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Optimal annual solar PV penetration for improved voltage regulation and power loss reduction under uncertainty conditions

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ABSTRACT

Given their technological, economic, and environmental advantages, the widespread adoption of renewable distributed generators (RDGs) in distribution systems (DSs) is becoming more prevalent. However, solar photovoltaic distributed generators (PV-DGs) face the challenge of intermittent behavior, which results in power output fluctuations and increased grid uncertainty. Therefore, addressing these uncertainties is crucial when determining their optimal allocation. The proposed method considers uncertainties related to both load demand and solar irradiation. The model is formulated as a stochastic mixed-integer nonlinear optimization problem, which is solved using the whale optimization algorithm (WOA). The standard IEEE 33-bus system is used to validate the proposed approach, and demand variations are modeled based on the IEEE reliability test system (IEEE-RTS). The objective is to simultaneously minimize total expected voltage deviation, real power loss, and reactive power loss while increasing solar PV penetration. The technique for order of preference by similarity to the ideal solution (TOPSIS) is applied to select the best solution. Simulated results indicate significant improvements: a 19.39% reduction in voltage deviation, an 18.42% decrease in total real power loss, and an 18.53% reduction in reactive power loss compared to the base case. Additionally, the model accommodates a total of 3.206625 MW of solar PV power in the DS.

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1. INTRODUCTION

A country's economic advancement heavily relies on the pivotal role of electricity. Governments around the globe are striving to establish an affordable, sustainable, and secure electricity supply to meet the needs of modern society. For developing countries, having a sufficient and sustainable electricity supply is essential for stimulating economic growth by facilitating industrial operations and ultimately enhancing the well-being of the population. Maintaining high power quality is a primary focus for electrical utilities as it guarantees a stable supply to consumers [1], [2].

As developing countries experience rapid economic expansion, population growth, and urbanization, their overall electricity demand has significantly risen [3], [4]. It is projected that this surge in demand will contribute to approximately 90% of the total global demand growth by the year 2040. To meet this increase in electricity consumption from safe, stable, sustainable, and environmentally friendly sources, countries and companies around the world have been developing technology for producing energy from various renewable energy sources [5]. Additionally, other technical issues, economic incentives, and technological advancement have also contributed to the push toward renewable energy [6], [7].

Photovoltaic (PV) solar energy has emerged as a highly promising renewable energy source, leading to a significant increase in solar plants worldwide in recent years. This form of energy has garnered considerable attention in terms of research and funding due to its cost-effectiveness and environmental friendliness. The international renewable energy agency (IRENA) reported that the global capacity of solar energy reached 192 GW in 2022, marking a 22% year-on-year increase. Solar energy handled approximately 65% of the overall growth in global renewable energy capacity during that year, which saw a total renewable generation capacity rise of 295 GW (+9.6%) [8]. At the end of 2020, the total global installed solar PV capacity had reached 710 GW, with an additional approximately 125 GW of new solar PV capacity added in the same year [9]. During the year 2021, renewable generation capacity witnessed a growth of 257 GW (representing a 9.1% increase). The major contributor to this capacity growth was solar energy, which added 133 GW (a 19% increase), followed by wind energy with 93 GW (a 13% increase) [10]. By the end of the preceding year, the worldwide renewable generation capacity had reached 3.37 TW, with solar energy making up 1.05 TW (equivalent to 31.2% of the total capacity) [8]. Moreover, the cost of solar PV energy witnessed a remarkable decline of 82% from 2010 to 2019 [11].

While renewable energy brings many advantages in terms of economics, society, environment, and technology, the intermittent nature of certain renewable sources like wind turbines (WT) and solar PV systems introduces several obstacles to the electricity supply. These challenges include issues such as power system instability, power fluctuations, voltage regulation problems, and reduced reliability [12]. The severity of these challenges depends on factors such as the scale, planning, and penetration level [13], [14]. The intermittent nature of solar PV could limit a network's ability to connect high PV penetration built upon specific situations occurring for a few hours annually [15]. However, voltage regulation is the main challenge in distribution systems (DSS), which limits the increase of PV penetration [16], [17].

The proper allocation of distributed generations (DGs) in modern DSs plays a critical role in enhancing overall system efficiency. Consequently, determining the optimal allocation of DG units is a crucial aspect of DG integration planning [18]. By appropriately identifying the size and placement of DGs in the DS, various performance factors like voltage profile, power loss reduction, and voltage stability can be improved [19]. In the literature review, numerous analytical techniques have been suggested for identifying the most optimal size and placement of DG, based on algebraic expressions. These methods can handle single objective functions, such as voltage improvement or power loss reduction [20], [21], or multi-objective functions, for instance, power loss and voltage profile [22], [23]. While analytical methods offer a comprehensive understanding of the system's behavior, they may not always provide the optimal solution. Hence, many studies have focused on optimizing DG planning considering real power loss [24], [25] the real power with voltage profile improvement [26], [27], real and reactive power losses [28], voltage profile, real power loss, and reactive power loss [29]. However, these studies were limited to the integration of DGs at a constant peak load, limiting their applicability. To reflect real-world scenarios in renewable distributed generators (RDGs) systems, it is essential to consider the use of probabilistic intermittent solar PV with time-varying load demand. Some studies have examined the implementation of probabilistic intermittent solar PV systems with varying load demands using analytical methods.

