A Hybrid Metaheuristic Approach for Optimal PV Placement and Sizing in Distribution Networks

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***Abstract*—Integrating renewable energy sources into distribution networks can improve operational efficiency and reduce power losses. This study proposes a hybrid optimization method combining Archimedes Optimization Algorithm (AOA), Football Team Training Optimization Algorithm (FFTOA), Teaching-Learning Based Optimization Algorithm (TLBOA), and Starfish Optimization Algorithm (SFOA) to determine the optimal placement and sizing of photovoltaic units. The hybrid strategy enhances the original AOA by improving convergence speed and reducing the risk of local optima. FTTOA with Fitness Distance Balance helps select better guiding solutions, TLBOA supports information sharing and population diversity, and SFOA strengthens exploration and solution regeneration. A Beta distribution is used to model solar irradiance uncertainty. The proposed method is tested on the IEEE 33-bus distribution system for PV allocation. Results show that PV integration improves voltage profiles and reduces energy losses. Compared with other methods, the proposed approach achieves competitive performance and improved stability while maintaining reasonable computational cost.**

Keywords- Beta distribution; Distribution system planning; Hybrid optimization algorithm; PV optimal placement; Renewable energy integration.

I. INTRODUCTION

The global transition toward sustainable energy has led to a rapid increase in the integration of renewable energy sources into power distribution networks [1]. Among these, photovoltaic (PV) systems have attracted significant attention due to their scalability, environmental benefits, and decreasing installation costs. However, the intermittent and stochastic nature of solar energy introduces considerable operational challenges for traditional radial distribution systems, including voltage instability, reverse power flows, and increased network losses [2]–[5]. These issues tend to become more significant as more PV systems are integrated into the network.

One of the key challenges in integrating PV into distribution networks is the uncertainty of solar irradiance. The reason is that the output power of PV systems is highly dependent on solar irradiance, which varies with weather conditions and time [6]. Hence, in the planning process, this uncertainty should be taken into account. To address this issue, probabilistic approaches should be implemented. Among them, the Beta probability distribution function is widely used due to its flexibility in capturing different uncertainty patterns within a bounded range [7]. By assuming identical α and β parameters across nodes, the variability of PV generation can be modeled in a simplified yet effective manner, preserving its essential characteristics while keeping the optimization problem more tractable.

In this context, the placement and sizing of PV units strongly affect the performance and cost of the distribution system. In practice, the planning problem often aims to minimize power losses while maintaining acceptable voltage levels and satisfying operational constraints. Improper allocation can increase system losses and lead to voltage issues, overload on lines, whereas proper integration helps improve voltage profiles and overall system performance [8]. However, this optimization problem is complex. It involves non-linear power flow relationships, multiple operational constraints, and the stochastic nature of PV generation. When these factors are considered together, the problem becomes highly complex [9].

To address these challenges, meta-heuristic algorithms such as Particle Swarm Optimization (PSO), Differential Evolution (DE), Genetic Algorithm (GA), and other recent methods are widely used because they can explore complex search spaces without gradient information [10–19]. However, each algorithm has limitations. Some provide strong exploration but converge slowly, while others converge quickly but may get trapped in local optima. Among them, the Archimedes Optimization Algorithm (AOA) performs well due to its balance between exploration and exploitation [10]–[13]. However, it may still suffer from premature convergence, especially in large constrained problems. Similarly, the Teaching-Learning-Based Optimization Algorithm (TLBOA) has strong local search ability but may lose diversity [15]. The Football Team Training Optimization Algorithm (FTTOA) improves exploration but can be unstable [14], while the Starfish Optimization Algorithm (SFOA) is robust in global search but may converge slowly in later stages [16].

To overcome these limitations, this paper proposes a novel hybrid optimization algorithm that integrates the strengths of multiple meta-heuristic techniques, including AOA, TLBOA, FTTOA, and SFOA. The hybridization strategy is designed to enhance both exploration and exploitation capabilities, improve convergence speed, and increase solution accuracy. By combining these algorithms, the proposed method aims to provide a more robust and efficient solution for the optimal placement and sizing of PV systems under stochastic conditions modeled with the Beta distribution, thereby minimizing energy loss in the grid. The effectiveness of the method is validated using the IEEE 33-bus sample distribution grid. Ruse and compare to conventional approaches in terms of convergence behavior and solution quality.

