RESEARCH PAPER

Reducing Power Loss and Increasing Voltage Stability with Effective Optimisation of Distributed Generators and DSTATCOM Location

Shridevi Akkewar[1], Dr. R. K. Dhatrak[2]
[1] RCERT Chandrapur, India. Email: shhrideviakkewar3251@gmail.com
[2] RCERT Chandrapur, India. Email: rkdhatrak@gmail.com

ABSTRACT
This paper introduces a Brown Bear Optimization (BBO)- based framework for determining the optimal placement and sizing of distributed generators (DGs), particularly solar photovoltaic (PV) and wind turbine (WT) units, with the objective of minimizing power losses and enhancing voltage stability in distribution networks. Since renewable-based DGs typically contribute only active power, the associated reactive power demand often remains unfulfilled. To address this challenge, an optimally sized distributed static synchronous compensator (DSTATCOM) is incorporated to provide reactive power support and to sustain system performance, even under conditions with limited DG participation. In addition, a time-domain investigation is conducted to evaluate the dynamic behavior of the DSTATCOM under fluctuating renewable generation. The proposed methodology is validated on the IEEE 33-bus distribution system, where results demonstrate a power loss reduction of approximately 91.3% and an improvement in the voltage deviation index from 0.0561 to 0.0050. These outcomes clearly emphasize the effectiveness of the BBO algorithm in optimizing DG and DSTATCOM allocation, leading to significant improvements in efficiency, reliability, and voltage stability of distribution networks.
Keywords: Distributed generation (DG), Brown Bear Optimization (BBO), Optimal location and sizing, Power loss reduction, Voltage stability, Distributed static synchronous compensator (DSTATCOM), Distribution network (DN)
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1 Introduction

Distributed generation (DG) has emerged as a crucial component of modern power distribution networks (DNs), providing localized energy supply through small-scale sources such as solar photovoltaics (PVs) and wind turbines (WTs) [1]. Distribution-level DG integration lessens the strain on transmission infrastructure while enhancing resilience, dependability, and voltage stability. How- ever, oversizing or incorrect distribution of DG units can result in voltage fluctu- ations, increased losses, and a negative impact on power quality [2]. To optimize their advantages and preserve system stability, it is crucial to ascertain the best location and capacity for DGs [3, 15, 16].

A number of optimization-based approaches have been put forth to deter- mine the best location and dimensions for DGs. Techniques like fuzzy-based controllers, swarm intelligence, genetic algorithms, and hybrid metaheuristics have demonstrated promise in lowering power loss and enhancing the voltage profile of distribution networks [17, 18]. However, a number of these methods have drawbacks, such as a high reliance on network topology, a risk of pre- mature stagnation, and slow convergence. Moreover, most methods primarily address DG units supplying only active power, often neglecting reactive power requirements, which are equally critical for ensuring stable operation [4–6].

Flexible AC transmission system (FACTS) devices, especially the distributed static synchronous compensator (DSTATCOM), have been extensively studied as a means of overcoming these constraints [7]. The DN is strengthened under both typical and demanding operating conditions thanks to DSTATCOM's re- active power compensation, improved voltage regulation, and improved power factor correction. A viable way to lower power losses and achieve a stable voltage profile is to integrate DSTATCOM with DGs that are optimally allocated [8].

In this work, a Brown Bear Optimization (BBO)-based approach for the joint distribution system allocation of DGs and DSTATCOM is presented. The suggested approach assesses the dynamic response of DSTATCOM under the variability of renewable generation while concentrating on reducing active power losses and enhancing voltage stability [9]. The IEEE 33-bus system is used to validate the methodology, and the results show notable improvements in the voltage deviation index and reductions in power loss. The results demonstrate that BBO offers a dependable and efficient way to improve the general stability and efficiency of distribution networks[10–12].