The objective of these studies was to optimize specific objective functions, for instance, minimizing power loss through the integration of wind energy [30], [31], or incorporating a combination of wind power, solar PV, and biomass individually or in combination [18]. However, dedicating a PV unit solely to minimize active or reactive power loss might restrict the extent of PV penetration. The DG optimal planning was performed using evolutionary programming (EP) to mitigate voltage violations, but it could lead to high system losses if a DG was designated solely for minimizing voltage deviation [32]. As a result, researchers have introduced multi-objective analytical techniques aimed at mitigating power losses and voltage profile deviations using various time-varying voltage-dependent load models [23], [33]. To obtain an optimal solution, optimization algorithms must be used to identify the optimal placement and size of DG units that maximize voltage regulation and minimize power losses throughout the year. In this study, the whale optimization algorithm (WOA) is applied to achieve the highest solar PV integration for voltage regulation and minimizing power losses in the IEEE 33-bus system.

This paper presents the following contributions and innovations: i) The study addresses a crucial aspect of the solar photovoltaic distributed generator (PV-DG) allocation problem by incorporating the uncertainties that arise from both load demand and solar irradiation; and ii) The allocation problem is effectively solved by considering multi-objective functions including real power loss, reactive power loss, and voltage deviation. The article's structure is as follows: i) Section 2 describes the methodological approach used for modeling dynamic load profiles and solar PV profiles and defines the problem; ii) Section 4 is dedicated to presenting and discussing the study's findings; and iii) In the end, the conclusions drawn from the research and recommendations for future studies are summarized in section 5.

2. METHOD

The proposed method addresses a stochastic problem concerning the optimal allocation of PV-DGs in balanced radial DSs. The optimization algorithms consider the uncertainties associated with PV-DGs and load demand to represent a realistic PV-DG allocation. The optimization objectives encompass voltage deviation, real power loss, and reactive power loss to achieve an optimal PV-DG allocation. The simulated DG is a solar-based renewable energy source that supplies only real power; therefore, it is presumed that the DG operates at a power factor of unity.

2.1. Probabilistic modeling of solar power

The Beta PDF in (1) was utilized to model solar irradiance, considering historical data spanning three years. To accommodate daily variations, each day was divided into 24 hours, with each hour having its specific solar irradiance PDF. The shape (β) and scale (α) parameters of the Beta PDF were computed for each hour, utilizing the mean (μ) and standard deviation (σ) obtained from historical data, as outlined in (2) and (3) [34]. To represent the variations in the solar irradiance, each hour was subdivided into 20 scenarios, with a step size of 0.05 kW/m², representing varying solar radiation levels. By using the determined mean and standard deviation, a PDF for solar irradiance was generated for each of the 20 scenarios within every hour, along with the associated probabilities for each scenario of solar radiation. Based on these PDFs, the PV output power was determined for each hour [35].

$$f(S) = \begin{cases} \frac{\Gamma(\beta+\alpha)}{\Gamma(\beta)\Gamma(\alpha)} S^{(\alpha-1)}(1-S)^{(\beta-1)}, for\ 0 \le S \le 1, \beta \ge 0 \\ 0, Otherwise \end{cases} \tag{1}$$

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

$$\alpha = \frac{(\beta \times \mu)}{1-\mu} \tag{3}$$

The probability for a specific solar irradiance scenario (s) during any hour can be calculated using (4). The output power generated by a solar PV module from (4) is subject to several factors, such as ambient temperature, solar irradiance, and PV module specifications. To represent the maximum power output from the PV module under a specific solar irradiance level (S) (6)-(9) can be employed. Additionally, the average output power, representing the total expected output power of a solar PV module over a specified period (t), denoted as $PV(t)$ (where t = 1 h), can be derived utilizing (1), (4), and (5) as in (10) and (11).

$$P_s\{G\} = \int_{S_1}^{S_2} f(S)\, ds \tag{4}$$

$$PV_{\circ}(S) = N \times FF \times V_y \times I_y \tag{5}$$

$$FF = \frac{V_{mpp} \times I_{mpp}}{V_{oc} \times I_{sc}} \tag{6}$$

$$I_y = S\left[I_{sc} + K_i \times \left(T_{cy} - 25\right)\right] \tag{7}$$

$$V_y = V_{oc} - K_v \times T_{cy} \tag{8}$$

$$T_{cy} = T_a + S\left(\frac{N_{OT}-20}{0.8}\right) \tag{9}$$

$$PV(S) = PV_{\circ}(S) \times f(S) \tag{10}$$

$$PV(t) = \int_0^1 PV(S) \times P_S \{G\} ds \tag{11}$$

The number of PV modules is denoted as N. Cell temperature and ambient temperature are denoted by Tcy and TA respectively. The voltage and current coefficients are denoted by Ki and Kv respectively. Nominal operating temperature is denoted by NOT.