II. Optimal mathematical model

A. Photovoltaic power modeling

In photovoltaic (PV) power modeling, solar irradiance G is a key random variable that directly affects the output power. Due to its variability and bounded nature, the normalized irradiance can be modeled using a Beta distribution defined over the interval [0, 1]. Let G denote the solar irradiance normalized by its maximum value G_{max}, i.e., G∈[0,1].

The probability density function (PDF) of G is given [7]

$$f(G) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} G^{\alpha-1}(1-G)^{\beta-1}, \quad (1)$$

where α and β are estimated from historical irradiance data. This model PV generation uncertainty for analysis and forecasting. For the discretized irradiance G_s, each probability is calculated based on the interval width ΔG as

$$\wp_s = \int_{G_s-\Delta G}^{G_s+\Delta G} f(G)\, dG, \quad (2)$$

For uniform discretization, it can be approximated by:

$$\wp_s \approx f(G_s).\Delta G. \quad (3)$$

The PV output power P_{PV} corresponding to G_s can then be approximated as a function of irradiance, the rated power of PV P_{rated}, and the standard irradiance G_{std}, typically 1000 W/m^2:

$$P_{PV}^{(s)} = P_{rated} \frac{G_s.G_{max}}{G_{std}}. \quad (4)$$

B. Objective function

Suppose that in the distribution grid, α and β are supposed to be identical and simultaneous at all nodes. By integration of PV-based DGs in the grid, at the irradiance G_s, the power loss in the grid is denoted by $\Delta P^{(s)}$ and the annual energy loss in the grid over daylight hours (T) is calculated

$$\Delta E = \sum_{s=1}^{s_{max}} \Delta P^{(s)} \times \wp_s \times T. \quad (5)$$

The annual energy loss is obtained by summing the expected energy losses over both daytime and non-daytime periods. Noted that for the distribution grid, the Back/Forward swept algorithm is used for power flow calculations, and then the annual energy loss can be obtained.

The main objective of this research is to determine the optimal position of PV-based DG (l_i) and its size ($P_{PV,i}$) to minimize the annual energy loss in the grid. Hence, the optimal problem is defined as

$$\Delta E = f(l_i, P_{PV,i}) \rightarrow min \quad (6)$$

Constraints

$$\begin{cases} 1 \le l_i \le l_{max} \\ P_{min} \le P_{PV,i} \le P_{max} \\ I_{jk} \le I_{jk,max} \\ U_{min} \le U_j \le U_{max} \end{cases} \quad (7)$$

where l_{max} is the maximum index of possible installation locations in the network; P_{min} and P_{max} is the minimum and maximum size of PV at the node l_i; $I_{jk,max}$ is the capacity of the line between the j^{th} and k^{th} node; U_{min} and U_{max} are the boundaries of voltage at nodes.

III. Proposal of a new algorithm for optimization

In recent years, many metaheuristic algorithms have been developed, each with its own strengths in solving optimization problems. For example, AOA provides a dynamic search mechanism, TLBOA is simple and effective with strong exploitation ability, SFOA offers a balanced hybrid search strategy, and FTTOA introduces diverse interactions to enhance population diversity. Motivated by these complementary advantages, this section proposes a new hybrid optimization algorithm. First, the main solution update mechanisms of these algorithms are briefly reviewed, followed by the development of a hybrid strategy that combines their strengths to achieve better performance.

A. Review of Solution Update Mechanisms

In this subsection, a brief update mechanism used in algorithms is summarized. Here, $r_1, r_2, \dots, r_{15}$ are independent random numbers uniformly distributed in [0,1]; $\mathbf{x}_r, \mathbf{x}_j$, and $\mathbf{x}_k$ are randomly selected in the population, while $\mathbf{x}_{best}$ denotes the best particle in the population, t stands for the iteration.