1.1 Contributions of the work

By addressing both active and reactive power support in distribution networks using an integrated DG–DSTATCOM allocation framework, this work advances the state-of-the-art and fills in the gaps found in the literature. The following is a summary of the primary contributions:

- A mathematical formulation is developed for determining the optimal loca- tion and capacity of distributed generators (DGs) with the dual objectives of minimizing active power losses and improving voltage stability.
- A Brown Bear Optimization (BBO) algorithm [19, 20] is employed to deter- mine the optimal siting and sizing of DG units, providing superior search balance and solution quality compared to conventional approaches.
- To address reactive power requirements often neglected by DGs, an optimally sized DSTATCOM is incorporated, and its placement is identified to further enhance voltage profile and reduce residual losses.
- A time-domain analysis is conducted to investigate the dynamic response of DSTATCOM under variable renewable generation, ensuring that the pro- posed solution remains robust under practical operating conditions.
- The effectiveness of the proposed strategy is validated on the IEEE 33- bus distribution system, where simulation results demonstrate a power loss reduction of approximately 91.3% and a voltage deviation improvement from 0.0561 to 0.0050, highlighting the strong capability of BBO in improving network efficiency, reliability, and voltage stability.

This study provides a comprehensive optimization framework that jointly addresses active and reactive power support in distribution networks, offering significant improvements over existing DG-only allocation strategies.

2 Proposed Methodology

Designing and assessing an optimization framework for the effective distribution of distributed generators (DGs) and a distributed static synchronous compen- sator (DSTATCOM) in distribution networks (DNs) is the aim of this study. In order to improve reliability and voltage quality, the suggested framework places special emphasis on solar photovoltaic (PV) and wind turbine (WT) units that are integrated at the distribution level. Using the Brown Bear Optimization (BBO) algorithm, the main goal is to reduce active power losses and enhance voltage stability [13, 14].

The approach focuses on concurrently addressing DSTATCOM's reactive power compensation and DGs' active power support. By striking a balance be- tween exploration and exploitation in the search space, the suggested BBO ap- proach facilitates effective convergence toward the best possible placement for DG and DSTATCOM. Algorithm. 1 shows the entire workflow [15].

2.1 Problem Formulation

Technical issues that distribution networks frequently face include high real power losses, inadequate voltage regulation, and elevated stress during renewable energy variability. A nonlinear optimization problem involving both continuous (sizing) and discrete (location) decision variables is used to model the ideal place- ment and sizing of DGs in order to counteract these effects. The following goals were taken into consideration for this study.

Active Power Loss Minimization One optimization goal is to reduce active power losses. The network's overall loss can be stated as follows:

$$F_1 = \sum_{(a,b)\in\Omega} R_{ab} \cdot \frac{P_{ab}^2 + Q_{ab}^2}{|V_a|^2} \quad (1)$$

where $|V_a|$ is the voltage magnitude at bus a, R_{ab} is the line resistance, and P_{ab} and Q_{ab} indicate the active and reactive power flows from bus a to bus b. The set of branches Ω is used for the summation.

Voltage Deviation Minimization Reducing voltage deviation across buses and keeping voltages near nominal values is another crucial goal. The definition of the voltage deviation index is:

$$F_2 = \frac{1}{N}\sum_{i=1}^{N}\frac{V_i - V_{\mathrm{ref}}}{V_{\mathrm{ref}}} \tag{2}$$

where N is the total number of buses, V_i is the voltage magnitude at the i^{th} bus, and V_{ref} is the nominal reference voltage. Better voltage stability is indicated by a lower F_2. In order to guarantee the viability and safe functioning of the DN, the optimization problem is resolved subject to system operating limits. The main limitations consist of:

- **Voltage limits:**

$$V_i^{\min} \le V_i \le V_i^{\max}, \qquad i = 1, 2, \ldots, N \tag{3}$$

- **Current capacity limits:**

$$I_l \le I_l^{\max}, \qquad l = 1, 2, \ldots, L \tag{4}$$

- **DG capacity limits:**

$$0 \le \sum_{j=1}^{N_{DG}} P_{DG,j} \le \sum_{a=1}^{N} \frac{P_a^2 + Q_a^2}{|V_a|^2} R_a \tag{5}$$

The acceptable lower and upper voltage limits are denoted by $V_i^{\min}$ and $V_i^{\max}$, respectively, and $I_l^{\max}$ represents line l's maximum current capacity, $P_{DG,j}$ rep- resents the active power injected by the j^{th} DG, and R_a represents the resistance of the branch attached to bus a.

