Franklin Open 13 (2025) 100421

Contents lists available at ScienceDirect

Franklin Open

journal homepage: www.elsevier.com/locate/fraope

Application of Deep Sleep Optimizer for strategic placement and sizing of distributed generation in power distribution systems

Mkhutazi Mditshwa *, Mkhululi E.S. Mnguni, Nomzamo Tshemese-Mvandaba, Innocent E. Davidson

Department of Electrical, Electronics, and Computer Engineering, Cape Peninsula University of Technology, Bellvile, Cape Town, 7530, South Africa

ARTICLE INFO

Keywords:
Distributed generators (DGs)
Genetic Algorithm (GA)
Deep Sleep Optimizer (DSO)
Teaching and learning-based optimization (TLBO)
Optimization algorithms

ABSTRACT

Strategic siting and sizing of renewable-dominated distributed generators (DGs) is pivotal to curbing technical losses and safeguarding voltage quality in modern distribution networks. This paper presents a fully scripted, direct Python-PowerFactory framework that eliminates the file-exchange overhead of conventional MATLAB co-simulation and embeds the recently conceived Deep-Sleep Optimizer (DSO) a meta-heuristic that alternates between "deep-sleep" global exploration and "wake" local exploitation. The proposed workflow is evaluated on the IEEE-33 radial feeder and rigorously benchmarked against the Genetic Algorithm (GA) and Teaching–Learning-Based Optimization (TLBO). The multi-objective problem minimizes real-power losses and maximizes the minimum voltage-stability index subject to generator, voltage, and thermal constraints. For fair comparison all solvers use identical population sizes and iteration budgets. DSO reaches steady convergence in fewer than 20 iterations, whereas TLBO and GA require roughly 40 and 70 iterations, respectively. In the single-DG case DSO and TLBO each halve active losses (to $\approx$91 kW, -56%) and raise the weakest node to 0.983 pu, outperforming GA's 0.978 pu. With two DGs, DSO yields the lowest loss (55.9 kW, -73%) using only 2.72 MW of capacity and completes in 528 s one third of TLBO's runtime. The most demanding three-DG scenario underscores DSO's superiority: losses plummet from 210 kW to 28.9 kW (-86%), the weakest-bus voltage climbs to 0.998 pu, no bus exceeds 1.013 pu, and the installed capacity (3.84 MW) is 30% lower than GA's requirement while runtime (666 s) is 81 % shorter than TLBO's. DSO also trims reactive losses by 81 % and produces the flattest voltage profile (standard deviation $<$ 0.005 pu) without breaching the 0.95-1.05 pu statutory band. Because both DSO and TLBO are parameter-free, the framework removes the need for heuristic tuning, making it attractive for day-to-day planning. Overall, the results establish DSO as a high-performance, low-maintenance optimization engine that unlocks deeper loss cuts and tighter voltage regulation than established methods at a computational cost compatible with routine distribution-planning studies. Future work will extend the methodology to time-series optimization with stochastic photovoltaic and load profiles, meshed feeders, and full techno-economic assessment.

1. Introduction

Efficient placement and capacity determination of distributed generators (DGs) in distribution systems is a key strategy to enhance system reliability and performance. This involves identifying ideal locations and optimal DG sizes to curtail energy losses, stabilize voltage levels, and uphold operational integrity [1,2]. The shift toward decentralized and renewable-based power generation through technologies like solar PV, wind turbines, and micro-CHP is reshaping energy systems worldwide [3]. DGs can decentralize power supply, reduce transmission losses, and increase system resilience [4], but their integration poses both technical and economic hurdles.

Improper siting and sizing of DG units can lead to excessive power losses, voltage instability, and reverse power flows, which may negatively impact the overall grid performance [5]. Therefore, optimizing DG placement and capacity is essential to ensuring an efficient and stable power system. This optimization process must consider various factors, including load demand patterns, network constraints, power loss minimization, voltage regulation, and economic feasibility [6]. To solve this complex problem, researchers and engineers employ a range of optimization techniques, such as metaheuristic algorithms [7–10], mathematical programming [11], and artificial intelligence-based methods [12,13].

* Corresponding author.
E-mail address: mditshwam@cput.ac.za (M. Mditshwa).

https://doi.org/10.1016/j.fraope.2025.100421
Received 13 March 2025; Received in revised form 30 September 2025; Accepted 6 November 2025
Available online 14 November 2025
2773-1863/

Appropriately sized and strategically situated distributed generators (DGs) possess the capacity to substantially improve voltage profiles, thereby mitigating deviations and augmenting overall system stability [9,14]. DG placement and sizing lead to substantial reductions in real and reactive power losses, contributing to more efficient power distribution [15,16]. Optimal DG integration promotes system reliability and security by solving the difficulties of increasing power demand and obsolete infrastructure, assuring a reliable power supply.

A variety of optimization strategies have been developed to address the complex task of determining the optimal placement and capacity of Distributed Generators (DGs). Each technique brings a unique set of mechanisms and strengths. In [17], a mixed-integer linear programming (MILP) approach was proposed for DG sizing. In [9], the League Championship Algorithm (LCA) was utilized to simultaneously identify the best locations and sizes of DG units. The method incorporates the Loss Sensitivity Factor (LSF) for site selection, followed by LCA-based determination of capacity. Tests conducted on IEEE 33-bus and 69-bus systems highlighted notable improvements in voltage control and reduced energy losses compared to standard approaches. Similarly, Shaikh et al. (2024) introduced the Black Widow Optimization (BWO) technique, a multi-objective method inspired by the mating behavior of black widow spiders. This algorithm was designed to optimize both DG and DSTATCOM deployment, enhancing voltage stability, minimizing energy losses, and reducing the quantity of equipment needed [10]. In [18], a hybrid Artificial Bee Colony (ABC) and Particle Swarm Optimization (PSO) technique was proposed for determining the optimal location of static var compensators (SVCs), while [19] presented an approach for optimal shunt capacitor placement using Constriction-Factor Particle Swarm Optimization (CFPSO). However, both studies primarily addressed voltage profile enhancement and did not consider power loss mitigation in distribution networks.

Particle Swarm Optimization (PSO) is another widely adopted method due to its simple implementation and high convergence performance. It has been frequently employed to optimize the location and sizing of renewable energy resources within radial distribution systems, with common objectives such as power loss reduction and voltage profile enhancement. Several studies have reported that PSO often achieves better outcomes than Genetic Algorithm (GA) when applied to these challenges [7,8].

A significant number of studies have implemented hybrid approaches that combine MATLAB and DIgSILENT PowerFactory for the purpose of DG optimization. In these setups, MATLAB executes the optimization algorithm, while DIgSILENT simulates the power network behavior. Although this co-simulation strategy is effective, it introduces delays because of the continual data exchange required between the two software environments.

For example, research in [20–22] used this method to optimize the location and capacity of battery energy storage systems (BESS). Metaheuristic algorithms were applied in MATLAB to perform optimization, with DIgSILENT handling the simulation feedback. However, this back-and-forth exchange of information between platforms at every iteration resulted in added computational burden.

While the co-simulation framework proved technically viable, the performance was hindered by the repetitive transfer of large datasets during iterative processes [23,24]. To overcome this limitation, the present study proposes a more efficient approach that utilizes Python to directly manage both the optimization and simulation tasks through its native interface with DIgSILENT PowerFactory. Python's powerful computational libraries and automation capabilities, combined with its direct access to DIgSILENT's simulation core, eliminate the need for inter-software communication. This integration significantly enhances computational speed and enables scalable implementation. In this work, the Deep Sleep Optimizer (DSO) algorithm is employed to demonstrate this Python-based optimization technique for the optimal siting and sizing of DGs in the IEEE 33-bus system.

Building on these prior studies, this paper focuses on the strategic placement and sizing of DGs with the dual objectives of minimizing power losses and enhancing voltage stability while ensuring economic feasibility. Unlike earlier co-simulation approaches, we propose a direct Python–PowerFactory framework that eliminates data-exchange overheads and enables faster, more scalable optimization. This study therefore aims to provide practical insights into DG integration strategies that strengthen both the efficiency and sustainability of modern distribution networks.

The Deep Sleep Optimizer (DSO) is a human behavior-inspired metaheuristic algorithm that mimics the sleep-wake cycle. It features global exploration during the deep sleep phase and refined local search during wakefulness, guided by mechanisms such as circadian rhythms and sleep homeostasis. Introduced in recent studies [25], DSO has shown promise in renewable energy planning, especially in multi-application energy storage systems, as demonstrated in [26].

Comparative studies have benchmarked DSO against other cutting-edge metaheuristic methods, including the Improved Golden Jackal Optimization Algorithm (IGJOA) [27], Hiking Optimization Algorithm (HOA) [28], and Wombat Optimization Algorithm (WOA) [29], revealing competitive or superior performance. However, this research focuses on comparing DSO with more widely used algorithms in DG planning: GA and TLBO. To date, DSO has not been explored for the specific problem of DG siting and sizing, positioning this study as a novel contribution to the field.

This research applies the DSO technique to optimize the allocation of DGs in a distribution system, capitalizing on its biologically motivated search strategy to minimize losses and improve voltage profiles. To the best of our knowledge, this marks the first application of DSO in the context of DG placement within the IEEE 33-bus network. The proposed approach is anticipated to deliver higher-quality solutions and support more effective integration of DGs into evolving power distribution architectures.

Contributions of this work

Based on the research gaps identified in the literature, the main contributions of this paper are summarized as follows:

1. This is the first study to apply the Deep Sleep Optimizer (DSO) for strategic placement and sizing of DG units in distribution networks.
2. A direct Python–PowerFactory framework is developed, which eliminates MATLAB co-simulation overhead and integrates optimization with simulation efficiently.
3. The proposed approach benchmarks DSO against Genetic Algorithm (GA) and Teaching–Learning-Based Optimization (TLBO), demonstrating superior convergence speed, computational efficiency, and power loss minimization.
4. Simulations on the IEEE 33-bus test system validate DSO's ability to enhance voltage stability and reduce both active and reactive losses across single-, double-, and triple-DG scenarios.
5. DSO, being parameter-free, reduces the implementation burden for practitioners and shows potential scalability for smart grid DG integration.