1) Archimedes Optimization Algorithm – AOA: The Archimedes Optimization Algorithm (AOA) is a physics-based metaheuristic for solving optimization problems [13]. It draws inspiration from Archimedes' principle of buoyancy, simulating how objects adjust their volume and density in water to reach equilibrium. AOA uses a group of candidate solutions that change over time through stages similar to objects sinking in a liquid. Each object updates its density and volume using equations that involve transfer functions, acceleration, and iteration progress, as detailed in [13]. In this algorithm, at the iteration t, the particle $\boldsymbol{x}_i$ is updated based on threshold TF [13]

$$\begin{cases} \boldsymbol{x}_i^{t+1} = \boldsymbol{x}_i^t + C_1.r_1 \cdot \boldsymbol{a}_i^t(\boldsymbol{x}_r^t - \boldsymbol{x}_i^t) \quad if \quad r_2 \le TF \\ \boldsymbol{x}_i^{t+1} = \boldsymbol{x}_i^t + C_2.r_3 \cdot \boldsymbol{a}_i^t(\boldsymbol{T}.\boldsymbol{x}_{best}^t - \boldsymbol{x}_i^t) \quad else \end{cases} \quad (8)$$

where $\boldsymbol{a}_i$ is the acceleration of $\mathbf{x}_i$, C_1 and C_2 are predefined constants. This mechanism enables a dynamic balance between exploration and exploitation via the transfer function, thereby facilitating control of the search process.

2) Football Team Training Optimization Algorithm (FTTOA)

Football Team Training Optimization Algorithm (FTTOA): The mathematical model of the FTTOA proposed in [14] contains an initialization phase, a collective training phase, a group training phase, and an individual extra training phase. In the collective training phase, the FTTOA randomizes agents into four categories: followers, discoverers, thinkers, and volatilities. The mechanism of particle update corresponding to the categories is described as (9), where $\mathbf{x}_{worst}$ is the worst particle in the population, and $T(t)$ is a time-varying perturbation factor. The diversity of roles enhances population diversity and helps avoid premature convergence.

$$\begin{cases} \boldsymbol{x}_i^{t+1} = \boldsymbol{x}_i^t + r_4.(\boldsymbol{x}_{best}^t - \boldsymbol{x}_i^t) \\ \boldsymbol{x}_i^{t+1} = \boldsymbol{x}_i^t + r_5.(\boldsymbol{x}_{best}^t - \boldsymbol{x}_i^t) - r_6 \cdot (\boldsymbol{x}_{worst}^t - \boldsymbol{x}_i^t) \\ \boldsymbol{x}_i^{t+1} = \boldsymbol{x}_i^t + r_7.(\boldsymbol{x}_{best}^t - \boldsymbol{x}_{worst}^t) \\ \boldsymbol{x}_i^{t+1} = \boldsymbol{x}_i^t.(1 + T(t)) \end{cases} \quad (9)$$

3) Teaching- Learning Based Optimization Algorithm (TLBOA): This optimization method is based on the influence of a teacher on learners' performance in a class. TLBOA consists of two phases: the "Teacher phase" and the "Learner phase". The Teacher phase represents learning from the teacher, while the Learner phase represents learning through interactions among learners [15]. In the Teacher phase, the main objective is to increase the learners' mean knowledge level. In the Learner phase, two learners are randomly selected from the population, as in (10). The learner with poorer knowledge moves toward the better learner, while the better learner explores new regions in the search direction, as in (11).

$$\boldsymbol{x}_i^{t+1} = \boldsymbol{x}_i^t + r_8.\left(\boldsymbol{x}_{best}^t - TF.\overline{\boldsymbol{x}}^t\right) \quad (10)$$

$$\boldsymbol{x}_i^{t+1} = \boldsymbol{x}_i^t + r_9.(\boldsymbol{x}_i^t - \boldsymbol{x}_r^t)sign(f(\boldsymbol{x}_r^t) - f(\boldsymbol{x}_i^t)) \quad (11)$$

where TF is a teaching factor. This strategy provides strong exploitation with a simple structure and no algorithm-specific parameters.