The BBO algorithm looks for the best solutions in this formulation that mini- mize F_1 and F_2 while closely following the aforementioned operating constraints. In the IEEE 33-bus distribution system, this guarantees a realistic, dependable, and effective distribution of DGs and DSTATCOM.

The primary objective of this research is to formulate and evaluate an opti- mization framework for the optimal siting and sizing of distributed generators (DGs), particularly solar and wind-based units, along with distributed static synchronous compensators (DSTATCOMs) in radial distribution networks. The methodology seeks to minimize active power losses and voltage deviations, thereby enhancing overall stability and efficiency. To achieve this, the Brown Bear Op- timization (BBO) [19, 20] algorithm is employed, inspired by the unique scent- marking and sniffing behaviors of brown bears, which provide an effective balance between exploration and exploitation in the search process [**?**].

The proposed framework is implemented on the IEEE 33-bus test system, where DGs and DSTATCOMs are optimally placed while satisfying operational limits such as bus voltage, branch current, and generation capacity. A schematic of the methodology is illustrated in Fig. 1.

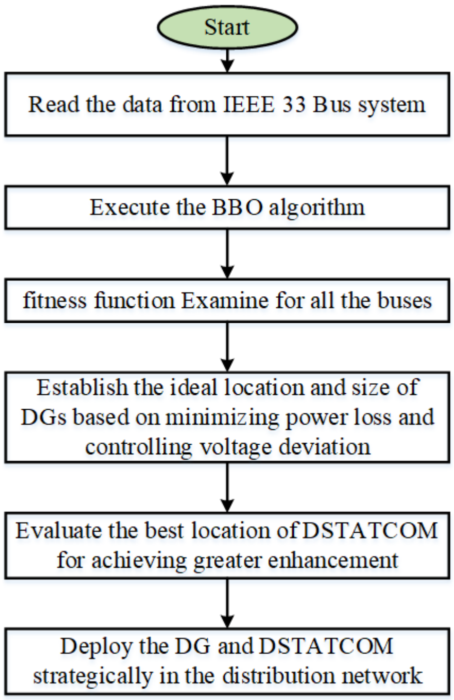

Fig. 1. Flowchart of the proposed Brown Bear Optimization (BBO)-based methodol- ogy for DG and DSTATCOM allocation.

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Distribution networks frequently encounter power quality issues such as high active power losses and unacceptable voltage variations. To mitigate these is- sues, the optimal allocation of DGs and DSTATCOMs is framed as a nonlinear optimization problem with the following objectives:

$$F = \min \ w_1 P_{\text{loss}} + w_2 V_{\text{dev}} , \qquad (6)$$ where

w_1 and w_2 are weighting factors, P_{loss} is the total real power loss, and V_{dev} represents the system-wide voltage deviation index. For this study, both weights are considered equal ($w_1 = w_2 = 0.5$) to provide a balanced trade-off.

2.2 Brown Bear Optimization (BBO)

The pedal scent-marking and sniffing behaviors of brown bears in their nat- ural habitat, which enable them to efficiently explore and exploit their territory, served as the model for the BBO algorithm [19, 20]. Scent marks stand in for decision variables (DG/DSTATCOM location and size), while each bear group represents a potential solution in the optimization context.