2.2. Load demand modeling

Due to the inherent uncertainty in load demand fluctuations over time, the uncertainty of load demand at each bus D_i (MVA) is represented using a normal PDF ($f(D_i)$, as shown in (12). The mean μ (MVA) and standard deviation σ (MVA) follow the IEEE reliability test system (IEEE-RTS) standards, as outlined in Figure 1 [36]. This approach is used in the absence of a standardized dynamic load profile for the typical IEEE distribution system and has been extensively applied in previous studies, such as [35]. As illustrated in Figure 1, the load curve represents four distinct 24-hour periods (96 hours) corresponding to the four seasons.

$$f(D_i) = \frac{1}{\sigma_i^S \times \sqrt{2\pi}} exp\left[-\frac{(D_i - \mu_i^S)^2}{2(\sigma_i^S)^2}\right] \tag{12}$$

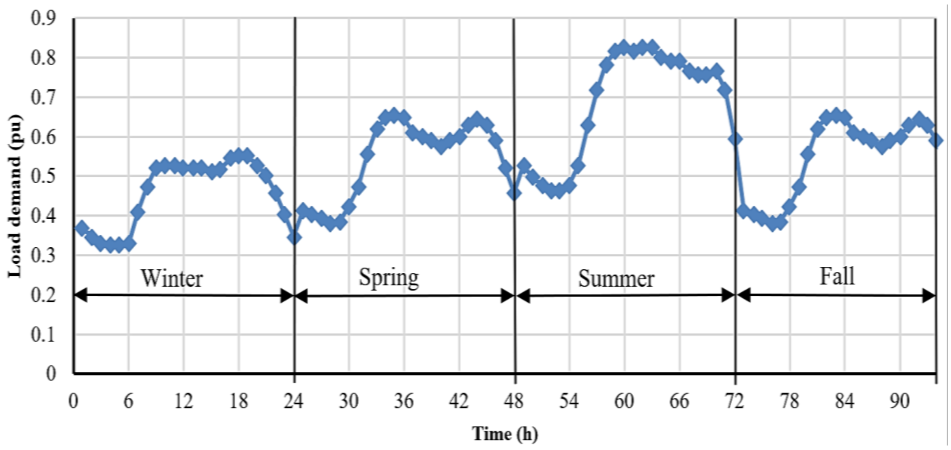

Figure 1. IEEE 33-bus system dynamic load profile following the IEEE-RTS load pattern

2.3. Problem formulation

If a DG unit is specifically allocated to minimize either active or reactive power loss, it may cause limitations on PV penetration due to high voltage deviations. On the other hand, if a PV unit is solely designated to minimize the voltage deviations, it may allow for high penetration levels but could lead to increased system losses [23]. To address these challenges, a multi-objective function (MOF) can be utilized, combining voltage deviation, active power loss, and reactive power loss.

2.3.1. Objective functions

The model is structured as a stochastic mixed-integer nonlinear multi-objective optimization problem, as depicted in (13). The fitness function includes three components: total voltage deviation (f_1), total real power loss (f_2), and total reactive power loss (f_3). These objectives are important in DS operation and planning, as they relate to the quality of power supply, system efficiency, and stability.

Total voltage deviation, as in (13), is a measure of the deviation of the voltage magnitude from its nominal value, which can affect the performance of electrical equipment and the quality of the power supply. The total expected real power loss is a measure of the energy wasted due to the flow of current through the transmission lines, as in (14), which can lead to inefficiencies and increased costs. The total expected reactive power loss is a measure of the power required to maintain the voltage levels in the power system, as in (15), which can also affect the efficiency and stability of the system.

$$F = min(f_1, f_2, f_3) \tag{13}$$

$$f_1 = \sum_{s=1}^{S} \sum_{t=1}^{T} \sum_{n=1}^{NB} \left| V_{ref} - V_{n,t,s} \right| \tag{14}$$

$$f_2 = \sum_{s=1}^{S} \sum_{t=1}^{T} \sum_{\substack{i=1 \\ i \neq j}}^{NB} \frac{P_{(i,j),t,s}^2 + Q_{(i,j),t,s}^2}{V_{(i,j),t,s}^2} \times \left(R_{(i,j),t,s}\right) \tag{15}$$

$$f_3 = \sum_{s=1}^{S} \sum_{t=1}^{T} \sum_{\substack{i=1 \\ i \neq j}}^{NB} \frac{P_{(i,j),t,s}^2 + Q_{(i,j),t,s}^2}{V_{(i,j),t,s}^2} \times \left(X_{(i,j),t,s}\right) \tag{16}$$

V_{ref} and $V_{n,t,s}$ are the reference (or nominal) voltage and actual voltage, respectively. P_{i+i} and Q_{i+i} denote the receiving real and reactive power flow, respectively.