2. Methodology

The approach used to address the optimal placement and sizing of Distributed Generators (DGs) follows a structured process incorporating a benchmark test system, mathematical modeling, and advanced optimization algorithms. The IEEE 33-bus radial distribution network serves as the testbed to assess the effectiveness of the optimization techniques. The problem is formulated with an objective function that simultaneously seeks to minimize both voltage deviations and real power

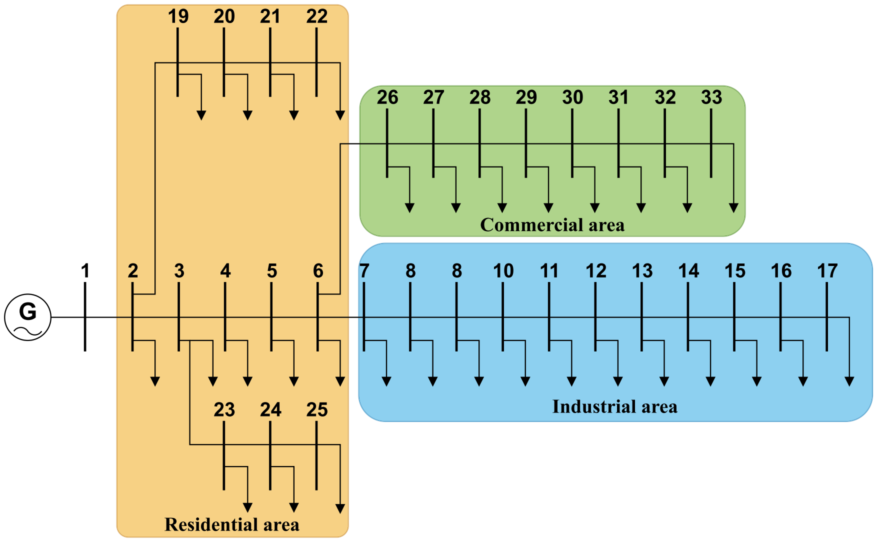


Fig. 1. Modified IEEE 33 bus distribution test system.

losses, while satisfying operational constraints such as voltage boundaries and generator capacity limits. The optimization process utilizes three algorithms Genetic Algorithm (GA), Teaching–Learning-Based Optimization (TLBO), and Deep Sleep Optimizer (DSO) to identify the most effective DG locations and corresponding capacities.

2.1. IEEE-33 bus distribution network

The benchmark network employed in this work is the radial **IEEE 33-bus** distribution feeder, modeled and simulated in DIgSILENT PowerFactory (Fig. 1). The feeder comprises 33 buses interconnected by 32 branches and operates at a nominal medium-voltage level of 12.66 kV. Bus-voltage magnitudes must remain within the admissible band of 0.95–1.05 p.u.

A single slack (synchronous) generator supplies the total network demand of 3.715 MW and 2.300 MVar, which is distributed across 32 load buses with diverse power factors. The base-case losses are 210.99 kW (active) and 141.84 kVar (reactive) [30]. All line parameters, load data, and generator settings follow the standard test-system benchmarks in [31,32].

2.2. Problem formulation

This paper aims to determine the most advantageous location and dimensions of DGs, while considering various objective functions and constraints. In this segment, a mathematical formulation of the objective function is established.

2.2.1. Objective function

The central goal of the formulated objective functions is to minimize real power losses and improve the voltage stability index (VSI) in a radial distribution network, while ensuring that bus voltages remain within acceptable operational limits. In this study, a weighted sum approach is adopted to consolidate the multi-objective problem into a single-objective formulation. The combined objective function is defined as:

$$\min f = w_1 f_1 + w_2 f_2 \tag{1}$$

Here, f_1 corresponds to the total real power losses, and f_2 refers to the voltage stability index. The weighting coefficients w_1 and w_2 are used to emphasize one objective over another, depending on the specific utility priorities or planning requirements. These weights are generally constrained as follows:

$$\sum_{k=1}^{n} w_k \quad \text{and} \quad 0 < w_k < 1 \tag{2}$$

The assignment of these weights is influenced by several factors, including generation costs, technological constraints, environmental concerns, and regulatory or market conditions. In this work, reducing power losses is given higher importance with a weight of 0.7, while improving voltage stability is assigned a weight of 0.3. This ratio is consistent with standard normalization practices in weighted objective optimization.

The objective function f_1 evaluates the ratio of total system losses after integrating DGs to the losses without DGs:

$$f_1 = \frac{P_{L(DG)}}{P_L} \tag{3}$$

where P_L represents the system-wide real power losses before DGs are added, and $P_{L(DG)}$ is the cumulative real power loss after DG installation. The post-integration losses are computed using:

$$P_{L(DG)} = \sum_{m=1}^{N} I_m^2 R_m \tag{4}$$

where I_m is the magnitude of the line current, and R_m denotes the resistance of branch m.

Radial distribution systems inherently experience greater voltage drops at buses further from the source, making them vulnerable to voltage collapse. To identify the most susceptible buses, the Voltage Stability Index (VSI) is employed as proposed in [33]:

$$I_{ri} = \frac{V_{si} - V_{ri}}{R_{ri} + jX_{ri}} \tag{5}$$

$$P_{ri}(ri) - jQ_{ri}(ri) = V_{ri}^* I_{ri} \tag{6}$$

$$VSI(ri) = |V_{si}|^4 - 4[P_{ri}(ri)R_{ri} + Q_{ri}(ri)X_{ri}]|V_{si}|^2 - 4[P_{ri}(ri)R_{ri} - Q_{ri}(ri)X_{ri}]^2 \tag{7}$$

In the above expressions, V_{si} represents the sending-end voltage, while V_{ri}, P_{ri}, Q_{ri}, R_{ri}, and X_{ri} correspond to the receiving-end voltage, real and reactive power, line resistance, and reactance, respectively.

The objective function related to voltage stability is represented as:

$$f_2 = \frac{1}{\min(\mathrm{VSI}(ri))}; \quad ri = 2, 3, \ldots, r_r \tag{8}$$

This formulation aims to enhance system stability by maximizing the minimum VSI across all buses.

2.2.2. Constraints

The integration of distributed generation (DG) into the distribution network can lead to reverse power flows and elevated current levels within the system, which often results in voltage rises at certain buses. To ensure stable operation, voltage magnitudes at all buses must be constrained within permissible minimum and maximum thresholds for each scenario and optimization method used. This requirement is expressed as:

$$|V_i|^{\min} \le |V_i| \le |V_i|^{\max} \tag{9}$$

where $|V_i|$ is the voltage magnitude at bus i, and the values for $V_i^{\min}$ and $V_i^{\max}$ are set to 0.95 p.u. and 1.05 p.u., respectively. These boundaries align with typical design tolerances of 5%–10% around the nominal voltage level [34].

To ensure feasible operation, DG units are also subject to active power limits:

$$P_{DG}^{\min} \le P_{DG} \le P_{DG}^{\max} \tag{10}$$

As DG systems generally have discrete outputs [35], their generation capacity depends on resource availability, adopted technologies, and site-specific environmental factors. Consequently, both active and reactive power outputs must satisfy the following operational limits:

$$Q_{DG}^{\min} \le Q_{DG} \le Q_{DG}^{\max} \tag{11}$$

Additionally, the apparent power flow through each distribution line must remain below its thermal capacity to prevent overloading:

$$S_{i,j} \le S_{\max,i,j} \tag{12}$$

where $S_{i,j}$ denotes the apparent power transmitted between buses i and j, and $S_{\max,i,j}$ is the line's rated thermal limit [36].

2.3. Optimization techniques

A multitude of meta-heuristic algorithms have been developed to address intricate optimization challenges. Notably, two of the most frequently employed methodologies are Particle Swarm Optimization (PSO) and the Genetic Algorithm (GA).

2.3.1. Genetic algorithm (GA)

The Genetic Algorithm (GA) constitutes an evolutionary optimization methodology that was pioneered by John Holland in the year 1975 [37]. The methodology is derived from the principles of natural selection and functions on a population of potential solutions (chromosomes), progressively refining them over successive generations through mechanisms of selection, crossover, and mutation to identify an optimal or near-optimal solution. The detailed procedural framework of Genetic Algorithms (GA) is delineated in the referenced literature [38,39]

2.3.2. Teaching and learning-based optimization

The Teaching–Learning-Based Optimization (TLBO) algorithm was originally proposed by Rao et al. [40] in the year 2011, drawing its inspiration from the pedagogical philosophy inherent in the classroom teaching–learning dynamic and emulating the impact that an educator exerts on the performance of students. TLBO is characterized as a heuristic stochastic search algorithm rooted in human behavioral patterns; however, it distinguishes itself by not necessitating any specific parameters tailored to the algorithm. The distinguished characteristics of the TLBO methodology, encompassing its uncomplicated conceptual framework, lack of parameters that are specific to the algorithm, rapid convergence rates, simplicity in implementation, and general efficacy, significantly enhance its attractiveness [41]. When compared to analogous meta-heuristic algorithms, TLBO is regarded as user-friendly, adaptive, and straightforward to apply; consequently, it is suited for addressing a diverse array of real-world optimization challenges [42], encompassing domains such as parameter optimization tasks [43,44], optimal placement and sizing of DGs [45], among others. The step-by-step implementation of TLBO is presented in [45].

2.3.3. Teaching–learning-based optimization (TLBO)

Teaching–Learning-Based Optimization (TLBO), first introduced by Rao et al. [40], is a parameter-free population-based meta-heuristic that mimics the knowledge transfer between a *teacher* and the *learners* in a classroom. Its absence of algorithm-specific tuning constants, simple conceptual structure, and rapid convergence have led to successful applications ranging from process design [41] and controller tuning [43, 44] to the optimal placement and sizing of distributed generators (DGs) in power-distribution networks [45].