4) Starfish Optimization Algorithm (SFOA): The Starfish Optimization Algorithm (SFOA) is developed based on simulating the characteristic behaviors of starfish in nature, including multi-dimensional (D) updates (five arms), predatory behavior, and regenerative ability [16]. According to [16], the exploration phase and exploitation phase are written (12) and (13), respectively.

$$\begin{cases} \boldsymbol{x}_i^{new} = \boldsymbol{E_t}\boldsymbol{x}_i^t + r_{11}(\boldsymbol{x}_r^t - \boldsymbol{x}_i^t) + r_{12}(\boldsymbol{x}_{best}^t - \boldsymbol{x}_i^t) \; as \; D > 5 \\ \boldsymbol{x}_i^{new} = \boldsymbol{x}_i^t \mp r_{13}.(\boldsymbol{x}_k^t - \boldsymbol{x}_i^t), k \in D \quad as \; D < 5 \end{cases} \quad (12)$$

$$\boldsymbol{x}_i^{new} = \boldsymbol{x}_i^t + r_{14}(\boldsymbol{x}_{best}^t - \boldsymbol{x}_k^t) - r_{15}\left(\boldsymbol{x}_r^t - \boldsymbol{x}_j^t\right), k \in D \quad (13)$$

The hybrid search mechanism improves both global exploration and local refinement.

From the above analysis, it can be observed that each algorithm has its own strengths. AOA provides a dynamic search transition, TLBOA offers efficient exploitation, SFOA introduces a balanced hybrid search mechanism, and FTTOA enhances diversity through multiple interaction strategies. However, none of them can individually fully balance exploration and exploitation in all cases. Therefore, combining these complementary mechanisms is expected to improve the overall optimization performance.

B. Proposed Hybrid Optimization Algorithm

This section proposes a new algorithm to solve the optimization problem defined in (6)–(7). The problem can be formulated as follows:

$$\Delta E = f(\boldsymbol{x}) \rightarrow min \quad (14)$$

Subject to

$$\boldsymbol{lb} \leq \boldsymbol{x} \leq \boldsymbol{ub} \quad (15)$$

where the decision vector is defined as:

$$\boldsymbol{x} = [l_1 \quad \cdots \quad l_n \quad P_{pv1} \quad \cdots \quad P_{pvn}]^T , \quad (16)$$

$\boldsymbol{lb}$and $\boldsymbol{ub}$ are the lower and upper bounds of $\boldsymbol{x}$, respectively. These bounds are derived from constraint (7). Other constraints in (7), such as voltage and current limits, are checked during fitness evaluation. Any solution violating these is given infinite fitness ($f(\boldsymbol{x}) = \infty$) and excluded from optimization.

To solve the optimization problem (14)–(16), the proposed algorithm integrates the key mechanisms of AOA, TLBOA, SFOA, and FTTOA to achieve a proper balance between exploration and exploitation. Each solution is updated through a probabilistic selection among these mechanisms, followed by a diversity maintenance strategy to avoid premature convergence. The FTTOA phase is modified from [14] by incorporating the Fitness-Distance Balance (FDB) mechanism ($\boldsymbol{x}_{FDB}$) to improve local exploitation. The main steps of the proposed algorithm are summarized in the pseudo-code below, where $r_{16}, r_{17}, \dots, r_{26}$ are uniformly distributed random numbers in [0,1], and "∘" denotes the Hadamard product.

Input:

Population size N_{pop}, maximum iterations Max_iter, lower bound lb, upper bound ub, dimension nD, objective function $f(\boldsymbol{x})$, number of discrete variables a

Output:

Global optimal solution $\boldsymbol{x}_{best}$and the best fitness value fit_{best}

1: Initialize population $\boldsymbol{x}_i, i = 1 \rightarrow N_{pop}$ and auxiliary parameters (D, V, A) as defined in [13]

Initialization repair

2: $\boldsymbol{x}_i(1{:}n) = round\left(\boldsymbol{x}_i(1{:}n)\right)$

3: $\boldsymbol{x}_i = \max(\boldsymbol{lb}, \min(\boldsymbol{x}_i, \boldsymbol{ub}))$