2.3.2. Constraints

During the optimization process for this study, both equality and inequality constraints were considered. These constraints include the power flow equations, (16) and (17), maximum power transfer in each branch (18), and maximum DG allocation in the DS (19).

$$PG_{i,t,s} - PD_{i,t,s} = \\ \sum_{\substack{i \in NB \\ i \neq j}} \left(V_{i,t,s}^2 \times G_{(i,j)} - V_{i,t,s} \times V_{j,t,s}\left(G_{(i,j)} \cos \delta_{(i,j),t,s} + B_{(i,j)} \sin \delta_{(i,j),t,s}\right)\right) \tag{17}$$

$$QG_{i,t,s} - QD_{i,t,s} = \\ \sum_{\substack{i \in NB \\ i \neq j}} \left(-V_{i,t,s}^2 \times B_{(i,j)} - V_{i,t,s} \times V_{j,t,s}\left(G_{(i,j)} \sin \delta_{(i,j),t,s} - B_{(i,j)} \cos \delta_{(i,j),t,s}\right)\right) \tag{18}$$

$$\sqrt{P_{(i,j),t,s} + Q_{(i,j),t,s}} \leq S_{(i,j),t,s}^{Max} \tag{19}$$

$$\begin{cases} \kappa \in \{0,1\} \\ NPV = \sum_{n=1}^{NB} \kappa \\ NPV \leq N^{Max} \end{cases} \tag{20}$$

Where (κ) is a binary number to identify the availability of PV-DGs at each bus. NPV and N^{Max} represent the number and maximum number of PV-DG locations in the DS.

2.3.3. Solving method

The optimization issue is formulated as a mixed integer nonlinear programming: multi-objective function to simultaneously voltage deviation, active power loss, and reactive power loss. The technique for ranking preference by similarity to the ideal solution (TOPSIS) is employed to select the optimal solution from a set of non-dominated solutions. TOPSIS is a multi-criteria decision-making method that can rank solutions in multi-objective optimization problems. This technique is applied at the end of each iteration to the optimal set of objective functions. The steps for applying TOPSIS to choose the optimal solution from a set of non-dominated solutions are illustrated in [37]. The optimization problem was solved by utilizing the WOA. The WOA consists of a pair of main phases: exploration and exploitation. During the exploitation phase, the algorithm uses two methods to update the search agent's position: the prey-encircling technique, which is represented by (21)-(25), and the spiral bubble-net attacking technique, represented by (26). Both techniques utilize the location of the best search agent to update the current agent's position. However, the spiral bubble-net attacking technique introduces an element of randomness, which allows for exploration. This randomness is reflected in (26). In the exploration phase, a random search is conducted, and the position of the current search agent is updated based on a randomly generated search agent. This behavior is mathematically represented by (27) and (28). By combining both exploitation and exploration techniques, the WOA algorithm can optimize search algorithms effectively. The flowchart in Figure 2 illustrates the overall methodology for applying the WOA to solve the formulated optimization problem.