Problem formulation (after [45]). Let

$$\mathbf{x}_i = \big[\underbrace{\mathrm{loc}_{i,1}, \ldots, \mathrm{loc}_{i,N_{DG}}}_{\text{bus locations}},\ \underbrace{P_{i,1}, \ldots, P_{i,N_{DG}}}_{\text{DG sizes (MW)}}\big]$$

denote the ith candidate solution (*learner*) in a class of size n. Each learner is evaluated through a multi-objective cost

$$F(\mathbf{x}_i) = \alpha\, \Delta P_{\mathrm{loss}}(\mathbf{x}_i) + \beta\, \Delta V_{\mathrm{dev}}(\mathbf{x}_i) + \gamma\, \big[1/\,\mathrm{SI}_{\min}(\mathbf{x}_i)\big],$$

where ΔP_{loss}, ΔV_{dev} and the minimum voltage-stability index $\mathrm{SI}_{\min}$ are defined in [45]. Search variables are bounded by system limits on DG real power, power factor, and node voltage

$$P_{DG}^{\min} \le P_{i,j} \le P_{DG}^{\max}, \qquad V^{\min} \le V_k \le V^{\max}\ (\forall k).$$

The algorithm seeks $\mathbf{x}^\star = \arg\min_{\mathbf{x}} F(\mathbf{x})$.

Teacher phase. The best learner $\mathbf{x}_{\mathrm{best}}$ acts as the teacher. For each learner i and each design variable j the difference vector is

$$\Delta_{j,i} = r_i\big(x_{\mathrm{best},j} - \mathrm{TF}\,\bar{x}_j\big), \tag{13}$$

where $\bar{x}_j$ is the class mean of variable j, $r_i \sim \mathcal{U}[0,1]$, and the *teaching factor*

$$\mathrm{TF} = \mathrm{round}\big(1 + \mathrm{rand}(0,1)\big) \in \{1,2\}.$$

The learner is updated as $x'_{j,i} = x_{j,i} + \Delta_{j,i}$ if this yields a lower cost.

Learner phase. A learner P interacts with a randomly chosen peer $Q \ne P$:

$$x''_{j,P} = \begin{cases} x'_{j,P} + r_P\big(x'_{j,Q} - x'_{j,P}\big), & F(\mathbf{x}'_Q) < F(\mathbf{x}'_P), \\ x'_{j,P} + r_P\big(x'_{j,P} - x'_{j,Q}\big), & \text{otherwise}. \end{cases} \tag{14}$$

If $\mathbf{x}''_P$ improves F, it replaces $\mathbf{x}'_P$. Steps (13)–(14) are repeated until the maximum number of iterations is reached or convergence is achieved.

Salient features. Because TLBO requires no algorithm-specific parameters (inertia weights, crossover rates, etc.), only the population size and the iteration budget need to be selected, simplifying deployment. Its two-stage knowledge-transfer mechanism accelerates convergence and has been shown to outperform GA and PSO for optimal DG placement on the IEEE 33- and 69-bus feeders [45].

2.3.4. Deep sleep optimizer algorithm

The Deep Sleep Optimizer (DSO) represents a human-centric meta-heuristic optimization algorithm, as delineated by Oladejo et al. [25], which draws its inspiration from the biological phenomena associated with the sleep-wake cycle. It models the process of deep sleep for global exploration and wakefulness for local exploitation. The algorithm is governed by a sleep homeostasis function and a circadian rhythm, which dynamically balance exploration and exploitation. The implementation approach of DSO is as follows:

- **Step 1: Initialize Population** A population of N candidate solutions (agents) is generated randomly within defined bounds:

$$X_i^0 = [x_1, x_2, \dots, x_n], \quad \text{for } i = 1, 2, \dots, N \tag{15}$$

where x_j represents the decision variables.
- **Step 2: Evaluate Fitness** Compute the fitness function for each agent:

$$f(X_i) = \text{Objective Function}(X_i) \tag{16}$$

- **Step 3: Sleep-Wake Cycle Model** The homeostatic pressure $H(t)$ is modeled as:

$$H(t) = \begin{cases} H_0(t) \cdot e^{(t_0 - t)/x_s}, & \text{(Sleep State)} \\ \mu(t) + (H_0(t) - \mu(t)) \cdot e^{(t_0 - t)/x_w}, & \text{(Wake State)} \end{cases} \tag{17}$$

where x_s is the sleep power index, x_w is the wake power index, $H_0(t)$ is the initial homeostatic value, and $\mu(t)$ is the wake threshold.
- **Step 4: Threshold-Based Sleep-Wake Regulation** Define maximum and minimum homeostatic thresholds:

$$H_{\max} = H_0^+ + a \cdot C(t) \tag{18}$$

$$H_{\min} = H_0^- + a \cdot C(t) \tag{19}$$

where a is the circadian cost per unit function, and $C(t)$ is given by:

$$C(t) = \sin\left(\frac{2\pi}{T}(t - \alpha)\right) \tag{20}$$

with α as a random circadian time shift in $[0, 1]$.
- **Step 5: Homeostatic Update Equation** The homeostatic value is updated as:

$$H_0(t) = \gamma + r \cdot (X_{\text{best}} - \mu(t) \cdot X_{\text{mean}}) \tag{21}$$

where X_{best} is the best agent's position, X_{mean} is the mean position of agents, r is a random number in $[0, 1]$, and γ represents the initial agent population.
- **Step 6: Exploration and Exploitation Update** The agent positions are updated depending on their sleep-wake states:
  - **Exploration (Deep Sleep - N3 Stage):**

$$X_i^{\text{new}} = X_i + r(X_{\text{best}} - X_i) \tag{22}$$

  - **Exploitation (Wake State):**

$$X_i^{\text{new}} = X_i - r(X_i - X_{\text{mean}}) \tag{23}$$

- **Step 7: Greedy Selection Strategy** The new position is accepted if the fitness improves:

$$X_i = \begin{cases} X_i^{\text{new}}, & \text{if } f(X_i^{\text{new}}) < f(X_i) \\ X_i, & \text{otherwise} \end{cases} \tag{24}$$

- **Step 8: Stopping Criterion** The algorithm terminates when the maximum number of iterations is reached or:

$$|f(X^{t+1}) - f(X^t)| < \epsilon \tag{25}$$

All three meta-heuristics were run with identical population sizes and iteration budgets to ensure a fair comparison; the remaining hyper-parameters follow the values recommended in the original papers. The complete set of settings is summarized in Table 1.

The flowchart in Fig. 2 outlines a structured workflow for optimizing a power system using PowerFactory (DIgSILENT) and Python-based Deep Sleep Optimizer (DSO) Algorithm. The process begins with initializing the power system by connecting to PowerFactory, activating the project and study case, and running a load flow analysis. Next, the lowest bus voltage is identified, and a cubicle is created at the weakest busbar, where a distributed generator (DG) is activated. Another load flow analysis is then performed to record initial conditions before proceeding to the optimization phase.

The optimization process employs the DSO algorithm, which iteratively searches for the best DG placement and sizing. A decision-making step checks whether the last iteration has been reached; if not, the population and fitness values are updated, and the process continues. Once the stopping criteria are met, the optimized solution, including the best DG position and fitness value, is stored. The results are then exported to a CSV file for further analysis. Finally, the workflow concludes with the development of a DSO knowledge database, which likely serves as a repository for optimized solutions and insights for future applications.

3. Results and analysis

Fig. 3 contrasts the convergence trajectories of the three meta-heuristics for the single-, double-, and triple-DG cases.[1] Three key observations emerge. For every DG scenario DSO reaches its final plateau in fewer than 20 iterations, whereas TLBO takes roughly 35–40 iterations and GA requires ∼70 iterations to stabilize. The faster descent of the DSO curves (cf. the steep initial slope in Figs. 3(a)–3(c)) confirms the higher exploitation pressure of its “deep-sleep” phase.

Table 3 lists the best fitness values at iteration 100:

Algorithm	1 DG	2 DGs	3 DGs
GA	1.5563	0.8027	0.8170
TLBO	0.9939	0.7228	0.3161
DSO	0.9939	0.7562	0.3856

For the single-DG case TLBO and DSO tie to three decimal places and surpass GA by ≈36%. With two DGs the difference narrows but TLBO still edges DSO. In the triple-DG run TLBO attains the global minimum (0.3161), 18% below DSO and 61% below GA, evidencing its superior exploration in higher-dimensional search spaces.

The GA curves exhibit oscillations after iteration 60 in Figs. 3(b)–3(c), symptomatic of premature convergence into local basins. In contrast, TLBO shows a smooth monotonic decline, while DSO's curve flattens earlier but with minor residual fluctuations an artefact of its stochastic dormancy-wake cycle. DSO offers the *fastest* route to a near-optimum, which is valuable in on-line or large-system studies. TLBO delivers the *best* ultimate fitness, particularly when three DGs are allowed, and therefore gives the greatest technical benefit if the additional run-time (Table 2) is acceptable. GA remains the least attractive: it converges slowly *and* to a sub-optimal plateau, highlighting the trade-off between computational simplicity and solution quality in classic evolutionary schemes.

3.0.1. Active-power-loss convergence

Fig. 4 complements the fitness curves by plotting *real power losses* against iteration count for the single-, double- and triple-DG studies. Three insights deserve emphasis:

(1) **Speed of loss abatement.** In every DG scenario DSO slashes the feeder losses most rapidly, attaining its steady plateau within the first ∼30 iterations. TLBO follows, stabilizing around 60–70 iterations, while GA continues a slow drift until iteration 100. The steeper initial descent of the DSO traces is consistent with the aggressive exploitation phase observed earlier in the fitness curves.

Starting from the base-case loss of 210.1 kW:

- *1 DG:* TLBO achieves the lowest loss (91.16 kW, 56.6% reduction), with DSO virtually tied at 91.42 kW; GA lags behind at 148.7 kW (29.2% reduction).

[1] The fitness function combines loss reduction and voltage-deviation penalty; a lower value therefore denotes a better solution.

Table 1
Parameter settings used for each meta-heuristic in the DG-placement study.