Algorithm 1 Brown Bear Optimization (BBO) for Optimal DG & DSTATCOM Allocation

Require: Network data, DG/DSTATCOM bounds, N_{pop}, T, weights (w_1, w_2)
Ensure: Best solution $\mathbf{x}^\star$
Initialize population $\{\mathbf{x}_i\}$ randomly within bounds
for each $\mathbf{x}_i$ **do**
    Run load flow → compute P_{loss}, V_{dev}
    Fitness: $F = w_1 P_{\text{loss}} + w_2 V_{\text{dev}} + \Pi(\mathbf{x}_i)$
end for
$\mathbf{x}^\star \leftarrow \arg\min F(\mathbf{x}_i)$
for $t = 1$ to T **do**
    Normalize progress $\theta = t/T$
    Identify best ($\mathbf{x}_b$) and worst ($\mathbf{x}_w$)
    for each candidate $\mathbf{x}_i$ **do**
        if $\theta \leq 1/3$ **then**
            Local refinement (pedal marking)
        else if $\theta \leq 2/3$ **then**
            Update: $\mathbf{x}_i \leftarrow \mathbf{x}_i + \beta(\mathbf{x}_b - \mathbf{x}_w)$
        else
            Update: $\mathbf{x}_i \leftarrow \mathbf{x}_i + \gamma(\mathbf{x}_b - |\mathbf{x}_i|)$
        end if
    end for
    for each candidate $\mathbf{x}_i$ **do**
        Sniffing: $\mathbf{x}_i \leftarrow \mathbf{x}_i + \rho(\mathbf{x}_j - \mathbf{x}_i)$, $j \neq i$
        Repair bounds, evaluate $F(\mathbf{x}_i)$
    end for
    Update $\mathbf{x}^\star$ with best solution
end for
return $\mathbf{x}^\star$

Initialization The initial population of bear groups is randomly generated as:

$$X_{i,j} = X_j^{\min} + \lambda \cdot \left(X_j^{\max} - X_j^{\min}\right), \tag{7}$$

where $X_{i,j}$ is the j^{th} decision variable of the i^{th} candidate solution, $X_j^{\min}$ and $X_j^{\max}$ are lower and upper bounds, and λ is a random number uniformly dis- tributed in [0,1].

Pedal Scent-Marking Behavior In order to update the candidate solutions, this stage imitates the bears' cautious stepping, foot twisting, and overall gait. To improve exploitation, solutions are updated either by guided shifts away from subpar solutions or by minor local refinements around the best solution, depending on the number of iterations.

Sniffing Behavior Bears can communicate and explore new areas thanks to sniffing. This stage of the algorithm enables random exploration by contrasting two potential solutions and moving in the direction of the ones that perform better:

$$X_i^{t+1} = X_i^t + \rho \cdot (X_j^t - X_i^t), \quad j \neq i, \tag{8}$$

where ρ is a uniformly distributed random coefficient.

Termination Scent marking and sniffing are repeated until convergence is reached or the maximum number of iterations is reached. The ideal distribution of DGs and DSTATCOM is represented by the best solution at termination.

2.3 Workflow

The methodological workflow of the proposed framework can be summarized as:

1. Initialize system parameters and read IEEE 33-bus data.
2. Generate an initial population of solutions (DG/DSTATCOM locations and sizes).
3. Evaluate the fitness function using the weighted objective of loss and voltage deviation.
4. Update the solutions using BBO operators (pedal scent marking and sniff- ing).
5. Check operational constraints and retain feasible solutions.
6. Iterate until convergence and finalize the optimal DG and DSTATCOM al- location.

2.4 Optimum Siting of DSTATCOM

The integration of a distributed static synchronous compensator (DSTATCOM) into distribution networks provides essential reactive power support and en- hances reliability, particularly when renewable DG units produce insufficient power. This device reduces voltage fluctuations, regulates power factor, and strengthens system stability.

The active and reactive power interaction between the DSTATCOM and the grid is given as:

$$P_{DS} = \frac{V_a V_{DS}}{X_L} \sin(\phi), \tag{9}$$

$$Q_{DS} = \frac{V_a^2}{X_L} - \frac{V_a V_{DS}}{X_L} \cos(\phi), \tag{10}$$

where V_a is the bus voltage, V_{DS} is the DSTATCOM terminal voltage, X_L is the line reactance, and ϕ is the phase angle difference between the two voltages.