$$\varepsilon_{dis} = C \times pop_{best} - pop(t) \tag{21}$$

$$pop(t+1) = pop_{best} - A \times \varepsilon_{dis} \tag{22}$$

$$A = 2 \times \alpha \times g - \alpha \tag{23}$$

$$C = 2 \times g \tag{24}$$

$$\alpha = 2 - t \times \frac{2}{iter_{max}} \tag{25}$$

$$pop(t+1) = D' \times e^{bl} \times cos(\pi l) + pop_{best}(t) \quad (26)$$

$$\varepsilon_{dis} = C \times pop_{rand} - pop \quad (27)$$

$$pop(t+1) = pop_{rand} - (A \times \varepsilon_{dis}) \quad (28)$$

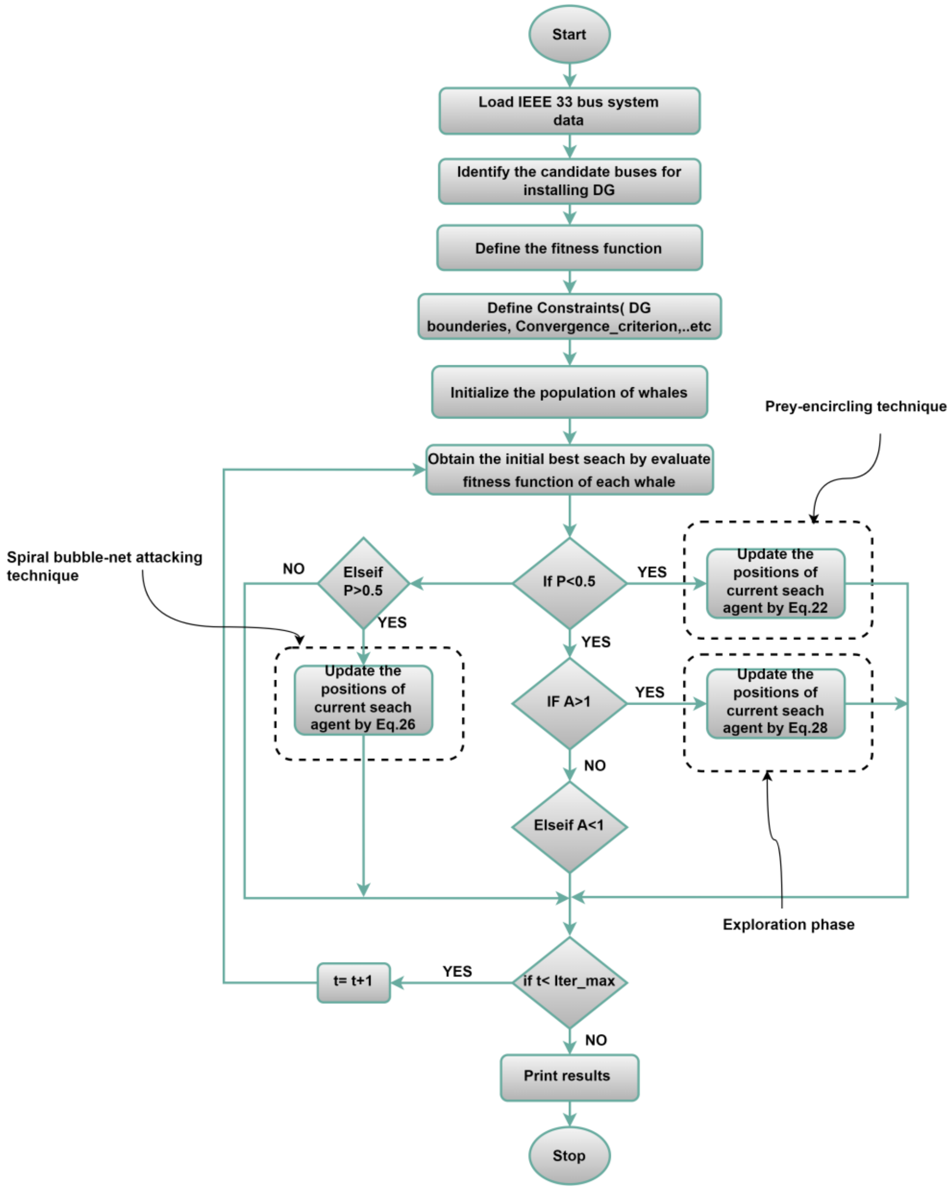

Figure 2. Flow chart for the optimization process

3. RESULTS AND DISCUSSION
3.1. Input data

The satellite weather data for three years (2017-2019) for a specific location in Seiyun, Hadramout, Yemen (coordinates 15.9495° N, 48.8096° E) was obtained from the national solar radiation database (NSRD) [38]. The data was divided into four seasons, each representing the aggregated data for three months. Using probabilistic modeling, the seasonal data was then converted into a daily representation by converting the three-month seasonal data into equivalent 24 samples. The final dataset consists of 4×24=96 samples. In the winter and spring seasons, solar irradiation begins between the 6th and 18th hour of the day, while in the summer and fall seasons, it begins between the 7th and 18th hour. The maximum solar irradiance recorded during winter reaches 1128 W/m^2, whereas in fall, the maximum value is lower at 765 W/m^2. The project site receives an average of 4.5 to 8.4 peak sunny hours throughout the year. Beta PDF values for 20 states of solar irradiance at three specific hours (8, 12, and 16) for each season are plotted in Figure 3(a) for winter, Figure 3(b) for spring, Figure 3(c) for summer, and Figure 3(d) for fall.

Utilizing the seasonal daily irradiance and seasonal average temperature, the expected hourly PV module output for each season is computed and represented in Figure 4(a). Additionally, a normalized curve for the expected daily PV output for each season is illustrated in Figure 4(b). For this study, the Trina 250 W PV module was specifically chosen. The technical specifications for this module can be found in Table 1 [39]. The PV module's output potential indicates that it can generate approximately 202.13 W in winter, 193.22 W in spring, 196.13 W in summer, and 187.48 W in fall. Remarkably, regardless of the season, the PV module attains its maximum output at the 12th hour, which signifies the peak performance period.