Parameter	GA	TLBO	DSO
Population size	30	30	30
Maximum generations/iterations	100	100	100
Mutation rate	0.02		
Crossover rate	0.70		
Elitism	Yes (best individual copied)		
Teaching factor T_F		Random $\{1, 2\}$	
Uniform scaling vector $r \sim U(0,1)$		Applied in teacher- and learner-phase moves	Applied in update step
Search bounds	$0 \leq P_{DG} \leq 3\,\text{MW},\ \ 0 \leq Q_{DG} \leq 2\,\text{MVar}$		
Objective function	minimize $(voltage - deviation + penalties) + 2\times$ real-power losses		
Stopping rule	iterate for the full 100 generations (no early termination)		

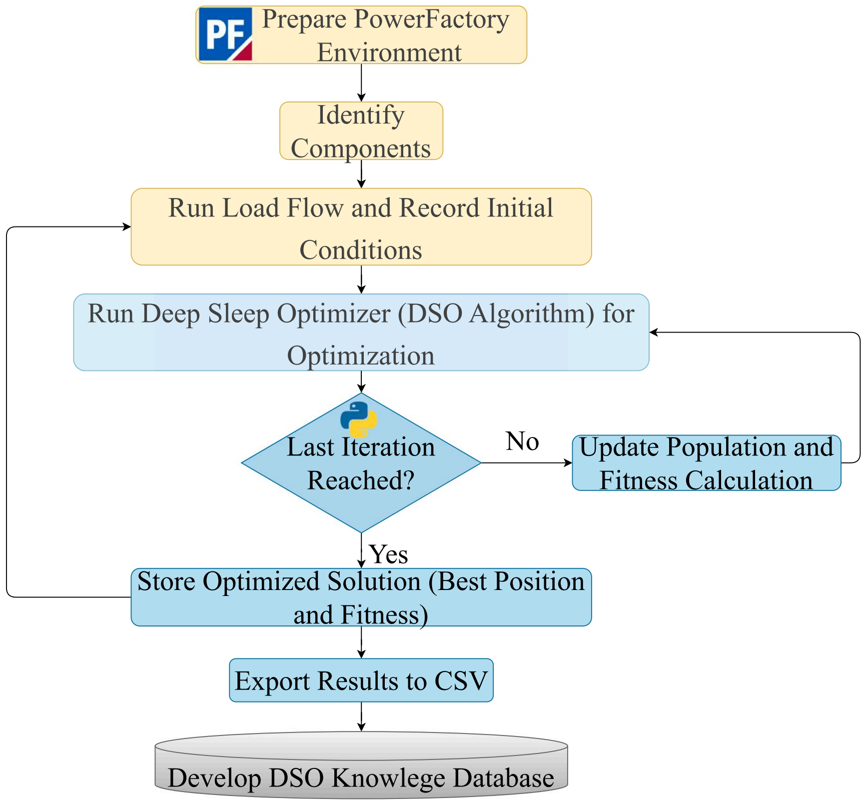
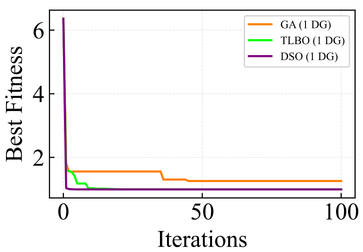
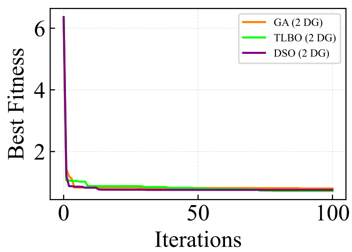


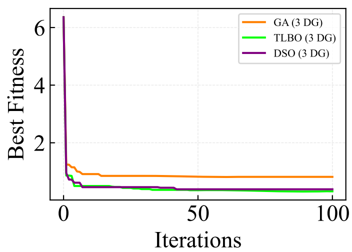
Fig. 2. The flowchart of the proposed Deep Sleep Optimizer algorithm interaction with the environment (DIgSILENT simulation).



(a) Best fitness vs iterations for 1 DG

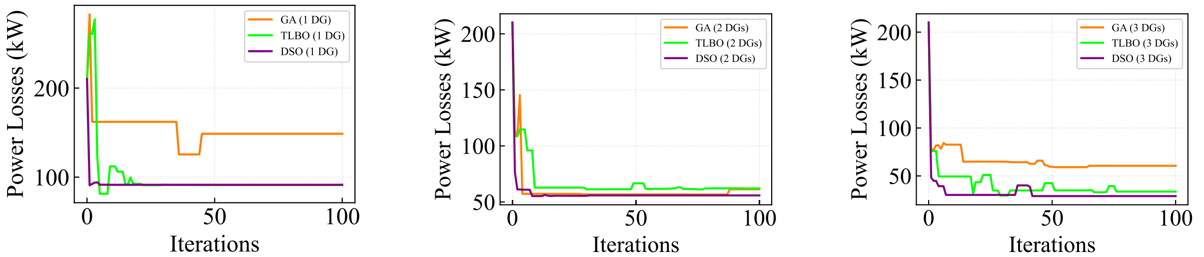


(b) Best fitness vs iterations for 2 DGs



(c) Best fitness vs iterations for 3 DGs

Fig. 3. Performance analysis of optimization algorithms: Best fitness.



(a) Best fitness vs power reduction for 1 DG

(b) Best fitness vs power reduction for 2 DGs

(c) Best fitness vs power reduction for 3 DGs

Fig. 4. Performance analysis of optimization algorithms: Power losses.

- *2 DGs:* DSO takes the lead (55.9 kW, 73.4% reduction), edging out GA (61.3 kW) and TLBO (62.1 kW).
- *3 DGs:* DSO again delivers the best result, driving losses down to 28.9 kW (86.2% reduction), followed by TLBO (33.7 kW, 84.0%) and GA (60.6 kW, 71.2%).

The GA curves display noticeable oscillations once the loss falls below ≈65 kW, indicating premature convergence into local optima. TLBO exhibits a smooth monotonic decline, whereas DSO flattens sooner with only minor residual fluctuations an artefact of its dormancy-wake cycle but still maintains the lowest loss envelope.

In practical terms a single DG located by TLBO/DSO already halves the losses, providing an attractive first step for network operators. When two DGs are affordable, all three optimizers deliver similar technical gains, yet DSO does so in the shortest run-time. A third DG is justified only when the marginal capital cost is offset by the extra 13%–16% loss reduction delivered chiefly by DSO, making it the preferred tool for high-penetration scenarios.

3.0.2. Voltage-profile convergence at the critical node

Fig. 5 tracks the per-unit voltage at the most-depressed node (bus 18) as the optimizers iterate.[2] Three trends can be distilled. With a single DG (Fig. 5a) both TLBO and DSO lift V_{18} above the 0.95 p.u. threshold after ≈10 iterations, whereas GA needs ∼40 iterations. The pattern repeats for the two- and three-DG cases (Fig. 5b–c), confirming the sharper initial learning rate of TLBO/DSO. At iteration 100 the voltages read $\{0.9775, 0.9787, 0.9836\}$ p.u. for GA, $\{0.9829, 0.9762, 0.9921\}$ p.u. for TLBO, and $\{0.9830, 0.9764, 0.9920\}$ p.u. for DSO ({1,2,3} DG respectively). Hence: (a) all algorithms satisfy the statutory limit (0.95–1.05 p.u.); (b) with *one* DG, TLBO/DSO outperform GA by about 0.5 percentage-points; (c) with *three* DGs, TLBO yields the highest voltage (0.9921 p.u.), closely tailed by DSO, while GA lags by 0.8 percentage-points.

The GA curves show small oscillations after iteration 60, indicating the algorithm is still exploring a shallow local basin. TLBO exhibits a smooth monotone rise, whereas DSO flattens a little earlier yet with negligible ripple consistent with its exploitation-oriented "deep-sleep" phase. If the primary objective is voltage compliance at the weakest bus, a single DG sized and placed by either TLBO or DSO already suffices. Additional DGs bring diminishing voltage benefit (0.983 → 0.992 p.u.) but remain valuable for loss minimization (Table 2).

3.0.3. Voltage-profile improvement along the feeder

Fig. 6 depicts the nodal voltage profiles before and after DG placemen. Three remarks can be made.

(1) **Elimination of the under-voltage pocket.** In the base case the minimum voltage on the IEEE-33 feeder is only 0.90 pu (buses 16–18). A single DG chosen by **TLBO** or **DSO** raises that floor to 0.99 pu, whereas **GA** lifts it to 0.98 pu. With two DGs the minimum rises further to 0.994 p.u. (DSO), 0.996 p.u. (TLBO) and 0.990 p.u. (GA); three DGs push every bus above 0.992 pu, fully removing the worst-voltage pocket.
The standard deviation of bus voltages shrinks from $\sigma_V^{\text{base}} = 0.030$ to 0.009 (TLBO), 0.010 (DSO) and 0.013 (GA) in the 1-DG case, indicating that TLBO and DSO yield a flatter profile. Adding a second DG halves σ_V again for all methods, and the third DG brings only marginal extra smoothing, suggesting a diminishing-returns point at two units for voltage-quality objectives.
The highest post-DG voltage never exceeds 1.017 p.u. (GA, bus 8 in the 3-DG run) and therefore stays well below the statutory 1.05 p.u. upper limit. TLBO's and DSO's profiles peak at 1.012 p.u. and 1.013 p.u. respectively, showing that both optimizers balance loss minimization with over-voltage avoidance automatically, even though no explicit over-voltage penalty was imposed.

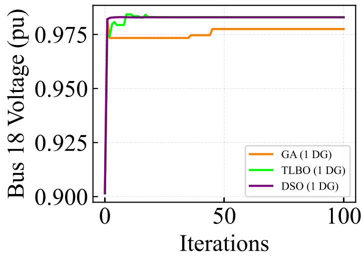
Deploying *one* DG at the optimized TLBO/DSO location is already sufficient to satisfy the conventional 0.95–1.05 p.u. voltage band. A *second* DG is advisable when a highly uniform profile ($\sigma_V < 0.005$) is required or when the operator seeks the additional loss reduction reported in Table 2; a *third* DG offers negligible voltage benefit but does contribute another 13%–16% loss abatement and therefore should be justified on economic, rather than voltage-quality, grounds.