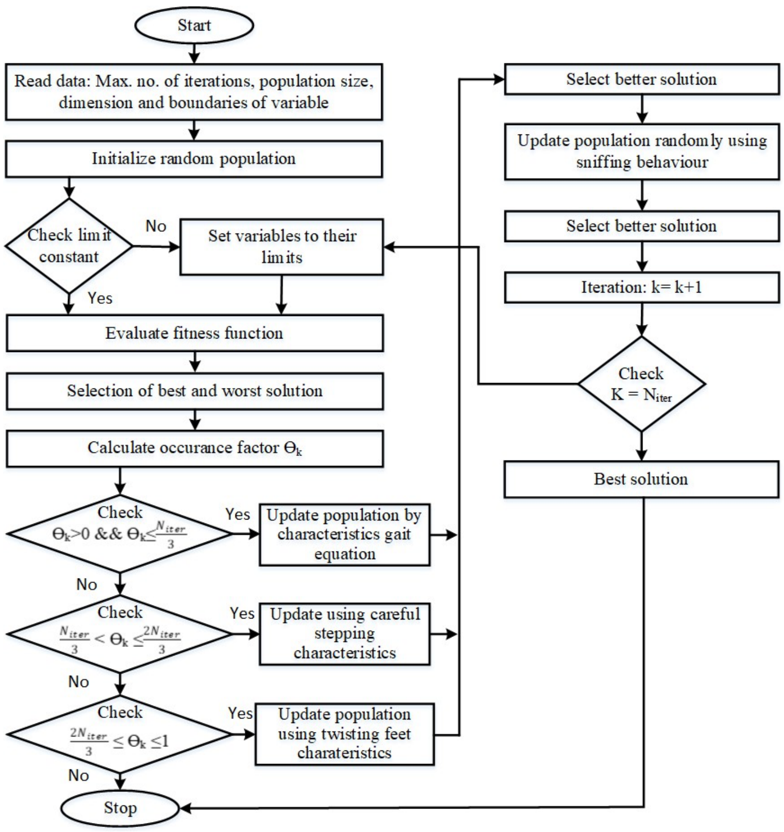

Fig. 2. Flowchart of the Brown Bear Optimization (BBO) algorithm applied for DG and DSTATCOM placement.

2.5 Results and Discussion

The proposed BBO-based approach was validated on the IEEE 33-bus distribu- tion system. To demonstrate its effectiveness, three scenarios were evaluated:

- **Case 1:** Base network without DG or DSTATCOM.
- **Case 2:** System with optimally placed DG units.
- **Case 3:** System with both DG and DSTATCOM.

Performance Outcomes Table 1 presents the optimized allocation and results. Solar PVs were placed at buses 6 and 14, wind units at buses 25 and 32, and the DSTATCOM at bus 30 with a capacity of 1260 kVAR.

Voltage Profile Analysis The voltage profile of the IEEE 33-bus system for all cases is illustrated in Fig. 3. In the base scenario, buses with weaker support (e.g.,

Table 1. Performance Evaluation of IEEE 33-Bus System

Parameter	IEEE 33-Bus System
Solar PV locations	6, 14
Wind turbine locations	25, 32
DSTATCOM location	30
Size of Solar PVs	1275 kW, 645 kW
Size of Wind units	395 kW, 690 kW
DSTATCOM rating	1260 kVAR
Base case power loss	212.4 kW
Power loss after DGs	72.8 kW
Power loss after DGs + DSTATCOM	21.1 kW
Base case voltage deviation	0.0568
Voltage deviation after DGs	0.0167
Voltage deviation after DGs + DSTATCOM	0.0050

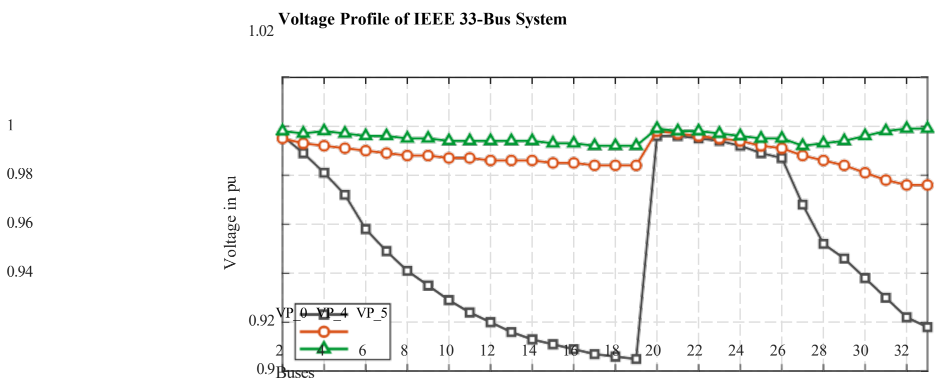

Fig. 3. Voltage profile of IEEE 33-bus system for base case, with DGs, and with DG + DSTATCOM.

