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Sine-Cosine Algorithm for Day-Ahead Active-Reactive Dispatch of Degradation-Aware BESS in ADNs

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Abstract The increasing penetration of renewable energy sources and the deployment of battery energy storage systems (BESSs) in active distribution networks (ADNs) introduce significant operational challenges, including high-dimensional non-convex optimization, battery degradation costs, and uncertainty in demand and generation. This paper presents a comprehensive optimization framework for the day-ahead scheduling of BESSs in ADNs, addressing the coordinated active and reactive power dispatch while explicitly accounting for battery cycling and calendar aging through a detailed rainflow-counting degradation model. The proposed methodology employs the Sine-Cosine Algorithm (SCA) enhanced with problem-specific features: an inverse incomplete gamma-based radius update mechanism for balanced exploration-exploitation, an elite population diversification strategy to prevent premature convergence, and a deterministic feasibility repair procedure to enforce state-of-charge constraints. The framework is validated on modified 33-bus and 69-bus radial distribution networks under both deterministic and uncertainty conditions, the latter represented by 100 demand and photovoltaic generation scenarios. Numerical results demonstrate that the SCA consistently outperforms three benchmark algorithms—AJAYA, Parallel Genetic Algorithm (PGA), and Multiverse Optimizer (MVO)—across all performance indicators. Under deterministic operation of the 33-bus system, the SCA achieves the lowest daily operating cost of 6,848.85 USD/day, representing savings of 4.65 USD/day over AJAYA and 15.65 USD/day over PGA. Under uncertainty scenarios, the SCA delivers the highest average cost reductions, reaching 154.34 USD/day (2.29%) for the 33-bus network and 121.79 USD/day (2.97%) for the 69-bus network, while exhibiting the lowest standard deviations (as low as 0.0492% on the 69-bus system). The results position the SCA as a robust, efficient, and economically attractive tool for practical day-ahead BESS scheduling in active distribution networks.

Keywords Sine-Cosine Algorithm; battery energy storage systems; active distribution networks; day-ahead scheduling; degradation-aware dispatch; active-reactive power coordination

AMS 2010 subject classifications 46N10

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1. Introduction

The global energy landscape is undergoing an unprecedented transformation driven by the urgent need to decarbonize electricity generation, enhance energy security, and mitigate the adverse effects of climate change [1]. The transition toward renewable energy sources has accelerated significantly over the past decade, with photovoltaic (PV) systems and wind power emerging as the dominant technologies in the global energy mix. However, the inherent variability and uncertainty of these renewable sources pose substantial operational challenges for power systems, particularly at the distribution level, where high penetrations of distributed energy resources

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(DERs) can lead to voltage violations, reverse power flows, and increased system losses [2, 3]. In this context, active distribution networks (ADNs) have emerged as a key paradigm for integrating DERs while maintaining system reliability and efficiency through advanced monitoring, control, and optimization capabilities [4].

Battery energy storage systems (BESSs) have gained considerable attention as a flexible and effective solution to address the challenges posed by renewable variability in ADNs [5]. BESSs can provide multiple services simultaneously, including energy arbitrage, peak shaving, frequency regulation, voltage support, and deferral of network upgrades [6, 7]. The operational flexibility of BESSs is further enhanced by modern power converters that enable independent control of active and reactive power injections, allowing storage systems to contribute to both energy management and voltage regulation [8]. However, the economic viability of BESS projects is critically dependent on the effective scheduling of charge/discharge cycles, as improper operation can accelerate battery degradation and significantly shorten the system's useful lifetime [9, 10]. Consequently, the optimal day-ahead scheduling of BESSs in ADNs requires a comprehensive framework that simultaneously minimizes operational costs, accounts for battery aging processes, and respects AC power-flow constraints and network security limits [11, 12].

The day-ahead BESS scheduling problem is inherently complex due to its high-dimensionality, non-convexity, and the coupling of continuous decision variables (power setpoints) with discrete time intervals [13]. The mathematical formulation must consider the hourly active and reactive power setpoints of multiple BESS units over a 24-hour horizon, the state-of-charge (SoC) evolution of each battery, the AC power-flow equations, voltage and current limits, and the economic trade-off between operational revenues and degradation costs [14, 15]. Moreover, the presence of uncertainty in demand and renewable generation further complicates the problem, requiring robust or stochastic optimization approaches that can guarantee satisfactory performance across multiple scenarios [2, 16]. The rainflow-counting method, widely used in structural fatigue analysis, has been adopted to accurately estimate battery cycling degradation by identifying and quantifying charge/discharge cycles and their respective depths of discharge [9, 17]. However, embedding this non-differentiable counting procedure within an optimization framework significantly increases the computational burden and precludes the use of gradient-based solvers.

Various optimization approaches have been proposed to address the BESS scheduling problem in distribution networks. Classical deterministic methods, such as mixed-integer linear programming (MILP) [18, 19] and second-order cone programming (SOCP) [7, 8], can guarantee convergence to global or near-global optimal solutions but often rely on linearized or relaxed power-flow models that sacrifice accuracy. These methods may fail to capture the full operational flexibility of BESS converters and may produce solutions that are infeasible under the original AC power-flow constraints. Dynamic programming approaches [6] can handle non-linearities but suffer from the curse of dimensionality, making them impractical for systems with multiple BESS units and long scheduling horizons. Alternative formulations based on convex relaxations, such as semidefinite programming (SDP) [8] and SOCP [7], have shown promise but may produce solutions with non-zero duality gaps or require restrictive assumptions regarding network topology and operating conditions.