4: Compute fitness values $f(\boldsymbol{x}_i)$ and determine the initial best solution $\boldsymbol{x}_{best}$ and fit_{best}

5: **For** $t = 1{:}Max\_iter$

6: Update control factor TF as defined in [13]

Compute operator selection probabilities

7: $p_{AOA} = \max\ (0.1, 0.45 - 0.35.TF)$

8: $p_{TLBO} = 0.35$

9: $p_{SFOA} = \min(0.45, 0.1 + 0.35.TF)$

FTTOA – Fitness Distance Balance Selection [14]

10: Compute normalized distance $dist_i$between $\boldsymbol{x}_i$and $\boldsymbol{x}_{best}$

11: Normalize fitness $fn_i$and distance dn_i

Compute selection score based on TF

12: **If** TF < 0.35 **then**

13: $S_i = 0.7.fn_i + 0.3.dn_i$

14: **Else if** TF < 0.75 **then**

15: $S_i = 0.5.fn_i + 0.5.dn_i$

16: **Else** $S_i = 0.7.(1 - fn_i) + 0.3.(1 - dn_i)$

17: Select FDB individual $\boldsymbol{x}_{FDB}$ with the maximum S_i

18: **If** TF > 0.75 **then** apply perturbation:

$\boldsymbol{x}_{FDB} = \boldsymbol{x}_{FDB} + 0.02. r_{16}. (\boldsymbol{ub} - \boldsymbol{lb})$.
Individual update
For each individual i **do**
Generate a random number $r_{17} \in [0,1]$
AOA Exploration/Exploitation
If $r_{17} < p_{AOA}$ **then**
Update acceleration $\boldsymbol{a}_i$ as defined in [13]
    If $TF < 0.5$ **then**
        $\boldsymbol{x}_i^{new} = \boldsymbol{x}_i + r_{18} \cdot \boldsymbol{a}_i \circ (\boldsymbol{x}_r - \boldsymbol{x}_i)$
    Else
    $\boldsymbol{x}_i^{new} = \boldsymbol{x}_{best} + r_{19} \cdot a_i \circ (\boldsymbol{x}_{best} - \boldsymbol{x}_i)$
    End If
TLBOA Phase [15]
Else if $r_{17} < p_{AOA} + p_{TLBO}$ **then**
    If (Teacher phase) **then**
    $\boldsymbol{x}_i^{new} = \boldsymbol{x}_i + r_{20}(\boldsymbol{x}_{best} - TF \cdot \overline{\boldsymbol{x}})$
    Else (Learner phase)
        Select individual $j \neq i$
        If $fit_i < fit_j$
        $\boldsymbol{x}_i^{new} = \boldsymbol{x}_i + r_{21} \cdot (\boldsymbol{x}_i - \boldsymbol{x}_j)$
        Else
        $\boldsymbol{x}_i^{new} = \boldsymbol{x}_i + r_{22} \cdot (\boldsymbol{x}_j - \boldsymbol{x}_i)$
        End If
    End If
SFOA Phase
Else if $r_{17} < p_{AOA} + p_{TLBO} + p_{SFOA}$ **then**
Select a random individual $\boldsymbol{x}_r$
$\boldsymbol{x}_i^{new} = \boldsymbol{x}_i + r_{23}(\boldsymbol{x}_r - \boldsymbol{x}_i) + r_{24}(\boldsymbol{x}_{best} - \boldsymbol{x}_i)$
FTTOA-based Exploitation
Else
    $\boldsymbol{x}_i^{new} = \boldsymbol{x}_i + r_{25} \cdot (\boldsymbol{x}_{FDB} - \boldsymbol{x}_i)$
Endif
Updated solution repair
$\boldsymbol{x}_i^{new}(1{:}n) = round\left(\boldsymbol{x}_i^{new}(1{:}n)\right)$
$\boldsymbol{x}_i^{new} = \max(\boldsymbol{lb}, \min(\boldsymbol{x}_i^{new}, \boldsymbol{ub}))$
Evaluate $f(\boldsymbol{x}_i^{new})$ and update $\boldsymbol{x}_i$ if $f(\boldsymbol{x}_i^{new}) \leq f(\boldsymbol{x}_i)$
End For
Diversity maintenance
Identify two of the worst individuals w_1, w_2
Individual w_1: random reinitialization
Individual w_2: SFOA regeneration: $\boldsymbol{x}_{w2}^{new} = \boldsymbol{x}_{best} + r_{26} \cdot (\boldsymbol{x}_r - \boldsymbol{x}_{w2})$
Evaluate and update if improved
Update global best solution $\boldsymbol{x}_{best}$ and fit_{best}
End For