bus 18) suffer from undervoltage conditions. Integration of DGs enhances bus voltages closer to 1.0 p.u., while the inclusion of DSTATCOM further stabilizes voltages across the system.

Loss Reduction Analysis The reduction in system losses is shown in Fig. 4. Losses reduce from 212.4 kW in the base case to 72.8 kW with DG integration. With DSTATCOM support, losses further decline to 21.1 kW, amounting to an overall reduction of approximately 90.1%. This emphasizes the complementary role of DSTATCOM in meeting the reactive power demand and maintaining network efficiency.

Discussion The BBO-based methodology consistently delivers superior perfor- mance by balancing active and reactive power optimization. Voltage deviations

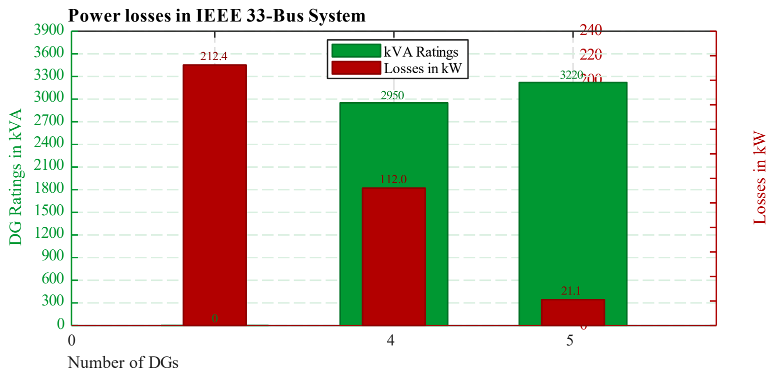

Fig. 4. Active power losses in IEEE 33-bus system under different scenarios.

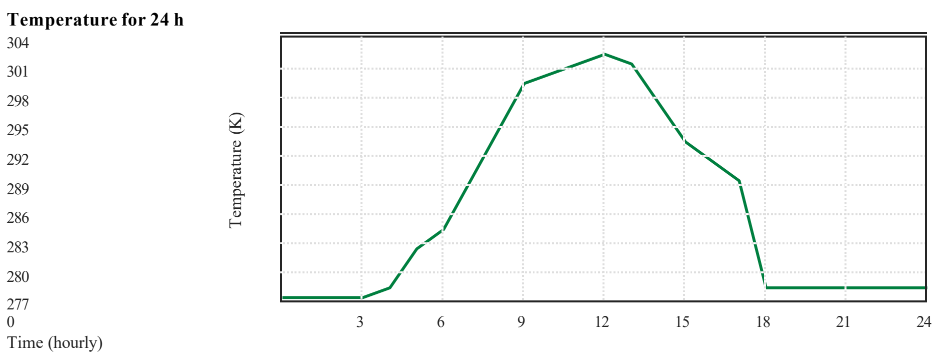

Fig. 5. Temperature profile over a 24-hour period.

are reduced from 0.0568 to 0.0050, and real power losses are curtailed by nearly 90%. This demonstrates not only technical benefits in terms of enhanced power quality but also significant operational efficiency for distribution networks with high renewable penetration.

3 Time-Domain Analysis

To validate the effectiveness of the proposed framework, a time-domain study was conducted on the IEEE 33-bus system. The optimal placements of DGs and the DSTATCOM obtained via Brown Bear Optimization (BBO) were subjected to variable renewable input. The stochastic behavior of solar irradiance and ambient temperature, representative of PV and load conditions, was modeled across a full day, as shown in Fig. 6 and Fig. 5.