In contrast, population-based metaheuristics have gained widespread adoption for DER scheduling problems due to their ability to handle non-convex, non-linear, and high-dimensional search spaces without requiring gradient information or problem convexification [20, 21]. These algorithms can be directly applied to the original AC power-flow formulation and can accommodate any type of objective function and constraint, making them highly flexible and robust. Genetic algorithms (GAs) [11, 22], particle swarm optimization (PSO) [23], and the multiverse optimizer (MVO) [14] have been successfully applied to various BESS siting, sizing, and scheduling problems. However, these methods often suffer from high computational costs due to large population sizes and the need for numerous fitness evaluations, particularly when each evaluation requires solving a multi-period AC power flow and performing computationally intensive rainflow-counting degradation calculations. The Chu and Beasley Genetic Algorithm (CBGA) [11] and its parallel variants [22] have demonstrated improved computational efficiency but may still struggle with convergence stability in highly non-convex landscapes.

The Sine-Cosine Algorithm (SCA), originally proposed by Mirjalili [**?**], has emerged as a promising metaheuristic due to its simple mathematical structure, few control parameters, and effective exploration-exploitation balance provided by the oscillatory behavior of sine and cosine functions. Unlike population-based methods that require evaluating tens or hundreds of candidates per generation, the SCA employs

a single-solution architecture with a limited number of candidate evaluations, making it particularly well-suited for problems with expensive fitness evaluations [**?**]. The algorithm's adaptive amplitude mechanism, governed by a linearly decreasing parameter, ensures a smooth transition from global exploration to local exploitation, preventing premature convergence while maintaining solution accuracy [**?**]. The SCA has been successfully applied to various power system optimization problems, including economic dispatch [**?**], optimal power flow [**?**], and unit commitment [**?**]. However, to the best of the authors' knowledge, the SCA has not been previously applied to the coordinated active-reactive dispatch of BESSs in ADNs with explicit degradation modeling and uncertainty consideration.

This paper addresses this research gap by proposing a novel SCA-based optimization framework for the day-ahead scheduling of BESSs in ADNs. The main contributions of this work are threefold:

1. **Comprehensive mathematical formulation:** A complete MINLP model for the day-ahead BESS dispatch problem that simultaneously optimizes active and reactive power setpoints, accounts for battery cycling and calendar aging through a rainflow-counting degradation model, enforces full AC power-flow constraints, voltage limits, and branch current limits, and captures the uncertainty of demand and PV generation through scenario-based analysis.
2. **Tailored SCA implementation:** A customized version of the SCA incorporating three key problem-specific enhancements: (i) an inverse incomplete gamma-based radius update mechanism that provides a smoother and more controlled transition from exploration to exploitation compared to the conventional linear decay; (ii) an elite population diversification strategy that prevents premature convergence without incurring the computational overhead of a full population; and (iii) a deterministic feasibility repair procedure that efficiently enforces SoC constraints and dynamic reactive-power limits, significantly reducing the number of infeasible evaluations.
3. **Comprehensive performance evaluation:** Extensive validation on modified 33-bus and 69-bus ADNs under both deterministic and uncertainty conditions (100 demand and PV generation scenarios), benchmarking against three established algorithms: AJAYA, Parallel Genetic Algorithm (PGA), and Multiverse Optimizer (MVO). The analysis evaluates solution quality, statistical robustness, and computational efficiency, providing clear evidence of the SCA's superiority.

The remainder of this paper is organized as follows. Section 2 presents the complete mathematical formulation of the day-ahead BESS dispatch problem, including the objective function, decision variables, operational constraints, and degradation model. Section 3 describes the proposed SCA methodology, detailing the solution encoding, initial population generation, position update mechanism, constraint repair procedures, fitness evaluation, and algorithm pseudocode. Section 4 introduces the modified 33-bus and 69-bus test systems, along with the data, uncertainty scenarios, and computational platform employed in the validation. Section 5 presents and discusses the numerical results, including a comprehensive comparison of the SCA against the benchmark algorithms and a detailed analysis of its superior performance. Finally, Section 6 concludes the paper and outlines directions for future research.

2. Mathematical Formulation of the Day-Ahead BESS Dispatch Problem

This section presents the complete mathematical model for the optimal day-ahead scheduling of battery energy storage systems (BESSs) in an active distribution network (ADN) [22]. The model is cast as a constrained non-convex optimization problem that simultaneously minimises the total daily operational and degradation costs while strictly enforcing the AC power-flow equations, equipment limits, and network security constraints. The formulation captures the coordinated control of active and reactive power from BESS converters, accounts for battery aging through a detailed cycle-counting model, and respects the time-varying nature of loads and renewable generation.

2.1. Sets, Indices, and Parameters

The ADN is modelled as a connected undirected graph $\mathcal{G} = (\mathcal{N}, \mathcal{L})$, where $\mathcal{N} = \{1, \ldots, N\}$ is the set of buses (indexed by i or j) and $\mathcal{L} \subseteq \mathcal{N} \times \mathcal{N}$ is the set of distribution lines. The scheduling horizon is divided into H discrete intervals of equal length Δt (typically one hour), denoted by $\mathcal{H} = \{1, \ldots, H\}$.