Table 2 reveals three clear trends. *First*, all meta-heuristics achieve sizeable loss mitigation compared to the base case, but their effectiveness grows non-linearly with the number of installed DGs. With a single unit, TLBO and DSO halve the feeder losses (56%–57%), whereas GA attains only 29%. When two units are allowed, the three solvers converge to a similar technical outcome (61–62 kW, ≈70% reduction), indicating that multiple placements can satisfy the loss objective once the solution space is expanded. The third DG distinguishes the algorithms: DSO drives losses down to 28.9 kW (86.2% reduction), outperforming TLBO (33.7 kW, 84.0%) and especially GA, which shows negligible improvement beyond its two-DG solution.

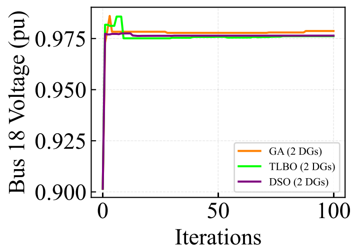
Second, the sizing vectors suggest that DSO allocates power almost evenly among the three sites (0.51–1.84 MW), while GA prefers one dominant DG accompanied by smaller satellites. The balanced dispatch in DSO produces the lowest aggregate MVA footprint for the same loss target, a potential cost advantage in practical procurement.

Third, GA remains the quickest optimizer for every DG count (386–491 s), making it attractive for time-constrained studies, whereas TLBO trades run-time for quality the 3-DG case requires 3500 s but still falls short of DSO's loss figure. DSO offers a middle ground in computational effort (491–666 s) yet delivers the overall best technical performance, especially in the multi-DG scenarios.

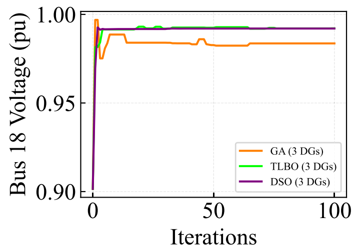
[2] The initial voltage is $V_{18}^{\text{base}} = 0.9015$ pu. A value above 0.95 p.u. is regarded as satisfactory in most distribution-code limits.



(a) Bus 18 Voltage (pu) vs iterations for 1 DG

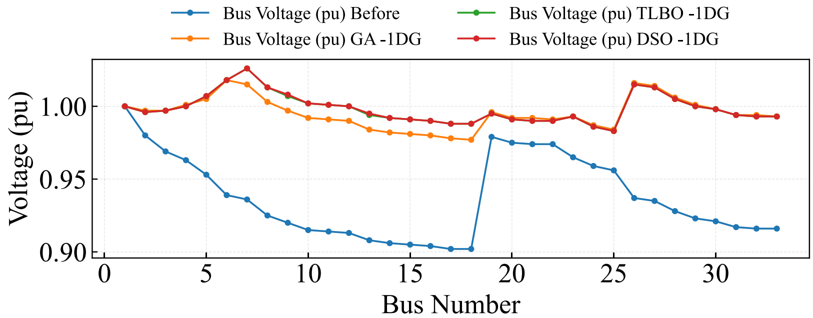


(b) Bus 18 Voltage (pu) vs iterations for 2 DGs

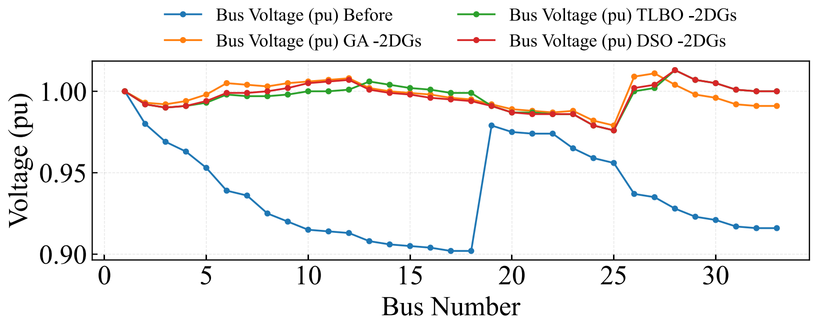


(c) Bus 18 Voltage (pu) vs iterations for 3 DGs

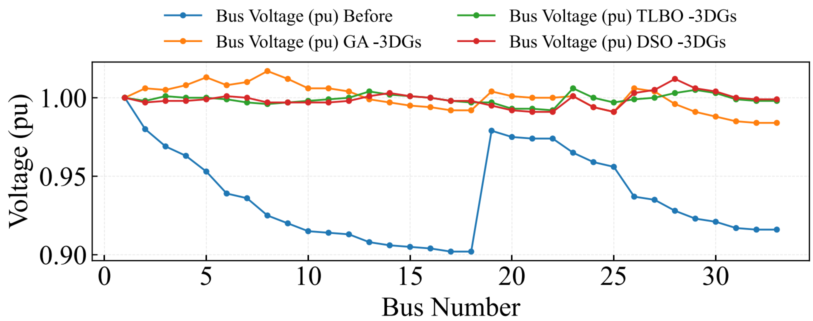
Fig. 5. Performance analysis of optimization algorithms: Bus 18 voltage (pu).



(a) System bus voltages before and after 1 DG placement and sizing



(b) System bus voltages before and after 2 DG placement and sizing



(c) System bus voltages before and after 3 DG placement and sizing

Fig. 6. Performance analysis of the distribution network: Bus voltage improvement.

In planning terms, a single DG located at bus 7 (TLBO/DSO) already provides an efficient “first step”. If budgets allow two DGs, all methods suffice; GA’s speed may be decisive. A third DG is justified only when the incremental capital cost is offset by the additional 13%–16% loss abatement delivered by TLBO and, more decisively, DSO making the latter the preferred tool for high-penetration scenarios.

4. Discussion

Early single-DG investigations on the IEEE-33 feeder most notably the PSO study by Prakash and Somasundaram [46] and the heuristic approach of Bayat et al. [47] lowered real losses by roughly 47% with a 2.6 MW unit at bus 6. Comparable reductions were obtained

Table 2
Comparison of GA, TLBO and DSO for optimal DG placement and sizing on the IEEE-33-bus feeder.

Metric	Base	GA			TLBO			DSO		
		1 DG	2 DG	3 DG	1 DG	2 DG	3 DG	1 DG	2 DG	3 DG
Number of DGs	–	1	2	3	1	2	3	1	2	3
Location (bus)	–	6	27 12	8 2 5	7	13 28	13 29 23	7	12 28	14 23 28
Optimal P (MW)	–	2.67	1.88 0.98	1.29 2.23 1.98	3.45	0.79 1.63	1.02 1.12 2.07	3.43	0.85 1.87	0.51 1.49 1.84
Total P (MW)	–	2.67	2.86	5.50	3.45	2.42	4.21	3.43	2.72	3.84
Optimal Q (MVar)	–	3.35	1.47 0.19	0.86 1.61 0.35	1.94	0.45 1.27	0.08 0.53 1.14	1.97	0.57 0.74	0.54 0.63 0.45
Total Q (MVar)	–	3.35	1.66	2.82	1.94	1.72	1.74	1.97	1.31	1.62
Optimal Size (MVA)	–	4.28	2.37 1.00	1.55 2.75 2.01	3.96	0.91 2.07	1.02 1.24 2.36	3.96	1.02 2.01	0.74 1.62 1.89
Total size (MVA)	–	4.28	3.31	6.18	3.96	2.97	4.56	3.96	3.02	4.17
Power losses (kW)	210.12	148.73	61.32	60.57	91.18	62.08	33.68	91.42	55.85	28.92
P_L reduction (%)	–	29.22	70.81	71.17	56.61	70.45	83.97	56.49	73.42	86.24
Reactive losses (kVar)	141.60	97.75	41.05	40.23	81.63	44.58	23.17	81.79	40.31	26.93
Q_L reduction (%)	–	30.97	71.01	71.59	42.35	68.52	83.64	42.24	71.53	80.98
CPU time (s)	–	386.38	490.89	476.75	762.44	1325.70	3517.20	490.84	528.22	665.98

Optimal P - active-power injection; optimal Q - reactive-power injection.

Table 3
Benchmark comparison of proposed and published methods for *1-DG* placement on the IEEE-33 feeder.

Ref. & Algorithm	DG size (kW) at bus	Total DG size (kW)	P_L (kW)	P_L Red. (%)	Q_L (kVar)	Q_L Red. (%)
[46] PSO (2016)	2589 (6)	2589	110.99	47.39	–	–
[49] SKHA (2017)	2590 (6)	2590	111.02	47.13		
[49] VCPSO (2020)	2591 (6)	2591	111.1	47.4	73.91	45.77
[47] Novel Heuristic (2019)	2600 (6)	2600	111.10	47.10		
[30] IAT (2024)	2431 (6)	2431	110.64	47.31		
Proposed GA	2670 (6)	2670	148.73	29.22	97.75	30.97
Proposed TLBO	3450 (7)	3450	91.16	56.62	81.63	42.35
Proposed DSO	**3430 (7)**	**3430**	**91.42**	**56.49**	**81.79**	**42.24**

Table 4
Benchmark comparison of proposed and published methods for *2-DG* placement on the IEEE-33 feeder.

Ref. & Algorithm	DG sizes (kW) at buses	Total DG size (kW)	P_L (kW)	P_L Red. (%)	Q_L (kVar)	Q_L Red. (%)
[48] MOPSO (2021)	3133.4 (6), 365.1 (16)	3499	105.7	47.97	74.81	44.65
[50] VCPSO (2020)	866.7 (13), 1323.2 (30)	2189.9	88.2	58.24	60.90	56.66
[46] PSO (2016)	1899 (6), 649.9 (14)	2548.6	91.3	56.73	–	–
Proposed GA	1880 (27), 980 (12)	2860	61.32	70.81	41.05	71.01
Proposed TLBO	790 (13), 1630 (28)	2420	62.08	70.45	44.58	68.52
Proposed DSO	**850 (12), 1870 (28)**	**2720**	**55.85**	**73.42**	**40.31**	**71.53**

with MRFO, SKHA and VCPSO variants [48,49]. By contrast, a single generator placed by TLBO or DSO in the present work cuts the loss to about 91 kW (≈56%), even though the installed capacity is of the same order, and crucially is shifted to bus 7, thereby removing the worst under-voltage pocket without over-stressing the source bus. A detailed comparison with earlier single-DG papers is given in Table 3.