Three operating scenarios were evaluated: (i) the base case without DG or DSTATCOM, (ii) with optimally allocated DG units, and (iii) with DGs and a DSTATCOM. The profiles in Fig. 6–5 drive the system through peak and off-

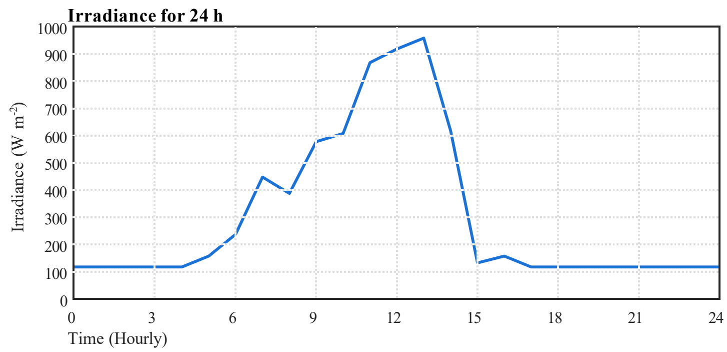

Fig. 6. Solar irradiance profile over a 24-hour period.

peak intervals, allowing assessment of voltage regulation and loss performance under realistic diurnal variability.

The results highlight that during low generation periods (e.g., early morning and late evening), voltages at certain buses fall below acceptable levels when only DGs are deployed. However, with the inclusion of a DSTATCOM at bus-30, volt- ages remain well within permissible limits across all hours. This confirms that DSTATCOM plays a critical role in maintaining dynamic stability when renew- able generation is insufficient. The dynamic voltage response of the IEEE 33-bus system under three different operating scenarios is depicted by the time-domain results shown in Fig. 7. The system's inability to maintain stability is demon- strated by the critical bus voltages in the base case without DG integration, which continuously fall below allowable limits. Although there are still notice- able drops during low generation hours, the network voltage greatly improves during periods of high renewable generation when properly positioned DG units are included. Voltage support is further improved by adding a DSTATCOM, which stabilizes the profile across all buses and keeps voltages well within al- lowable bounds. It is evident that this DG and DSTATCOM deployment works better together to reduce voltage variations and guarantee dependable operation in variable renewable environments.

4 Comparative Analysis

The performance of the proposed BBO-based methodology was benchmarked against several state-of-the-art optimization techniques, including LSFS, BFOA, WCA, and ALO. Table 2 summarizes the results, including optimal DG sizing, kVA capacity, system losses, percentage loss reduction, and minimum bus volt- age.

It is evident from Table 2 that the proposed BBO consistently outperforms other algorithms by achieving the lowest power loss (21.0 kW) and the highest percentage reduction (90.1%). Furthermore, the minimum bus voltage in the