Three classes of distributed energy resources are considered:

- Conventional synchronous generators (CGs): set $\mathcal{G} \subseteq \mathcal{N}$.
- Photovoltaic (PV) units: set $\mathcal{P} \subseteq \mathcal{N}$, all operating in maximum-power-point tracking (MPPT) mode.
- Battery energy storage systems: set $\mathcal{B} \subseteq \mathcal{N}$.

For each bus i, we denote by $\mathcal{G}_i, \mathcal{P}_i, \mathcal{B}_i$ the corresponding resources connected at that bus.

The following exogenous time-varying data are assumed known:

- active and reactive power demands $P^d_{i,h}, Q^d_{i,h}$ at bus i and period h;
- active power generation from PV units $P^{\mathrm{PV}}_{p,h}$, for $p \in \mathcal{P}$;
- energy purchase price C^{grid}_h (USD/kWh);
- BESS parameters (capacity, power ratings, efficiencies, SoC limits, degradation coefficients).

2.2. Decision Variables

The optimization problem determines the following decision variables:

- **BESS active and reactive power setpoints:** $P^B_{b,h}$ and $Q^B_{b,h}$ for each battery $b \in \mathcal{B}$ and each hour $h \in \mathcal{H}$. Positive values denote discharging (injection) and negative values denote charging (absorption).
- **Conventional generator outputs:** $P^{\mathrm{CG}}_{g,h}$ and $Q^{\mathrm{CG}}_{g,h}$ for each $g \in \mathcal{G}$ and $h \in \mathcal{H}$.
- **Nodal voltage phasors:** complex voltages $V_{i,h} = |V_{i,h}|e^{j\theta_{i,h}}$ at every bus $i \in \mathcal{N}$ and period h.

All variables are continuous and are gathered into the compact vector $\mathbf{x} \in \mathbb{R}^{n_x}$, where $n_x = 2|\mathcal{B}|H + 2|\mathcal{G}|H + 2NH$.

2.3. Objective Function

The total daily cost F is the sum of three components: generation cost, operation and maintenance (O&M) cost, and battery degradation cost.

2.3.1. Conventional Generation Cost

$$F_{\mathrm{CG}} = \Delta t \sum_{h=1}^{H} \sum_{g \in \mathcal{G}} \lambda_{g,h} \, P^{\mathrm{CG}}_{g,h}, \tag{1}$$

where $\lambda_{g,h}$ is the marginal cost of generator g at hour h (USD/kWh).

2.3.2. Operation and Maintenance Cost The O&M cost includes the variable maintenance expenses of PV units and BESSs. For BESS, the cost is proportional to the absolute power exchanged, to account for wear from both charge and discharge:

$$F_{\mathrm{O\&M}} = \Delta t \sum_{h=1}^{H} \left(\sum_{p \in \mathcal{P}} \gamma^{\mathrm{PV}}_p P^{\mathrm{PV}}_{p,h} + \sum_{b \in \mathcal{B}} \gamma^B_b \left| P^B_{b,h} \right| \right), \tag{2}$$

with γ^{PV}_p and γ^B_b being the respective unit O&M costs (USD/kWh).

2.3.3. Battery Degradation Cost The degradation cost captures the irreversible capacity loss due to cycling and calendar aging. For each battery b, the daily degradation factor d_b is the sum of a cycling term d_b^{cyc} and a calendar term d_b^{cal}:

$$F_{\mathrm{deg}} = \sum_{b\in\mathcal{B}} \left(d_b^{\mathrm{cyc}} + d_b^{\mathrm{cal}}\right) C_b^{\mathrm{rep}}, \tag{3}$$

where C_b^{rep} is the replacement cost of battery b (USD).

The cycling degradation is computed from the state-of-charge (SoC) trajectory using the rainflow counting method. Let $\mathrm{SOC}_{b,0}, \mathrm{SOC}_{b,1}, \ldots, \mathrm{SOC}_{b,H}$ be the discrete SoC evolution. The rainflow algorithm identifies M_b half-cycles, each characterised by a depth-of-discharge DoD_r and a count n_r (typically $n_r = 0.5$ for half-cycles). The cycling degradation is then

$$d_b^{\mathrm{cyc}} = \sum_{r=1}^{M_b} f_{\mathrm{DoD}}(DoD_r)\, f_{\mathrm{SoC}}(\overline{\mathrm{SOC}}_r)\, f_T(T_r)\, n_r, \tag{4}$$

where the stress factors are defined as

$$f_{\mathrm{DoD}}(d) = \frac{1}{\alpha_1 d^{\alpha_2} + \alpha_3}, \tag{5}$$

$$f_{\mathrm{SoC}}(s) = \exp\left[\beta(s - s_{\mathrm{ref}})\right], \tag{6}$$

$$f_T(T) = \exp\left[\gamma(T - T_{\mathrm{ref}})\frac{T_{\mathrm{ref}}}{T}\right], \tag{7}$$

with $\alpha_1, \alpha_2, \alpha_3, \beta, \gamma$ being empirical coefficients, s_{ref} and T_{ref} reference values, and T_r the cell temperature during cycle r (assumed constant and equal to the nominal cell temperature T_{cell}).