With two distributed generators the gap widens. Variable-constant PSO (VCPSO) of Al-Ajmi [50] reports 88.2 kW (58% reduction) for a combined 2.19 MW at buses 13 and 30, whereas our DSO solution achieves 55.85 kW (73% reduction) with only 2.72 MW. Reactive-loss statistics show a similar trend: studies that publish Q_L results rarely exceed a 57% saving, while GA, TLBO and DSO reach 71%, 69% and 72%, respectively. Table 4 summarizes these findings.

When three DG units are allowed the superiority of the present workflow is most evident. Improved MOEHO [51] and the analytical technique of [30] leave 95 kW and 81 kW of losses, respectively, whereas DSO brings that figure down to 28.92 kW, an 86% reduction. Notably, the total capacity installed by DSO (3.84 MW) is still smaller than that of many meta-heuristic counterparts, yet it produces the lowest active *and* reactive losses while lifting every bus above 0.98 p.u.. A side benefit is that spreading three medium-sized units across buses 14, 23 and 28 avoids the local over-voltages identified in [52]. The complete three-DG comparison is provided in Table 5.

Voltage-profile results reinforce the loss findings. With one optimally placed DG, the weakest node (bus 18) rises from 0.90 p.u. to 0.99 p.u., and all critical far-end buses exceed 0.98 p.u.; the detailed values appear in Table 6. Adding a second generator boosts bus 18 to 0.994 p.u. and flattens the profile further (Table 7). A third DG brings only a modest incremental gain (Table 8), confirming that two units already satisfy common regulatory voltage limits while delivering a substantial loss reduction.

Computational effort offers additional perspective. Our TLBO implementation requires about 1326 s for the two-DG case and 3517 s for three

Table 5
Benchmark comparison of proposed and published methods for *3-DG* placement on the IEEE-33 feeder.

Ref. & Algorithm	DG sizes (kW) at buses	Total DG size (kW)	P_L (kW)	P_L Red. (%)	Q_L (kVar)	Q_L Red. (%)
[51] IMO-EHO (2018)	1057 (14), 1054 (24), 1741 (30)	3852	95.00	54.76	–	–
[48] MOPSO (2021)	1057 (6), 1054 (16), 1741 (25)	3267.9	82.77	59.26	58.39	56.80
[52] MOPSO (2020)	1676 (3), 955 (24), 1301 (31)	3933	87.30	58.43	–	–
[30] IAT (2024)	1312 (6), 462 (18), 657 (32)	2431	80.90	61.48	–	–
[52] MOPSO (2020)	1676 (3), 955 (24), 1301 (31)	3933	87.30	58.43	–	–
[53] I-DBEA (2021)	1098 (13), 1097 (24), 1715 (30)	3910	94.85	54.83	–	–
Proposed GA	1290 (8), 2230 (2), 1980 (5)	5510	60.57	71.17	40.23	71.59
Proposed TLBO	1020 (13), 1120 (29), 2070 (23)	4210	33.68	83.97	23.17	83.64
Proposed DSO	**510, 1490, 1840 (14, 23, 28)**	**3840**	**28.92**	**86.24**	**26.93**	**80.98**

Table 6
Far-end bus-voltage improvement with one optimally placed DG (GA, TLBO, and DSO).

Bus No.	Base (p.u.)	GA (p.u.)	TLBO (p.u.)	DSO (p.u.)	Best improvement (%)
18	0.90	0.98	0.99	0.99	**10.00**
22	0.97	0.99	0.99	0.99	**2.06**
25	0.96	0.98	0.98	0.98	**2.08**
33	0.92	0.99	0.99	0.99	**7.61**

Table 7
Far-end bus-voltage improvement with **2** optimally placed DGs (GA, TLBO, and DSO).

Bus No.	Base (p.u.)	GA (p.u.)	TLBO (p.u.)	DSO (p.u.)	Best improvement (%)
18	0.90	1.00	1.00	0.994	**11.11**
22	0.97	0.99	0.99	0.986	**2.06**
25	0.96	0.98	0.98	0.976	**2.08**
33	0.92	0.99	1.00	1.00	**8.70**

Table 8
Far-end bus-voltage improvement with **3** optimally placed DGs (GA, TLBO, and DSO).

Bus No.	Base (p.u.)	GA (p.u.)	TLBO (p.u.)	DSO (p.u.)	Best improvement (%)
18	0.902	0.992	0.997	0.998	**10.64**
22	0.974	1.000	0.992	0.991	**2.67**
25	0.956	0.991	0.997	0.991	**4.29**
33	0.916	0.984	0.998	0.999	**9.06**

DGs, whereas the Python DSO workflow completes the same studies in roughly 530 s and 666 s, respectively less than half the TLBO run-time and still several minutes quicker than the co-simulation approaches reported in most earlier PSO-based studies, which usually omit explicit CPU figures. GA remains the fastest algorithm overall but converges to the least attractive fitness plateau; TLBO attains an excellent single-DG solution yet incurs the longest run-time. DSO therefore represents the best compromise between computational cost and technical benefit.

In practice, a single DSO- or TLBO-sited generator already halves feeder losses and resolves the major under-voltage. A second DG yields a further fifteen-percent saving at modest additional capacity and run-time, making it attractive for networks with limited investment budgets. Deploying a third unit is economically warranted only when the marginal capital cost is outweighed by the extra thirteen-to-sixteen-percent loss abatement and by the resilience benefit of multiple injection points an outcome achieved only by DSO without excessive computation.

The present study models static demand and renewable output. Incorporating time-series load and photovoltaic data into the DSO framework will clarify its year-round benefit. Furthermore, the majority of published papers omit reactive-loss results, hindering perfect like-for-like comparisons; adoption of a common reporting template would enable more definitive benchmarking in future work. Nevertheless, by delivering the lowest real and reactive losses, competitive run-times and a voltage profile that comfortably satisfies statutory limits, the proposed DSO-based planning method constitutes a substantive advance over existing approaches to distributed-generation integration on radial feeders.

5. Conclusion and future work

This paper has presented a systematic assessment of three meta-heuristic optimizers Genetic Algorithm (GA), Teaching–Learning-Based Optimization (TLBO) and the newly introduced Deep-Sleep Optimizer (DSO) for the strategic placement and sizing of distributed-generation units on the IEEE-33 radial feeder. A direct Python interface to DIgSILENT PowerFactory was used so that the optimization routine and the unbalanced load-flow engine communicate without the file-exchange penalties typical of co-simulation approaches. The study considered single, double and triple DG scenarios and benchmarked the results against the best-performing methods in the open literature.

Across all penetration levels the proposed DSO consistently achieved either the lowest or near-lowest real and reactive losses while maintaining voltage magnitudes within the statutory 0.95–1.05 p.u. band. With a single DG, TLBO and DSO each reduced active losses by approximately fifty-six per cent an improvement of almost ten percentage points over earlier PSO-based or heuristic schemes while simultaneously eliminating the under-voltage pocket at the distal section of the feeder. When two DGs were allowed, DSO lowered real losses to 55.9 kW (a seventy-three per-cent reduction) using a combined rating of only 2.72 MW; the best published alternative required more capacity yet still left 88 kW of losses on the network. In the three-DG study, DSO further reduced the losses to 28.9 kW, an eighty-six-per-cent mitigation that more than halves the next-best value reported in the literature. At the same time DSO held the maximum node voltage below 1.05 p.u. and raised the weakest node above 0.99 p.u., demonstrating that loss minimization is not achieved at the expense of over-voltage risk. Computationally, GA remained the fastest solver but converged to the least attractive fitness plateaux. TLBO delivered competitive single-DG results, albeit with three-to-four times the computation time of DSO. DSO therefore offered the most balanced trade-off between technical benefit and run-time, completing the two- and three-DG studies in roughly nine and eleven minutes, respectively, on a standard desktop.

The work contributes four distinctive advances. First, it is the inaugural application of the Deep-Sleep Optimizer to distribution-system planning and demonstrates that its sleep-wake search strategy yields high-quality solutions in fewer iterations than conventional population-based methods. Second, the end-to-end Python workflow removes third-party data-exchange overheads, making large-scale feeder studies feasible without recourse to surrogate power-flow models. Third, all experiments report a complete technical metric set active and reactive losses, node voltages, computation time and voltage-stability index filling a gap in the existing literature, which typically omits one or more of these performance criteria. Fourth, both TLBO and DSO are parameter-free, reducing the burden on network engineers who must often apply such tools without the luxury of time-consuming hyper-parameter tuning.

Future research will extend the framework in three directions. First, the present static-load analysis will be generalized to time-series optimization with stochastic photovoltaic and load traces to quantify year-round benefits and capture reverse-power-flow conditions. Second, the method will be applied to meshed and larger-scale feeders, including the IEEE-118 prototype and real South African distribution networks, to evaluate scalability. Third, an economic layer that combines capital expenditure, loss-related energy charges and potential feed-in tariffs will allow a true cost–benefit assessment of alternative DG deployment strategies. Additional work will integrate protection studies, reliability indices and cyber–physical constraints so that the Deep-Sleep Optimizer can serve as a holistic planning tool for modern smart-grid environments.