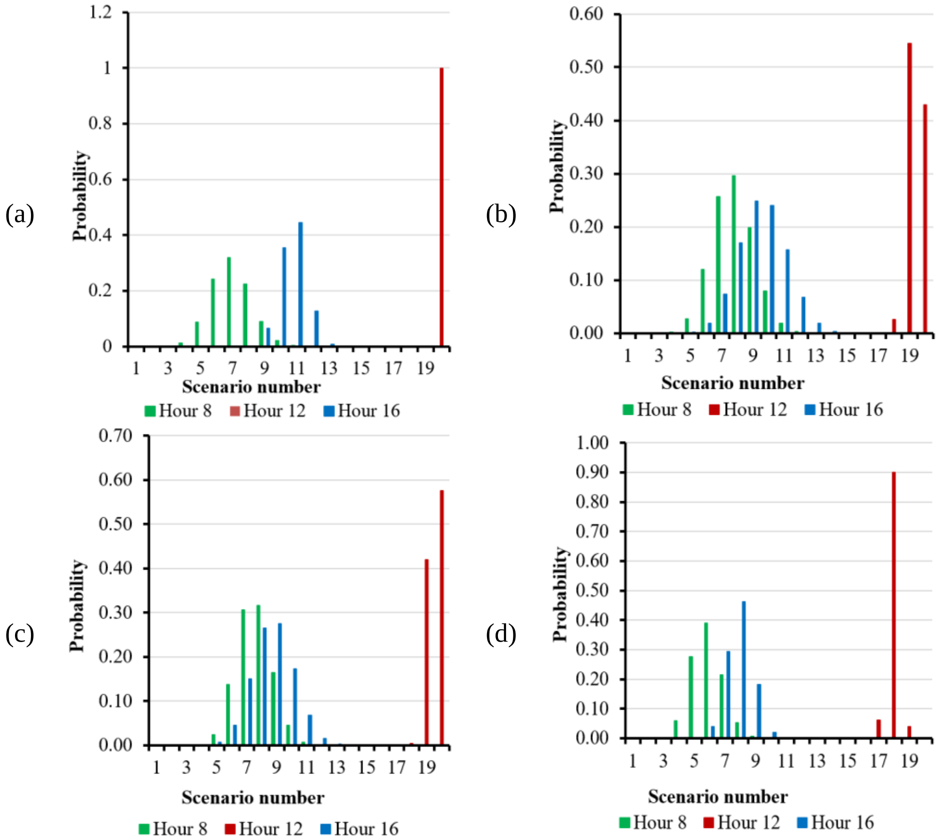

Figure 3. Solar irradiance probability for (a) winter, (b) spring, (c) summer, and (d) fall

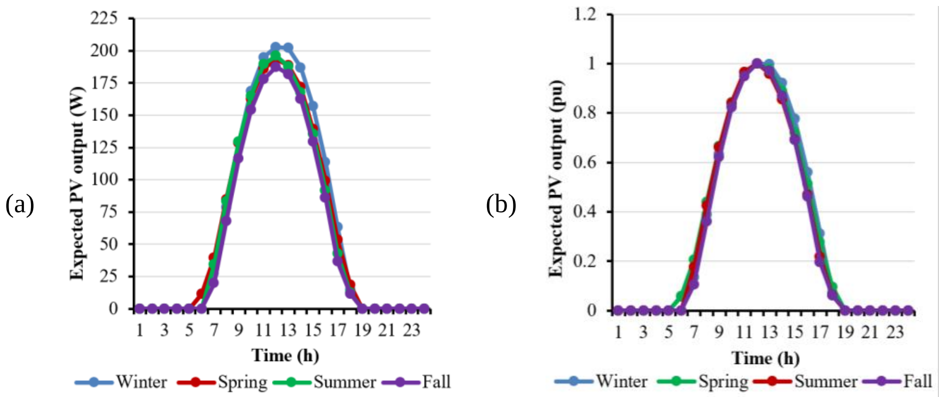

Figure 4. Output of the chosen PV module (a) expected output and (b) normalized output

Table 1. Solar PV module specifications

Characteristics	Value	Characteristics	Value
Vmpp (V)	30.0	NOCT (℃)	44
Impp (A)	8.34	Ki (A/℃)	0.00448
Voc (V)	37.5	Kv (V/℃)	0.12
Isc (A)	8.97		

3.2. Case studies

To validate the results obtained for the proposed model, a comparison of results has been conducted for the following case studies: i) Case I: probabilistic power flow (PLF) of the base case without PV-DGs installation; and ii) Case II: PLF incorporates optimal placement of PV-DGS while accounting for two key uncertainties: variations in load demand and fluctuations in solar radiation levels.

3.3. Numerical results

3.3.1. Objective functions

The optimal PV-DGs are strategically installed to minimize three key objective functions simultaneously, encompassing total voltage deviation, real power loss, and reactive power loss. In the base case, the pre-installation power flow analysis reveals a total voltage deviation of 96.16 pu, real power loss of 7.38 MW, and reactive power loss of 7.91 MVAR. Upon the installation of the optimal PV-DGs, a notable decrease is observed across all objective functions. Specifically, the optimal PV-DGs result in a total voltage deviation reduction of 77.50 pu, real power loss of 6.02 MW, and reactive power loss of 4.0 MVAR, as presented in Table 2. This reduction in objective functions signifies a substantial improvement, with voltage deviation reduced by 19.39%, real power loss by 18.42%, and reactive power loss by 18.53%.