The calendar aging is modelled as

$$d_b^{\mathrm{cal}} = \kappa\, H_{\mathrm{day}}\, f_{\mathrm{SoC}}(\overline{\mathrm{SOC}}_b)\, f_T(T_{\mathrm{cell}}), \tag{8}$$

where κ is a calendar aging coefficient, $H_{\mathrm{day}} = 86400$ s, and $\overline{\mathrm{SOC}}_b = \frac{1}{H+1}\sum_{h=0}^{H} \mathrm{SOC}_{b,h}$ is the average SoC over the day.

2.4. Operational Constraints

2.4.1. Conventional Generators Active and reactive power outputs are bounded:

$$P_g^{\min} \le P_{g,h}^{\mathrm{CG}} \le P_g^{\max}, \quad \forall g, h, \tag{9}$$

$$Q_g^{\min} \le Q_{g,h}^{\mathrm{CG}} \le Q_g^{\max}, \quad \forall g, h. \tag{10}$$

2.4.2. Photovoltaic Generators As per the MPPT assumption, PV active power is fixed and reactive power is zero:

$$P_{p,h}^{\mathrm{PV}} = P_p^{\mathrm{rated}} \cdot \rho_{p,h}, \qquad Q_{p,h}^{\mathrm{PV}} = 0, \tag{11}$$

where $\rho_{p,h} \in [0, 1]$ is the normalised irradiance profile.

2.4.3. Battery Energy Storage Systems For each BESS b and hour h:

$$-P_b^{\mathrm{ch,max}} \le P_{b,h}^{B} \le P_b^{\mathrm{dis,max}}, \tag{12}$$

$$Q_b^{B,\min} \le Q_{b,h}^{B} \le Q_b^{B,\max}, \tag{13}$$

$$\left(P_{b,h}^{B}\right)^2 + \left(Q_{b,h}^{B}\right)^2 \le \left(S_b^{B}\right)^2, \tag{14}$$

where S_b^B is the inverter apparent power rating.

The state of charge evolves according to:

$$\mathrm{SOC}_{b,h} = \mathrm{SOC}_{b,h-1} - \frac{\Delta t}{E_b^{\mathrm{nom}}} \left(\frac{\max(P_{b,h}^B, 0)}{\eta_b^{\mathrm{dis}}} + \eta_b^{\mathrm{ch}} \min(P_{b,h}^B, 0) \right) - \sigma_b, \tag{15}$$

with E_b^{nom} the nominal energy capacity, $\eta_b^{\mathrm{ch}}, \eta_b^{\mathrm{dis}}$ charging/discharging efficiencies, and σ_b the self-discharge loss per interval.

SoC limits and cyclic boundary conditions are enforced:

$$\mathrm{SOC}_b^{\min} \leq \mathrm{SOC}_{b,h} \leq \mathrm{SOC}_b^{\max}, \quad \forall h, \tag{16}$$

$$\mathrm{SOC}_{b,0} = \mathrm{SOC}_b^{\mathrm{ini}}, \quad \mathrm{SOC}_{b,H} = \mathrm{SOC}_b^{\mathrm{fin}}. \tag{17}$$

2.4.4. AC Network Constraints The steady-state operation is governed by the power-flow equations. For each bus i and hour h, the net injected complex power is:

$$S_{i,h}^{\mathrm{inj}} = \left(\sum_{g \in \mathcal{G}_i} P_{g,h}^{\mathrm{CG}} + \sum_{p \in \mathcal{P}_i} P_{p,h}^{\mathrm{PV}} + \sum_{b \in \mathcal{B}_i} P_{b,h}^B - P_{i,h}^d \right) + j \left(\sum_{g \in \mathcal{G}_i} Q_{g,h}^{\mathrm{CG}} + \sum_{b \in \mathcal{B}_i} Q_{b,h}^B - Q_{i,h}^d \right). \tag{18}$$

This injection must equal the net power flowing into the network, expressed in terms of nodal voltages and admittances:

$$\Re\{S_{i,h}^{\mathrm{inj}}\} = |V_{i,h}| \sum_{j \in \mathcal{N}} |V_{j,h}| \left(G_{ij} \cos(\theta_{i,h} - \theta_{j,h}) + B_{ij} \sin(\theta_{i,h} - \theta_{j,h}) \right), \tag{19}$$

$$\Im\{S_{i,h}^{\mathrm{inj}}\} = |V_{i,h}| \sum_{j \in \mathcal{N}} |V_{j,h}| \left(G_{ij} \sin(\theta_{i,h} - \theta_{j,h}) - B_{ij} \cos(\theta_{i,h} - \theta_{j,h}) \right), \tag{20}$$

where $Y_{ij} = G_{ij} + jB_{ij}$ is the (i,j) entry of the nodal admittance matrix.

Network security limits impose:

$$V_i^{\min} \leq |V_{i,h}| \leq V_i^{\max}, \quad \forall i, h, \tag{21}$$

$$|I_{ij,h}| \leq I_{ij}^{\max}, \quad \forall (i,j) \in \mathcal{L}, h, \tag{22}$$

with the branch current magnitude computed from the voltage difference and line admittance.