Nomenclature

Abbreviations

BES Battery-Energy Storage
CSV Comma-Separated Values
DG Distributed Generator
DSO Deep-Sleep Optimizer
GA Genetic Algorithm
I-DBEA Improved Decomposition based Evolutionary Algorithm
IAT Improved Analytic Technique
IMO-EHO Improved Multi-Objective Elephant Herding Optimization
MOPSO Multi-Objective Particle Swarm Optimization
MVA Mega-Volt-Ampere
MVar Mega VoltAmpere reactive
MW Mega-Watt
PSO Particle Swarm Optimization
PV Photovoltaic Generation
SKHA Stud Krill herd Algorithm
TLBO Teaching–Learning-Based Optimization
VCPSO Variable-Constants Particle Swarm Optimization
VSI Voltage-Stability Index

Symbols

α Circadian time shift
ϵ Convergence tolerance
γ Initial population constant in DSO
$\mu(t)$ Wake threshold in DSO
$C(t)$ Circadian rhythm function
f Weighted objective function
f_1 Power-loss term of objective function
f_2 Voltage-stability term of objective function
$H(t)$ Homeostatic pressure in DSO
$H_0(t)$ Initial homeostatic pressure
I_m Magnitude of line current in branch m
P_L Total system real-power loss before DG
P_{DG} Active-power output of a DG
$P_{L(DG)}$ Real-power loss after DG integration
P_{ri}, Q_{ri} Real and reactive power at receiving end of branch i
Q_{DG} Reactive-power output of a DG
r Uniform random number in $[0, 1]$
R_m Resistance of branch m
R_{ri}, X_{ri} Resistance and reactance of branch i
$S_{\max,i,j}$ Thermal limit of line i-j
$S_{i,j}$ Apparent power between buses i and j
V_i Voltage magnitude at bus i
V_{ri} Receiving-end voltage of branch i
V_{si} Sending-end voltage of branch i
$VSI(ri)$ Voltage Stability Index at bus i
w_1, w_2 Weighting coefficients for f_1 and f_2
x_s, x_w Sleep and wake power indices
X_{best} Best solution in current population
X_{mean} Mean position of current population

CRediT authorship contribution statement

Mkhutazi Mditshwa: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Mkhululi E.S. Mnguni:** Writing – review & editing, Visualization, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Nomzamo Tshemese-Mvandaba:** Writing – review & editing, Visualization, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Innocent E. Davidson:** Writing – review & editing, Visualization, Supervision, Methodology, Investigation, Funding acquisition.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used ChatGPT in order to improve the text flow. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] M. Ntombela, K. Musasa, M.C. Leoaneka, Power loss minimization and voltage profile improvement by system reconfiguration, DG sizing, and placement, Computation 10 (10) (2022) http://dx.doi.org/10.3390/computation10100180, URL https://www.mdpi.com/2079-3197/10/10/180.

[2] P. Mehta, P. Bhatt, V. Pandya, Optimal selection of distributed generating units and its placement for voltage stability enhancement and energy loss minimization, Ain Shams Eng. J. 9 (2) (2018) 187–201, http://dx.doi.org/10.1016/j.asej.2015.10.009, URL https://www.sciencedirect.com/science/article/pii/S2090447915001756.

[3] V. Saxena, S. Manna, S.K. Rajput, P. Kumar, B. Sharma, M.H. Alsharif, M.-K. Kim, Navigating the complexities of distributed generation: Integration, challenges, and solutions, Energy Rep. 12 (2024) 3302–3322, http://dx.doi.org/10.1016/j.egyr.2024.09.017, URL https://www.sciencedirect.com/science/article/pii/S2352484724005948.

[4] T. Adefarati, R. Bansal, Integration of renewable distributed generators into the distribution system: a review, IET Renew. Power Gener. 10 (7) (2016) 873–884, http://dx.doi.org/10.1049/iet-rpg.2015.0378, URL https://ietresearch.onlinelibrary.wiley.com/doi/abs/10.1049/iet-rpg.2015.0378.

[5] P. Prakash, D.K. Khatod, Optimal sizing and siting techniques for distributed generation in distribution systems: A review, Renew. Sustain. Energy Rev. 57 (2016) 111–130, http://dx.doi.org/10.1016/j.rser.2015.12.099, URL https://www.sciencedirect.com/science/article/pii/S1364032115014823.

[6] K.S. Sambaiah, T. Jayabarathi, Loss minimization techniques for optimal operation and planning of distribution systems: A review of different methodologies, Int. Trans. Electr. Energy Syst. 30 (2) (2020) e12230, http://dx.doi.org/10.1002/2050-7038.12230, URL https://onlinelibrary.wiley.com/doi/abs/10.1002/2050-7038.12230 e12230 ITEES-19-0825.R1.

[7] M.K. Pandey, R.N. Mahia, O.P. Mahela, Optimal placement and sizing of RE generators to minimize loss and improve voltage profile in radial distribution network using PSO, in: 2024 2nd International Conference on Device Intelligence, Computing and Communication Technologies, DICCT, 2024, pp. 623–628, http://dx.doi.org/10.1109/DICCT61038.2024.10532810.

[8] Y. Khalid Hamad, A. Nasser Hussain, Y.N. Lafta, A. Al-Naji, J. Chahl, Multi-objective optimization of renewable distributed generation placement and sizing for technical and economic benefits improvement in distribution system, IEEE Access 12 (2024) 164226–164247, http://dx.doi.org/10.1109/ACCESS.2024.3492119.