IV. VALIDATION AND DISCUSSION

To verify the proposed method, the IEEE 33-bus distribution system is used in this study. The network is shown in Fig. 1, and its data can be found in [17]. The total active load of the system is 3.715 MW. Using the BFS algorithm, the total power loss is approximately 210 kW, and the minimum voltage is 0.9042 pu at bus 18. This test system is then used to evaluate the optimal placement and sizing of PV units while considering the uncertainty of solar irradiance. The load is assumed constant. A Beta distribution with $\alpha = 5$ and $\beta = 3$ is used to represent solar variability, indicating a slight bias toward higher generation levels. The maximum solar irradiance is set to $G_{max} = 1100$ W/m², which defines the upper bound of the irradiance used in the stochastic PV model. The irradiance range [0, G_max] is discretized into 12 states, and the corresponding probability of each state is calculated using the Beta distribution. The daytime is from 6:00 to 17:00. In this study, three PV units are considered, with their capacities ranging from 50 kW to 1200 kW. The proposed algorithm is applied under these conditions to determine the optimal locations and sizes of the PV units. The resulting optimal configurations, along with the corresponding annual energy losses, are presented in Table I.

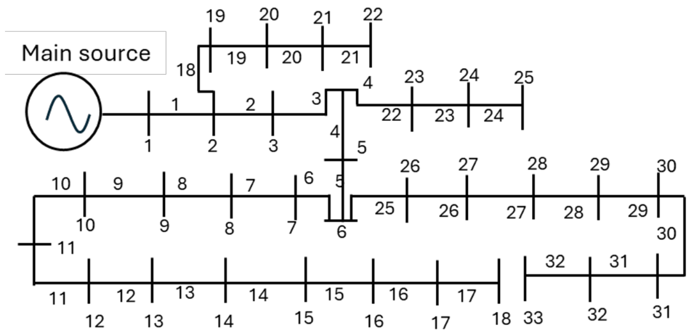
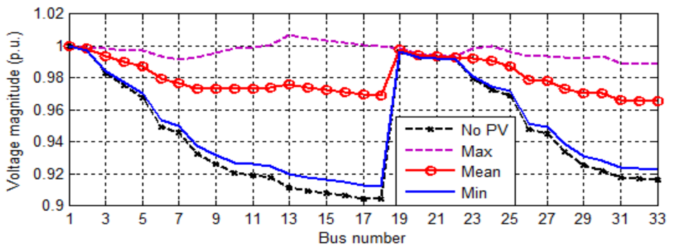


Figure 1. The IEEE 33-bus standard test system

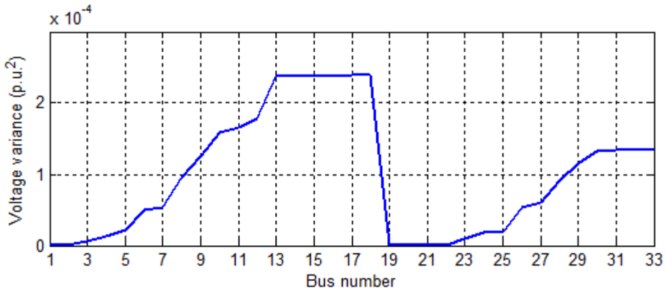
TABLE I. RESULTS OF DETERMINING THE OPTIMAL POSITION AND SIZE OF PV USING THE PROPOSED ALGORITHM

Position/size (kW)	Energy loss (MWh)	Reduction rate (%)
13/1118.3 24/1200 30/1200	316.630 (daytime)	62.5% (daytime) 28.6%(full day)