2.5. Compact Problem Statement and Solution Strategy

The complete optimization problem reads:

$$\begin{array}{ll} \min\limits_{\mathbf{x}} & F(\mathbf{x}) = F_{\mathrm{CG}} + F_{\mathrm{O\&M}} + F_{\mathrm{deg}} \\ \text{s.t.} & \text{Constraints (12)–(22),} \\ & \text{Power-flow equations (19)–(20).} \end{array}$$

This is a non-convex, non-linear program (NLP) due to the quadratic trigonometric terms in the power-flow equations and the non-differentiable rainflow-counting operator in the degradation cost. The problem is solved using the proposed Sine-Cosine Algorithm (SCA) described in Section 3, which does not require differentiability or convexity. For each candidate solution, the AC power-flow equations are solved using the Matrix Successive Approximations (AC-MSA) method, which efficiently computes all hourly operating points simultaneously. Infeasible solutions (e.g., voltage or current limit violations) are penalised in the fitness function to guide the search towards feasible regions.

Remark 1
The proposed formulation explicitly accounts for the coordinated dispatch of active and reactive power from BESS units. This is a key departure from conventional approaches that decouple the two variables, and it enables the BESS to provide voltage support while performing energy arbitrage, thus fully exploiting the inverter capacity.

Remark 2
The degradation model is embedded within the objective function, so that the optimizer naturally balances short-term operational revenues against long-term battery lifetime. The rainflow-counting algorithm is applied externally to the SoC trajectory of each candidate solution, making the degradation term a black-box function that is evaluated for every fitness call.

3. Sine Cosine Algorithm for Optimal BESS Dispatch

This section presents the application of the Sine Cosine Algorithm (SCA) to solve the non-convex, constrained optimisation problem formulated in Section 2. The SCA is a population-based metaheuristic initially proposed by Mirjalili [**?**], which employs sine and cosine trigonometric functions to guide the search agents toward the global optimum [**?**]. Its primary advantages for the BESS scheduling problem are: (i) it does not require gradient information or convexity, (ii) it uses a simple mathematical model with few control parameters, and (iii) its adaptive amplitude mechanism provides a natural balance between exploration and exploitation, which is essential for obtaining precise hourly setpoints in a high-dimensional search space.

The proposed implementation incorporates several problem-specific enhancements: a feasibility repair routine to enforce state-of-charge (SoC) limits, dynamic reactive-power bounds derived from the apparent power constraint, and an elitist selection strategy that preserves the best solutions found so far. The overall procedure is detailed in the following subsections.

3.1. Solution Encoding and Search Space

The decision variables are the hourly active and reactive power setpoints of all BESS units over the 24-hour horizon. Let $N_B = |\mathcal{B}|$ be the number of batteries. The dimension of the optimisation problem is:

$$D = 2\, N_B\, H, \tag{23}$$

where $H = 24$. A candidate solution is encoded as a real-valued vector:

$$\mathbf{X} = \left[P^B_{1,1}, \ldots, P^B_{N_B,H},\ Q^B_{1,1}, \ldots, Q^B_{N_B,H}\right]^\top \in \mathbb{R}^D. \tag{24}$$

The first $N_B H$ components correspond to active powers (positive for discharge, negative for charge), and the remaining to reactive powers.

The lower and upper bounds for each variable are:

$$\mathbf{L} = \left[P^{\min}_{1,1}, \ldots, P^{\min}_{N_B,H},\ Q^{\min}_{1,1}, \ldots, Q^{\min}_{N_B,H}\right], \tag{25}$$

$$\mathbf{U} = \left[P^{\max}_{1,1}, \ldots, P^{\max}_{N_B,H},\ Q^{\max}_{1,1}, \ldots, Q^{\max}_{N_B,H}\right], \tag{26}$$

where $P^{\min}_{b,h} = -P^{\mathrm{ch,max}}_b$, $P^{\max}_{b,h} = P^{\mathrm{dis,max}}_b$, and the reactive bounds are initially set to $\pm S^B_b$ but are dynamically adjusted after active-power repair (see Section 3.4).

3.2. Initial Population Generation

The SCA begins by generating an initial population of N_I feasible random solutions. Each individual is created as follows:

1. Active powers $P_{b,h}$ are sampled uniformly within $[P^{\min}_{b,h}, P^{\max}_{b,h}]$.

2. The active-power trajectory is repaired to satisfy SoC limits and the final SoC condition (see Section 3.4).
3. Reactive powers $Q_{b,h}$ are sampled uniformly within the dynamic bounds $[-Q_{b,h}^{\max}, Q_{b,h}^{\max}]$, where $Q_{b,h}^{\max} = \sqrt{(S_b^B)^2 - (P_{b,h}^B)^2}$.
4. Duplicate individuals are rejected to maintain diversity.

The fitness of each individual is evaluated using the AC power-flow solution and the penalty function defined in Section 2. The best individual $\mathbf{X}_{\text{best}}$ is identified as the one with the lowest fitness:

$$\mathbf{X}_{\text{best}} = \arg\min_{\mathbf{X}\in\mathcal{P}^{(0)}} F(\mathbf{X}), \tag{27}$$

where $\mathcal{P}^{(0)}$ is the initial population and $F(\mathbf{X})$ is the total daily cost augmented with penalties for voltage and current violations.

