependent REG and seasonal demand fluctuations. To support such planning, a five-year dataset capturing actual solar radiation and load consumption patterns was employed in this study. Simulations based on the IEEE 33-bus test system under three PV penetration scenarios provided insights into the optimisation and convergence behaviour of both the standard GWO method and OBL-GWO methods. On average, optimal DG allocation using the proposed OBL-GWO method resulted in reductions of approximately 11.24 percentage points in power-loss reduction, 10% in TVD reduction, 6.79% in VSI, and 2.74% in $V_{\min}$ across the three scenarios. The statistical analysis over 30 independent runs further demonstrated improved robustness and repeatability, while controlled benchmarking against GWO, PSO, and GA confirmed superior overall solution quality. The weight-sensitivity analysis showed the expected trade-off among the technical objectives while supporting equal weighting as a balanced baseline when no specific operational preference is imposed. Moreover, the persistent cloudy-week case demonstrated that OBL-GWO maintains robust optimisation performance under prolonged adverse irradiance conditions. Scalability validation on the IEEE 69- and 118-bus systems further confirmed that the proposed method retains its solution-quality and convergence advantages as network size increases.

From a sustainability perspective, the reductions in network losses and improvements in voltage performance demonstrate that optimised PV-DG allocation can support more efficient renewable-energy utilisation and more reliable operation of active distribution networks under seasonal uncertainty. The proposed framework therefore contributes specifically to the technical dimension of sustainable distribution-network planning. Although the results are promising, the present study remains limited to technical performance

criteria and does not account for the economic factors associated with PV-DG investment, operation, maintenance, and grid integration. Future research should therefore extend the framework to incorporate comprehensive techno-economic optimisation and investigate unbalanced multi-feeder systems, real-time weather forecasting, dynamic load prediction, and machine learning-assisted optimisation.

Author Contributions: A.A. and A.D. were responsible for the conceptualisation of the study. A.A. developed the methodology and implemented the software. Validation of the results was carried out collaboratively by A.A. and A.D. A.A. performed the formal analysis and conducted the investigation. Resources were provided by A.A. and A.D., while data curation was managed by A.A. The original draft of the manuscript was prepared by A.A. and A.D., and both authors contributed to reviewing and editing the manuscript. Visualisation was carried out by A.A. A.D. supervised the project and was responsible for project administration and funding acquisition. All authors have read and agreed to the published version of the manuscript.

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