The results show that the optimal PV units are placed at buses 13, 24, and 30 with capacities of 1183 kW, 1200 kW, and 1200 kW, respectively, in the IEEE 33-bus radial distribution system. This placement follows the structure of the network, where buses farther from the main source are more affected by power losses and voltage drops. In particular, buses 24 and 30 are located near the end of the feeder, so they are assigned the maximum PV capacity because they can reduce losses more effectively. Meanwhile, the slightly smaller size of bus 13 suggests that some system limits prevent installing a larger PV unit at that location. The annual energy loss is calculated as 316.630 MWh during the daytime period (6:00–17:00). For the remaining hours, the system operates under base-case conditions. Overall, the total annual energy loss is reduced from 1839.6 MWh to 1313.08 MWh (28.6%), while a reduction of 62.5% is observed during daytime operation (6:00–17:00). This time range matches the operating hours of PV systems, so it helps clearly show their effect on reducing losses. Therefore, this value represents the network performance when PV is active, rather than over the full 24-hour period. In addition, the Beta distribution is used to model solar irradiance, which helps account for the variability of solar power in the analysis. This makes the results more realistic because PV output is not constant in practice. Overall, the results show that the proposed method can effectively find suitable locations and sizes for PV systems in the IEEE 33-bus network, especially at buses farther from the source, where loss reduction is more important under changing solar conditions.



(a)



(b)

Figure 2. Statistical and deterministic characteristics of nodal voltages under different operating conditions: (a) voltage magnitude profiles (p.u.) and (b) voltage variance.

By installing PV systems as given in Table I, the nodal voltage characteristics of the radial distribution network (supplied from the main source at Bus 1) are shown in Fig. 2. In Fig. 2(a), the minimum voltage curve corresponds to the case of very low irradiance, where PV generation is negligible; therefore, it is almost identical to the case without PV. Under this condition, the voltage gradually decreases from the main source to the end buses due to line losses, which is typical for a radial network. In contrast, when the irradiance reaches its maximum (e.g., at midday), all PV units generate their rated power. This significantly changes the power flow along the feeder, especially at buses where PV is installed (Buses 13, 24, and 30). As a result, the voltage profile is improved, and the voltage drop along the feeder is reduced. In some sections, a slight voltage rise can be observed, with the maximum voltage reaching approximately 1.01 p.u. The mean curve lies between the minimum and maximum cases and represents the average operating condition. It reflects the most probable daytime operating state under stochastic PV generation, providing a realistic indicator of voltage performance in practical operation. Fig. 2(b) presents the voltage variance along the feeder. It can be observed that the variance is relatively low near the main source (Bus 1), where the voltage is strongly regulated. As the distance from the source increases, the variance becomes larger, particularly around the buses where PV systems are connected. This indicates that these buses are more sensitive to changes in PV output. Overall, PV integration improves the voltage profile along the feeder but also introduces higher variability at buses located far from the main source and near PV installation points.

To evaluate the efficiency of the proposed algorithm compared to other algorithms, including AOA, FTTOA, SFOA, and TLBOA, the same population size and parameters of the Beta distribution are used. Comparison results are shown in Tables II, III, and IV.

TABLE II. COMPARISON OF OPTIMIZATION TECHNIQUES USING 30-RUN STATISTICS

Method	Fitness value (MWh)				Mean iteration	Mean times
	Best	*Worst*	*Mean*	*Std*		
Proposed	316.63	317.98	316.74	0.306	38	26.02
AOA	317.39	324.32	319.45	1.664	74	12.03
SFOA	316.63	317.96	316.78	0.358	75	22.96
FTTOA	317.39	336.31	320.46	4.115	85	29.65
TLBOA	316.63	321.79	317.16	1.209	39	45.89