Table 2. Optimal objective function

Objective function	Case I	Case II
f_1 (pu)	96.16	77.5091
f_2 (MW)	7.38	6.020
f_3 (MVAR)	4.91	4.00

3.3.2. Optimal PV-DG allocation

This study seeks to advance the penetration level of PV in the DS while reducing the objective functions. The optimal sites, aggregate capacity, and recommended number of PV modules are outlined in Table 3. The optimal sites for PV-DGs are limited to 10 locations as stated in (18). The aggregate optimal capacity of PV-DGs is 3.206625 MW installed at different points within the DS. The largest installation is at bus 30 with capacity of 1.65175 MW. It's worth mentioning that the maximum power of the PV panels used in this research is 250 W.

Table 3. Optimal location and sizing of PV-DGs in IEEE 33-bus DS

Location (Bus)	Size (MW)	Number of PV modules	Location (Bus)	Size (MW)	Number of PV modules
27	0.208	832	25	0.027975	112
10	0.42575	1703	3	0.50575	2023
24	0.2055	822	21	0.007125	29
30	1.65175	6607	20	0.051	204
28	0.062225	249	16	0.06155	246

3.3.3. Voltage profile

The voltage profiles of the test system in each season without PV-DGs are depicted in Figure 5(a) for winter, Figure 5(b) for spring, Figure 5(c) for summer, and Figure 5(d) for fall. Across all seasons, certain buses, such as Bus 10-18 and Bus 29-33, experience voltage issues. The most severe undervoltage problems are observed during the summer season due to the heightened demand. It is noteworthy that IEEE standard limits for bus voltages, with a maximum of 1.05 pu and a minimum of 0.95 pu, are considered to identify undervoltage and overvoltage issues in the system. With the installation of optimal PV-DGs, the voltage profiles during all seasons are significantly improved, as depicted in Figure 6(a) for winter, Figure 6(b) for spring, Figure 6(c) for summer, and Figure 6(d) for fall. However, during high-demand hours in the summer and fall seasons, certain buses still experience under-voltage issues.

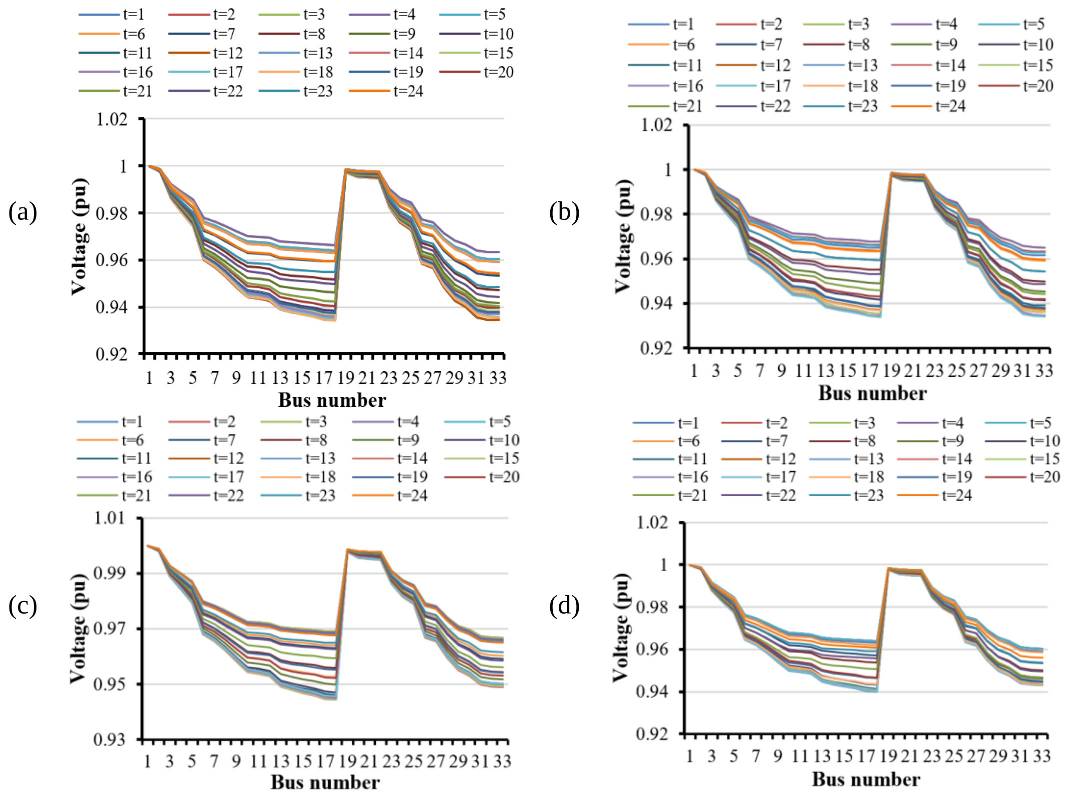

Figure 5. Bus voltage profile without PV-DGs for (a) summer, (b) fall, (c) spring, and (d) winter