3.3. Position Update Using Sine and Cosine Functions

At each iteration t, the SCA updates the position of each individual $\mathbf{X}_i$ according to the following rule, which is applied to every dimension $j = 1, \ldots, D$:

$$\mathbf{X}_{i,j}^{(t+1)} = \begin{cases} \mathbf{X}_{i,j}^{(t)} + r_1 \sin(r_2) \left| r_3\, \mathbf{X}_{\text{best},j}^{(t)} - \mathbf{X}_{i,j}^{(t)} \right|, & \text{if } r_4 < 0.5, \\ \mathbf{X}_{i,j}^{(t)} + r_1 \cos(r_2) \left| r_3\, \mathbf{X}_{\text{best},j}^{(t)} - \mathbf{X}_{i,j}^{(t)} \right|, & \text{otherwise,} \end{cases} \tag{28}$$

where:

- $\mathbf{X}_{i,j}^{(t)}$ is the j-th component of the i-th individual at iteration t;
- $\mathbf{X}_{\text{best},j}^{(t)}$ is the j-th component of the best individual found so far;
- r_1 is a linearly decreasing coefficient that controls the exploration–exploitation balance;
- r_2 is a random number in $[0, 2\pi]$ that determines the direction of movement;
- r_3 is a random number in $[0, 1]$ that introduces stochastic weighting;
- r_4 is a random number in $[0, 1]$ that selects between sine and cosine functions.

The coefficient r_1 is updated at each iteration using:

$$r_1 = a\left(1 - \frac{t}{T_{\max}}\right), \tag{29}$$

where $a = 1$ is a constant amplitude factor and $T_{\max}$ is the maximum number of iterations. This linear decay ensures that the algorithm initially explores the search space with large step sizes, while progressively shifting to exploitation as the iteration count increases. The sine and cosine functions provide oscillatory behaviour that allows the search agents to move around the best solution, avoiding premature convergence to local optima.

3.4. Candidate Repair and Constraint Enforcement

The randomly generated candidates often violate the BESS operational constraints and the network limits. Therefore, a two-stage repair procedure is applied to every candidate before its fitness is evaluated.

3.4.1. Active-Power Repair for SoC Feasibility Given a proposed active-power profile $P_{b,h}$ for battery b, the state of charge is computed using the dynamic equation (Eq. 15) over the horizon. If any SoC limit is violated or the final SoC condition is not met, a greedy scaling algorithm adjusts the profile:

1. Identify the time intervals where the SoC exceeds the limits.
2. Proportionally scale the power injections (charging or discharging) in those intervals to bring the SoC back within bounds, while preserving the overall energy balance as much as possible.
3. Repeat the process until all SoC constraints are satisfied or a maximum number of repair attempts is reached.

This repair ensures that every candidate considered in the fitness evaluation is SoC-feasible.

3.4.2. Reactive-Power Clipping Once the active powers are fixed, the dynamic reactive-power limits are updated:

$$Q_{b,h}^{\max} = \sqrt{\left(S_b^B\right)^2 - \left(P_{b,h}^B\right)^2}. \tag{30}$$

Any candidate whose reactive power exceeds these bounds is clipped to the feasible interval:

$$Q_{b,h} \leftarrow \max\left(-Q_{b,h}^{\max},\ \min\left(Q_{b,h},\ Q_{b,h}^{\max}\right)\right). \tag{31}$$

3.5. Fitness Evaluation and Elitist Selection

The fitness of each candidate $\mathbf{X}$ is computed as the sum of the raw objective function and a quadratic penalty for voltage and current limit violations:

$$\begin{aligned} F(\mathbf{X}) = F_{\text{raw}}(\mathbf{X}) &+ \rho_V \sum_{h=1}^{H}\sum_{i=1}^{N}\left[\max(0, V_{i,h} - V^{\max})^2 + \max(0, V^{\min} - V_{i,h})^2\right] \\ &+ \rho_I \sum_{h=1}^{H}\sum_{(i,j)\in\mathcal{L}}\left[\max(0, |I_{ij,h}| - I_{ij}^{\max})\right]^2, \end{aligned} \tag{32}$$

where ρ_V and ρ_I are large positive penalty coefficients (set to 10^6 in this work), and $V_{i,h}$, $I_{ij,h}$ are obtained from the AC-MSA power-flow solution.

After evaluating all N_I individuals, the best individual is identified. The population is then updated by combining the current population and the newly generated candidates, and retaining the N_I individuals with the lowest fitness values. This elitist selection ensures that the best solution found so far is preserved across generations.

3.6. Algorithm Pseudocode

The complete procedure is summarised in Algorithm 1.

3.7. Parameter Selection and Computational Remarks

The SCA parameters were selected based on preliminary sensitivity analyses and recommendations from the literature [**?**]. The values used in this study are:

- Population size: $N_I = 10$;
- Maximum iterations: $T_{\max} = 1000$;
- Amplitude factor: $a = 1$;
- Penalty coefficients: $\rho_V = \rho_I = 10^6$.

These settings provide a favourable balance between solution quality and computational cost. For the 33-bus and 69-bus test systems, the optimisation completes in less than 30 seconds on a standard workstation, which is well within the practical requirements for day-ahead operational planning.