The results in Tables II–IV provide a comprehensive comparison of the proposed method against the competing algorithms in terms of solution quality, stability, convergence behavior, computational efficiency, and grid performance. The results in Table II confirm that the proposed method and SFOA are the two top approaches, while AOA, FTTOA, and TLBOA perform worse overall. The proposed method achieves a low mean fitness value of 316.74 MWh, nearly matching the best value (316.63 MWh) and outperforming AOA (319.45 MWh) and FTTOA (320.46 MWh). SFOA has a slightly higher mean (316.78 MWh), close to the proposed method. TLBOA's mean (317.16 MWh) is also good but remains below the leading methods.In terms of stability, the proposed method has the smallest standard deviation (0.306 MWh), followed by SFOA (0.358 MWh). TLBOA's variation is moderate (1.209 MWh), while AOA (1.664 MWh) and FTTOA (4.115 MWh) show much higher variability, confirming the reliability of the proposed method and SFOA. Regarding convergence behavior, the proposed method requires significantly fewer iterations (38) to reach high-quality solutions compared to AOA (74), SFOA (75), and FTTOA (85), and is comparable to TLBOA (39), indicating faster convergence toward near-optimal solutions. For computational efficiency, AOA is the fastest (12.03 s per run), with SFOA (22.96 s) and the proposed method (26.02 s) following. FTTOA and TLBOA are slower, especially TLBOA (45.89 s). Moreover, Table III shows that the proposed method, SFOA, and TLBOA all achieve the same best solution at nodes 13, 24, and 30, with similar sizes. In contrast, AOA and FTTOA yield different node or size arrangements. While SFOA is competitive in quality and stability, the proposed method stands out for its consistency, making it preferable for practical use. In addition, the results in Table IV demonstrate that the proposed method achieves strong overall grid performance. Its total installed capacity is 3518.3 kW, matching SFOA and TLBOA, slightly higher than AOA (3515.5 kW), and lower than FTTOA (3600 kW). This indicates that good results are achieved without needing excessive capacity. For the voltage profile, the proposed method maintains minimum and maximum voltages of 0.9125 pu and 1.0072 pu, identical to SFOA and TLBOA, and better than FTTOA (max 1.0121 pu). AOA yields slightly lower values in both cases. Thus, the proposed method ensures stable and safe voltage levels. In terms of energy loss reduction, the proposed method provides an annual saving of 526.802 MWh, the highest value, equal to SFOA and TLBOA, and slightly better than AOA (526.046 MWh) and FTTOA (526.048 MWh). This confirms its effectiveness in reducing losses. Overall, the results indicate that the proposed method achieves competitive solution quality, improved stability, and fast convergence while maintaining a reasonable computational cost. In addition, it provides consistent optimization performance and effective energy-loss reduction, making it a suitable approach for practical PV planning problems.

TABLE III. OPTIMAL SOLUTION WITH THE BEST RUN

Methods	**Proposed**	**TLBOA**	**SFOA**	**FTTOA**	**AOA**
Node/size in kW	13/1118.3 24/1200 30/1200			13/1200 24/1200 30/1200	13/1115.5 24/1200 31/1200

TABLE IV. GRID PERFORMANCE COMPARISON BASED ON BEST-RUN SOLUTIONS

Method	**Total capacity** (kW)	**Voltage** (pu)		**Energy saving** (MWh)
		Min	***Max***	
Proposed	3518.3	0.9125	1.0072	526.802
AOA	3515.5	0.9124	1.0071	526.046
SFOA	3518.3	0.9125	1.0072	526.802
FTTOA	3600.0	0.9129	1.0121	526.048
TLBOA	3518.3	0.9125	1.0072	526.802

V. CONCLUSION

This paper proposes a hybrid optimization method that combines AOA, SFOA, FTTOA, and TLBOA to determine the optimal placement and sizing of PV units in a distribution system, considering solar uncertainty using a Beta distribution. Results on the IEEE 33-bus system show that PV integration significantly improves performance, reducing total annual energy loss by 28.6% and up to 62.5% during daytime operation. The voltage profile is also improved and maintained within a safe range. Compared with the original algorithms, the proposed method achieves lower average energy loss, better stability, and faster convergence. Although SFOA provides similar solution quality, the proposed method is more consistent and requires fewer iterations. Overall, it is an effective and reliable approach for PV planning.

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