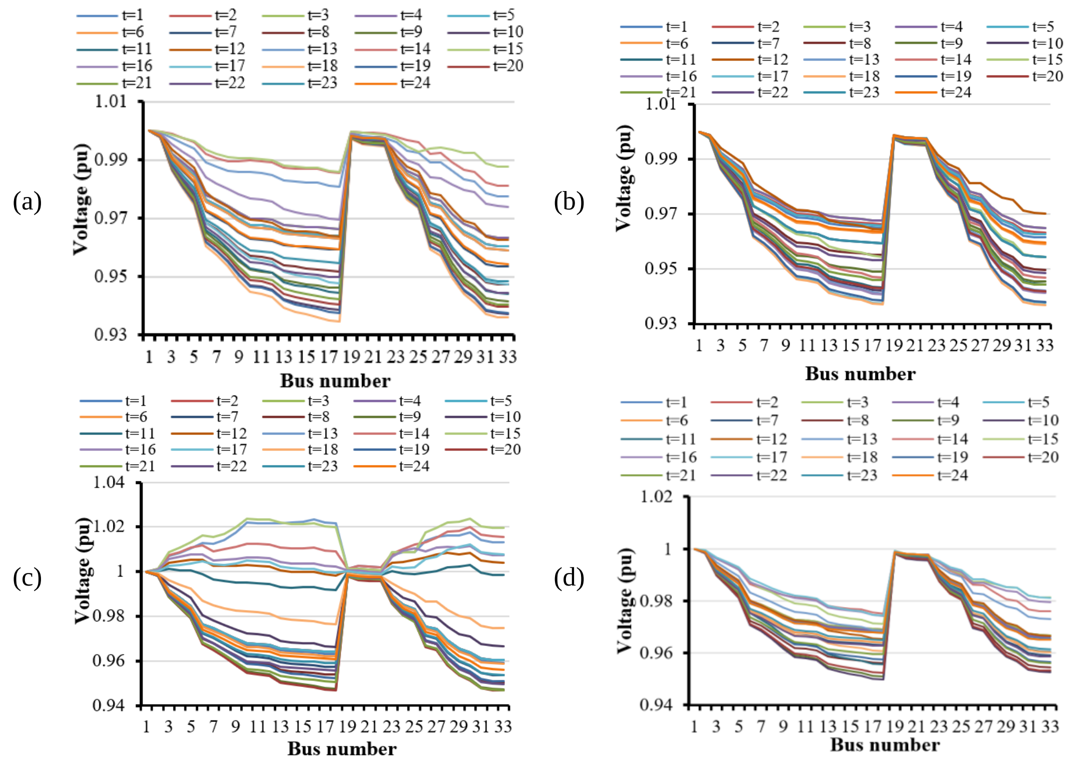

Figure 6. Bus voltage profile with optimal PV-DGs for (a) summer, (b) fall, (c) spring, and (d) winter

3.3.4. Power loss

Table 4 presents the power loss observed in each season both with and without the installation of PV-DGs. The optimal installation of PV-DGs significantly improves both real and reactive power loss across all seasons. Particularly noteworthy is the pronounced reduction in losses during winter, attributed to the heightened solar irradiation characteristic of that season. The percentage of power loss reduction is contingent upon the solar irradiation level throughout each hour, as well as the alignment between load demand and solar PV generation. Superior alignment yields significant reductions in power loss, whereas mismatched alignment results in increased losses.

Table 4. Seasonal optimal power loss

Season	Real power loss (MW)		Reactive power loss (MVAR)	
	Without PV-DGs	With PV-DGs	Without PV-DGs	With PV-DGs
Summer	2.145677	1.580964	1.428414	1.060132
Fall	2.02042	1.72368	1.344896	1.152238
Spring	1.815257	1.747514	1.208345	1.144874
Winter	1.406003	0.968089	0.935847	0.650654

4. CONCLUSION

The research proposes a planning model for determining the best sizes and distribution of PV-DGs in DS. The approach is structured as a probabilistic mixed-integer nonlinear multi-criteria optimization problem. The goal is to enhance the integration level of PV systems in the DS while concurrently reducing three target metrics: voltage deviations, active power loss, and reactive power loss. The proposed model incorporates variabilities linked with solar radiation and load demand. The WOA is implemented to address the constructed model. The formulated model optimally integrates a solar PV output of 3.206625 MW. Moreover, it reduces voltage deviation by 19.39%, real power loss by 18.42%, and reactive power loss by 18.53%. The model demonstrates varying levels of power loss reduction across seasons, with the highest recorded in winter due to increased solar irradiation. Additionally, the voltage profile improves significantly across all seasons. However, under-voltage issues persist in some buses due to mismatches between load and solar PV generation, hindering maximum power loss reduction. Future research could focus on optimal demand response program (DRP) scheduling in DS that incorporates PV-DG placement to offer further improvements in power loss and voltage deviations by better aligning the load profile with PV generation patterns.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Sanjeevikumar Padmanaban	✓						✓			✓		✓		✓

C : **C**onceptualization
M : **M**ethodology
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Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

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

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