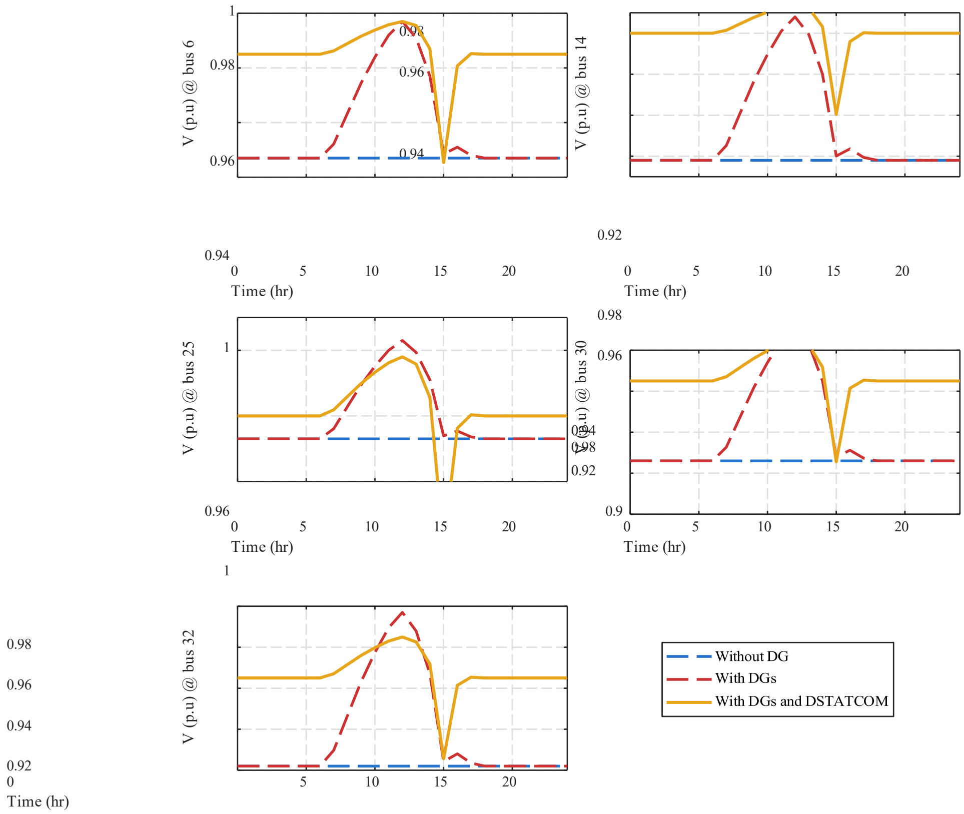

Fig. 7. Time-domain analysis of the IEEE 33-bus system under varying renewable generation with DGs and DSTATCOM.

Table 2. Comparison of Optimization Techniques on IEEE 33-Bus System

Technique	DG Size (kW)	DG Size (kVAR)	Total kVA	Loss (kW)	Loss Red. (%)
LSFSA	1185.4 (6), 470.2 (18), 912.8 (30)	685.3 (6), 272.4 (18), 528.6 (30)	2965.5	26.9	86.9
BFOA [31]	662.1 (14), 128.3 (18), 1101.2 (32)	386.4 (14), 74.8 (18), 642.2 (32)	2190.3	36.8	82.6
BFOA [32]	592.5 (14), 602.7 (25), 926.2 (30)	302.1 (14), 414.2 (25), 498.6 (30)	2420.1	28.2	86.1
WCA [33]	966.8 (25), 1048.1 (29), 529.5 (11)	461.2 (23), 558.6 (30), 528.1 (14)	2940.7	25.1	87.3
ALO [34]	1053.7 (30), 522.2 (13), 231.8 (10)	605.1 (30), 302.4 (13), 132.2 (10)	2115.2	30.9	85.2
BBO (Proposed)	1260 (30), 1285 (6), 648 (14), 680 (32), 390 (25)	1255 (30)	3255.4	21.0	90.1

BBO case is maintained above 0.984 p.u., highlighting superior voltage support compared to alternatives.

5 Conclusion of the work

The presented research demonstrates a robust framework for the optimal place- ment and sizing of distributed generators and DSTATCOMs in distribution networks. The use of the Brown Bear Optimization (BBO) algorithm enables efficient exploration–exploitation balance, ensuring precise location and sizing decisions.
Key findings are summarized as follows:

- Solar PV units were placed at buses 6 and 14, wind turbines at buses 25 and 32, and a DSTATCOM at bus 30 with a rating of 1260 kVAR.
- Power losses were reduced from a base case of 212.4 kW to 72.8 kW with DG integration, and further to 21.0 kW with DSTATCOM support.
- Voltage deviations decreased from 0.0568 in the base case to 0.0167 with DGs, and to 0.0050 with DGs and DSTATCOM.
- Comparative results confirm that BBO achieves superior performance rela- tive to LSFS, BFOA, WCA, and ALO.
- Time-domain simulations validate that voltage remains within limits dur- ing fluctuating renewable generation, proving the resilience of the proposed framework.

Overall, the BBO-based methodology ensures significant improvements in both technical and operational performance of distribution systems, making it highly suitable for modern networks with high penetration of renewable energy.

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