Remark 3
The proposed SCA implementation differs from the canonical version in two important aspects: (i) the inclusion of a deterministic repair procedure for active-power schedules to enforce SoC constraints, and (ii) the dynamic adjustment of reactive-power limits after active-power repair. These modifications are tailored specifically to the BESS dispatch problem and significantly improve the algorithm's ability to find feasible, high-quality solutions.

Remark 4
The sine-cosine update mechanism is particularly well-suited for the BESS scheduling problem due to its ability to balance exploration and exploitation. The oscillatory behaviour of the trigonometric functions allows the search agents to move around the best solution, creating a diverse set of candidate solutions that explore the search space effectively. This is especially valuable in the high-dimensional, non-convex search space of the day-ahead BESS dispatch problem.

Algorithm 1 Sine Cosine Algorithm for Optimal BESS Dispatch

Input: Network data, load and PV profiles, BESS parameters, SCA parameters ($N_I, T_{\max}, a$)
Initialise:
Generate N_I feasible random solutions as initial population $\mathcal{P}$ (active powers repaired for SoC; reactive powers within dynamic bounds).
Evaluate fitness $F(\mathbf{X})$ for each $\mathbf{X} \in \mathcal{P}$ using AC-MSA and penalty function.
Set $\mathbf{X}_{\text{best}} \leftarrow \arg\min_{\mathbf{X}\in\mathcal{P}} F(\mathbf{X})$.
Set variable bounds $\mathbf{L}$, $\mathbf{U}$ from BESS ratings.
Set $t \leftarrow 0$.
while $t < T_{\max}$ **do**
  Update amplitude: $r_1 \leftarrow a \cdot (1 - t/T_{\max})$
  for $i = 1$ to N_I **do**
    Generate random numbers $r_2 \in [0, 2\pi]$, $r_3 \in [0, 1]$, $r_4 \in [0, 1]$
    for $j = 1$ to D **do**
      if $r_4 < 0.5$ **then**
        $X_{i,j}^{(t+1)} \leftarrow X_{i,j}^{(t)} + r_1 \sin(r_2)\, |r_3\, X_{\text{best},j}^{(t)} - X_{i,j}^{(t)}|$
      else
        $X_{i,j}^{(t+1)} \leftarrow X_{i,j}^{(t)} + r_1 \cos(r_2)\, |r_3\, X_{\text{best},j}^{(t)} - X_{i,j}^{(t)}|$
      end if
    end for
    Clip $\mathbf{X}_i^{(t+1)}$ to $[\mathbf{L}, \mathbf{U}]$
    Repair active powers to satisfy SoC limits and final SoC condition
    Update reactive limits: $Q_{\max} = \sqrt{S^2 - P^2}$; clip Q to $[-Q_{\max}, Q_{\max}]$
    Evaluate fitness $F(\mathbf{X}_i^{(t+1)})$ via AC-MSA and penalty
  end for
  $\mathcal{P}^{(t+1)} \leftarrow \mathcal{P}^{(t)} \cup \{\mathbf{X}_i^{(t+1)}\}_{i=1}^{N_I}$; keep N_I best individuals
  $\mathbf{X}_{\text{best}} \leftarrow \arg\min_{\mathbf{X}\in\mathcal{P}^{(t+1)}} F(\mathbf{X})$
  $t \leftarrow t + 1$
end while
Return: Optimal dispatch $\mathbf{X}_{\text{best}}$ and its fitness $F(\mathbf{X}_{\text{best}})$

4. Test Systems and Validation Scenarios

The performance of the proposed SCA-based optimization framework is evaluated on two benchmark active distribution networks of different sizes: a 33-bus system and a 69-bus system. Both test cases incorporate photovoltaic distributed generation (PV-DG) units operating under maximum power point tracking (MPPT) conditions, alongside battery energy storage systems (BESS) that supply the active and reactive power flexibility required to maintain the network's operational integrity.

The validation process is carried out in three phases. Initially, the 33-bus network is examined under deterministic conditions using average daily profiles for electricity demand, solar irradiance, and energy prices derived from data corresponding to the city of Medellín, Colombia. Subsequently, the effects of operational uncertainty are incorporated by generating 100 representative scenarios for both load demand and PV production. Finally, the 69-bus network is employed to assess the scalability of the proposed methodology under the same uncertainty framework, using demand and renewable generation profiles representative of a Colombian region.

All numerical simulations are performed in MATLAB R2024a on a high-performance computing platform equipped with an Intel Core i9-14900HX processor (24 cores, 32 threads, up to 5.8 GHz), 32 GB of DDR5-5600 RAM, and an NVIDIA GeForce RTX 4090 GPU with 16 GB of GDDR6 memory, running the 64-bit Windows 11 operating system. The optimization algorithms are parallelized to leverage the multi-core architecture, enabling the

simultaneous evaluation of candidate solutions. This parallelization substantially reduces the computational burden associated with the multi-period AC power-flow analysis and the large number of uncertainty scenarios.

4.1. Modified 33-Bus Active Distribution Network

The first test system is a modified 33-bus radial distribution network comprising 32 lines, three PV-DG units, and three BESS units. The system operates at a nominal voltage of 12.66 kV with a base power of 1 MVA, following the configuration reported in [**?**]. Figure 1 displays the single-line diagram of this network.