[9] D. Benkhetta, A. Rouina, A. Necira, Optimal placement and sizing of DG units using LCA algorithm, EAI Endorsed Trans. Energy Web 11 (1) (2024) 8, http://dx.doi.org/10.4108/ew.4345.
[10] R. Shaikh, A. Stojcevski, M. Seyedmahmoudian, J. Chandran, A multi-objective approach for optimal sizing and placement of distributed generators and distribution static compensators in a distribution network using the black widow optimization algorithm, Sustainability 16 (11) (2024) http://dx.doi.org/10.3390/su16114577, URL https://www.mdpi.com/2071-1050/16/11/4577.
[11] H. HassanzadehFard, A. Jalilian, Optimal sizing and location of renewable energy based DG units in distribution systems considering load growth, Int. J. Electr. Power Energy Syst. 101 (2018) 356–370, http://dx.doi.org/10.1016/j.ijepes.2018.03.038, URL https://www.sciencedirect.com/science/article/pii/S0142061517300601.
[12] A.B. Kanase-Patil, A.P. Kaldate, S.D. Lokhande, H. Panchal, M. Suresh, V. Priya, A review of artificial intelligence-based optimization techniques for the sizing of integrated renewable energy systems in smart cities, Environ. Technol. Rev. 9 (1) (2020) 111–136, http://dx.doi.org/10.1080/21622515.2020.1836035.
[13] A. Kumar, R. Verma, N.K. Choudhary, N. Singh, "Optimal placement and sizing of distributed generation in power distribution system: a comprehensive review", Energy Sources, Part A: Recover. Util. Environ. Eff. 45 (3) (2023) 7160–7185, http://dx.doi.org/10.1080/15567036.2023.2216167.
[14] R.B. Magadum, D.B. Kulkarni, Optimal placement and sizing of multiple distributed generators in power distribution networks, Int. J. Ambient Energy 45 (1) (2024) 2288136, http://dx.doi.org/10.1080/01430750.2023.2288136.
[15] Prashant, N.K. Agarwal, S.K. Bisoyi, A.K. Rawat, M.P. Kishore, A strategic technique for optimum placement and sizing of distributed generator in power system networks employing genetic algorithm, in: P.K. Jha, B. Tripathi, E. Natarajan, H. Sharma (Eds.), Proceedings of Congress on Control, Robotics, and Mechatronics, Springer Nature Singapore, Singapore, 2024, pp. 25–42.
[16] V.F. Dos Santos Júnior, R. Santos Freire Ferraz, A.C. Rueda-Medina, Allocation and sizing of distributed generators in distribution system using multi-objective optimization, in: 2023 15th Seminar on Power Electronics and Control, SEPOC, 2023, pp. 1–6, http://dx.doi.org/10.1109/SEPOC58810.2023.10322617.
[17] H. Akter, H.O.R. Howlader, F. Mamud, A.Y. Saber, A. Yona, T. Senjyu, Optimal sizing and performance analysis of hybrid microgrid for remote island of developing country: Effect of sustainable parameters, benefits and installation barriers, Frankl. Open 6 (2024) 100074, http://dx.doi.org/10.1016/j.fraope.2024.100074, URL https://www.sciencedirect.com/science/article/pii/S2773186324000057.
[18] H. Rahman, R. Mia, M. Rahman, M.F.A. Limon, M.S. Iqbal, M.F. Jubayer, M.R. Karim, M.J.A. Soeb, Optimizing SVC placement for enhanced voltage stability using a novel index and hybrid ABC-pso algorithm, Frankl. Open 11 (2025) 100299, http://dx.doi.org/10.1016/j.fraope.2025.100299, URL https://www.sciencedirect.com/science/article/pii/S2773186325000878.
[19] S.A. Salimon, O.I. Omofuma, O.O. Akinrogunde, T.G. Thomas, T.E. Edwin, Optimal allocation of shunt capacitors in radial distribution networks using constriction-factor particle swarm optimization and its techno-economic analysis, Frankl. Open 7 (2024) 100093, http://dx.doi.org/10.1016/j.fraope.2024.100093, URL https://www.sciencedirect.com/science/article/pii/S2773186324000240.
[20] M.R. Jannesar, A. Sedighi, M. Savaghebi, J.M. Guerrero, Optimal placement, sizing, and daily charge/discharge of battery energy storage in low voltage distribution network with high photovoltaic penetration, Appl. Energy 226 (2018) 957–966, http://dx.doi.org/10.1016/j.apenergy.2018.06.036, URL https://www.sciencedirect.com/science/article/pii/S0306261918309061.
[21] A. Parajuli, S. Gurung, K. Chapagain, Optimal placement and sizing of battery energy storage systems for improvement of system frequency stability, Electricity 5 (3) (2024) 662–683, http://dx.doi.org/10.3390/electricity5030033, URL https://www.mdpi.com/2673-4826/5/3/33.
[22] N.-C. Yang, Y.-C. Zhang, E.W. Adinda, Sizing and sitting of battery energy storage systems in distribution networks with transient stability consideration, Mathematics 10 (19) (2022) http://dx.doi.org/10.3390/math10193420, URL https://www.mdpi.com/2227-7390/10/19/3420.
[23] A. Latif, M. Shahzad, P. Palensky, W. Gawlik, An alternate PowerFactory Matlab coupling approach, in: 2015 International Symposium on Smart Electric Distribution Systems and Technologies, EDST, 2015, pp. 486–491, http://dx.doi.org/10.1109/SEDST.2015.7315257.
[24] K. Johnstone, S.M. Blair, M.H. Syed, A. Emhemed, G.M. Burt, T.I. Strasser, Co-simulation approach using PowerFactory and MATLAB/Simulink to enable validation of distributed control concepts within future power systems, CIRED 2017 (2017) 2192–2196, http://dx.doi.org/10.1049/oap-cired.2017.1175, URL https://digital-library.theiet.org/doi/abs/10.1049/oap-cired.2017.1175.
[25] S.O. Oladejo, S.O. Ekwe, L.A. Akinyemi, S.A. Mirjalili, The deep sleep optimizer: A human-based metaheuristic approach, IEEE Access 11 (2023) 83639–83665, http://dx.doi.org/10.1109/ACCESS.2023.3298105.
[26] C.E. Okafor, K.A. Folly, Optimal sizing of battery energy storage system (BESS) for multiple applications using regression analysis and deep sleep optimizer algorithm, Sci. Afr. 26 (2024) e02424, http://dx.doi.org/10.1016/j.sciaf.2024.e02424, URL https://www.sciencedirect.com/science/article/pii/S2468227624003661.
[27] Y. Li, Q. Yu, Z. Wang, Z. Du, Z. Jin, An improved golden jackal optimization algorithm based on mixed strategies, Mathematics 12 (10) (2024) http://dx.doi.org/10.3390/math12101506, URL https://www.mdpi.com/2227-7390/12/10/1506.
[28] S.O. Oladejo, S.O. Ekwe, S. Mirjalili, The hiking optimization algorithm: A novel human-based metaheuristic approach, Knowl.-Based Syst. 296 (2024) 111880, http://dx.doi.org/10.1016/j.knosys.2024.111880, URL https://www.sciencedirect.com/science/article/pii/S0950705124005148.
[29] Z. Benmamoun, K. Khlie, M. Dehghani, Y. Gherabi, WOA: Wombat optimization algorithm for solving supply chain optimization problems, Mathematics 12 (7) (2024) http://dx.doi.org/10.3390/math12071059, URL https://www.mdpi.com/2227-7390/12/7/1059.
[30] R.A. Lone, S.J. Iqbal, A.S. Anees, Optimal location and sizing of distributed generation for distribution systems: An improved analytical technique, Int. J. Green Energy 21 (3) (2024) 682–700, http://dx.doi.org/10.1080/15435075.2023.2207638.
[31] S.H. Dolatabadi, M. Ghorbanian, P. Siano, N.D. Hatziargyriou, An enhanced IEEE 33 bus benchmark test system for distribution system studies, IEEE Trans. Power Syst. 36 (3) (2021) 2565–2572, http://dx.doi.org/10.1109/TPWRS.2020.3038030.
[32] V. Vita, Development of a decision-making algorithm for the optimum size and placement of distributed generation units in distribution networks, Energies 10 (9) (2017) http://dx.doi.org/10.3390/en10091433, URL https://www.mdpi.com/1996-1073/10/9/1433.
[33] M. Chakravorty, D. Das, Voltage stability analysis of radial distribution networks, Int. J. Electr. Power Energy Syst. 23 (2) (2001) 129–135, http://dx.doi.org/10.1016/S0142-0615(00)00040-5, URL https://www.sciencedirect.com/science/article/pii/S0142061500000405.
[34] E. Drayer, F. Meyer, J. Hegemann, M. Braun, Control strategies for a decentralized, real-time operation of distribution grids, in: 2015 IEEE Eindhoven PowerTech, 2015, pp. 1–6, http://dx.doi.org/10.1109/PTC.2015.7232749.
[35] R. Prakash, B. Sujatha, Optimal placement and sizing of DG for power loss minimization and vsi improvement using bat algorithm, in: 2016 National Power Systems Conference, NPSC, 2016, pp. 1–6, http://dx.doi.org/10.1109/NPSC.2016.7858964.
[36] D. Yang, J. Jia, W. Wu, W. Cai, D. An, K. Luo, B. Yang, Optimal placement and sizing of distributed generators based on multiobjective particle swarm optimization, Front. Energy Res. Volume 9 - 2021 (2021) http://dx.doi.org/10.3389/fenrg.2021.770342, URL https://www.frontiersin.org/journals/energy-research/articles/10.3389/fenrg.2021.770342.
[37] J.H. Holland, Genetic algorithms and adaptation, ISBN: 978-1-4684-8941-5, 1984, http://dx.doi.org/10.1007/978-1-4684-8941-5_21.
[38] I. Khenissi, R. Sellami, M.A. Fakhfakh, R. Neji, Power loss minimization using optimal placement and sizing of photovoltaic distributed generation under daily load consumption profile with PSO and GA algorithms, J. Control. Autom. Electr. Syst. 32 (5) (2021) 1317–1331, http://dx.doi.org/10.1007/s40313-021-00744-7.
[39] S.A. Taher, M. Hasani, A. Karimian, A novel method for optimal capacitor placement and sizing in distribution systems with nonlinear loads and DG using GA, Commun. Nonlinear Sci. Numer. Simul. 16 (2) (2011) 851–862, http://dx.doi.org/10.1016/j.cnsns.2010.05.011, URL https://www.sciencedirect.com/science/article/pii/S1007570410002819.
[40] R. Rao, V. Savsani, D. Vakharia, Teaching-learning-based optimization: A novel method for constrained mechanical design optimization problems, Computer-Aided Des. 43 (3) (2011) 303–315, http://dx.doi.org/10.1016/j.cad.2010.12.015, URL https://www.sciencedirect.com/science/article/pii/S0010448510002484.
[41] G. Zhou, Y. Zhou, W. Deng, S. Yin, Y. Zhang, Advances in teaching–learning-based optimization algorithm: A comprehensive survey(ICIC2022), Neurocomputing 561 (2023) 126898, http://dx.doi.org/10.1016/j.neucom.2023.126898, URL https://www.sciencedirect.com/science/article/pii/S0925231223010214.
[42] M. Farshchin, C. Camp, M. Maniat, Multi-class teaching–learning-based optimization for truss design with frequency constraints, Eng. Struct. 106 (2016) 355–369, http://dx.doi.org/10.1016/j.engstruct.2015.10.039, URL https://www.sciencedirect.com/science/article/pii/S0141029615006732.
[43] R. Venkata Rao, V. Kalyankar, Parameter optimization of modern machining processes using teaching–learning-based optimization algorithm, Eng. Appl. Artif. Intell. 26 (1) (2013) 524–531, http://dx.doi.org/10.1016/j.engappai.2012.06.007, URL https://www.sciencedirect.com/science/article/pii/S0952197612001509.
[44] S. Chatterjee, V. Mukherjee, PID controller for automatic voltage regulator using teaching–learning based optimization technique, Int. J. Electr. Power Energy Syst. 77 (2016) 418–429, http://dx.doi.org/10.1016/j.ijepes.2015.11.010, URL https://www.sciencedirect.com/science/article/pii/S0142061515004305.
[45] B. Mohanty, S. Tripathy, A teaching learning based optimization technique for optimal location and size of DG in distribution network, J. Electr. Syst. Inf. Technol. 3 (1) (2016) 33–44, http://dx.doi.org/10.1016/j.jesit.2015.11.007, URL https://www.sciencedirect.com/science/article/pii/S2314717216300010.
[46] D. Prakash, C. Lakshminarayana, Multiple DG placements in distribution system for power loss reduction using PSO algorithm, Procedia Technol. 25 (2016) 785–792, http://dx.doi.org/10.1016/j.protcy.2016.08.173, URL https://www.sciencedirect.com/science/article/pii/S2212017316305205, 1st Global Colloquium on Recent Advancements and Effectual Researches in Engineering, Science and Technology - RAEREST 2016 on April 22nd & 23rd April 2016.
[47] A. Bayat, A. Bagheri, Optimal active and reactive power allocation in distribution networks using a novel heuristic approach, Appl. Energy 233–234 (2019) 71–85, http://dx.doi.org/10.1016/j.apenergy.2018.10.030, URL https://www.sciencedirect.com/science/article/pii/S0306261918315800.

[48] W. Haider, S.J.U. Hassan, A. Mehdi, A. Hussain, G.O.M. Adjayeng, C.-H. Kim, Voltage profile enhancement and loss minimization using optimal placement and sizing of distributed generation in reconfigured network, Machines 9 (1) (2021) http://dx.doi.org/10.3390/machines9010020, URL https://www.mdpi.com/2075-1702/9/1/20.

[49] S. ChithraDevi, L. Lakshminarasimman, R. Balamurugan, Stud krill herd algorithm for multiple DG placement and sizing in a radial distribution system, Eng. Sci. Technol. an Int. J. 20 (2) (2017) 748–759, http://dx.doi.org/10.1016/j.jestch.2016.11.009, URL https://www.sciencedirect.com/science/article/pii/S2215098616306498.

[50] B.N. Alajmi, M.F. AlHajri, N.A. Ahmed, I. Abdelsalam, M.I. Marei, Multi-objective optimization of optimal placement and sizing of distributed generators in distribution networks, IEEJ Trans. Electr. Electron. Eng. 18 (6) (2023) 817–833, http://dx.doi.org/10.1002/tee.23784, arXiv:https://onlinelibrary.wiley.com/doi/pdf/10.1002/tee.23784 URL https://onlinelibrary.wiley.com/doi/abs/10.1002/tee.23784.

[51] N.K. Meena, S. Parashar, A. Swarnkar, N. Gupta, K.R. Niazi, Improved elephant herding optimization for multiobjective der accommodation in distribution systems, IEEE Trans. Ind. Informatics 14 (3) (2018) 1029–1039, http://dx.doi.org/10.1109/TII.2017.2748220.

[52] S. Kamel, A. Selim, W. Ahmed, F. Jurado, Single- and multi-objective optimization for photovoltaic distributed generators implementation in probabilistic power flow algorithm, Electr. Eng. 102 (1) (2020) 331–347, http://dx.doi.org/10.1007/s00202-019-00878-7.

[53] A. Ali, M.U. Keerio, J.A. Laghari, Optimal site and size of distributed generation allocation in radial distribution network using multi-objective optimization, J. Mod. Power Syst. Clean Energy 9 (2) (2021) 404–415, http://dx.doi.org/10.35833/MPCE.2019.000055.