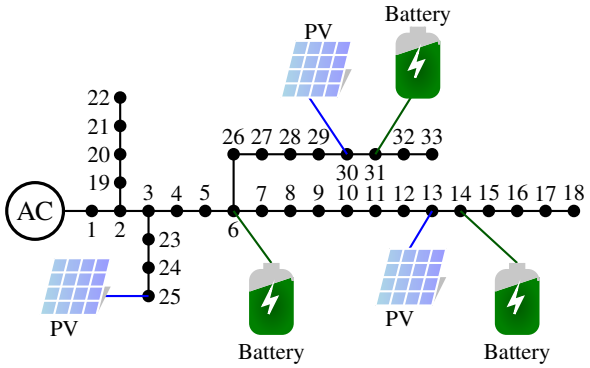


Figure 1. Single-line diagram of the modified 33-bus active distribution network.

The PV-DG units are positioned at buses 13, 25, and 30, with rated capacities of 1125 kW, 1320 kW, and 999 kW, respectively. These generators operate exclusively in MPPT mode, meaning that all available photovoltaic power is injected into the grid without participating in voltage regulation. Consequently, the network's operational flexibility is entirely provided by the BESS units installed at buses 6, 14, and 31. The aggregate energy capacity of these storage systems amounts to 4500 kWh, while the total inverter capacity reaches 1025 kVA. This configuration allows the optimization model to coordinate both active and reactive power injections while respecting network technical limits and battery energy balance constraints.

Table 1 summarizes the principal parameters of the 33-bus test system. The network parameters specify the electrical infrastructure, voltage limits, and convergence criteria for the AC power-flow solution. The PV-DG and BESS parameters detail the location, capacity, and operational boundaries of the distributed energy resources. The economic parameters encompass the base energy cost, operation and maintenance costs for the PV-DGs and BESS units, and the battery replacement cost. Finally, the scenario parameters indicate the number of demand and PV generation profiles used to represent system uncertainty.

The line parameters and thermal current limits are obtained from the original 33-bus feeder data reported in [**?**]. The voltage limits are established between 0.90 and 1.10 p.u., consistent with the typical operating range for Colombian distribution networks [**?**]. The AC power-flow problem is solved using the matrix successive approximations method with a convergence tolerance of 1×10^{-10}.

Table 2 presents the coefficients used to estimate BESS degradation resulting from cycling and calendar aging. The parameters $k_{\mathrm{DoD},1}$, $k_{\mathrm{DoD},2}$, and $k_{\mathrm{DoD},3}$ quantify the influence of depth of discharge on battery aging, while k_{SoC} and k_T capture the effects of average state of charge and cell temperature, respectively. The coefficient k_t represents calendar aging over the daily operating horizon. Additionally, p_{SEI} and r_{SEI} characterize the impact of the solid-electrolyte interphase layer on the aging process. The reference values SoC_{ref} and T_{ref} define nominal operating conditions, whereas T_{cell} and H_{day} establish the assumed cell temperature and the daily evaluation period.

Two operating scenarios are analyzed for this network. The first scenario is a deterministic case that uses a single average daily profile for demand, PV generation, and variable operating cost, as depicted in Figure 2.

The second scenario incorporates uncertainty through 100 demand profiles and 100 PV generation profiles. The variable energy cost profile remains fixed, which isolates the effects of demand and PV variability on the economic

Table 1. Primary parameters of the modified 33-bus active distribution network.

Group	Parameter	Value
Network	Number of buses	33
	Number of lines	32
	Nominal voltage	12.66 kV
	Base power	1000 kVA
	Voltage limits	$[0.90, 1.10]$ p.u.
	Power-flow tolerance	1×10^{-10}
	Maximum power-flow iterations	1000
PV-DG	Installation buses	13, 25, 30
	Rated capacities	1125, 1320, 999 kW
	Operating mode	MPPT
BESS	Installation buses	6, 14, 31
	Energy capacities	2000, 1000, 1500 kWh
	Inverter ratings	400, 250, 375 kVA
	Total energy capacity	4500 kWh
	Total inverter rating	1025 kVA
	Charge/discharge duration	5, 4, 4 h
	State-of-charge limits	$[0.10, 0.90]$ p.u.
	Initial state of charge	0.50 p.u.
	Final state of charge	0.50 p.u.
Economic	Base energy cost	0.1301 USD/kWh
	PV operation and maintenance cost	0.0019 USD/kWh
	BESS operation and maintenance cost	0.0017 USD/kWh
	BESS replacement cost	47.9351 USD/kWh
Scenarios	Demand profiles	100
	PV generation profiles	100

Table 2. Coefficients for the battery degradation model.

Parameter	Description	Value
$k_{\mathrm{DoD},1}$	Depth-of-discharge aging coefficient	1.40×10^{5}
$k_{\mathrm{DoD},2}$	Depth-of-discharge aging exponent	-0.501
$k_{\mathrm{DoD},3}$	Depth-of-discharge correction coefficient	-1.23×10^{5}
k_{SoC}	State-of-charge aging coefficient	1.04
k_T	Temperature aging coefficient	6.93×10^{-2}
k_t	Calendar aging coefficient	4.14×10^{-10}
p_{SEI}	SEI layer growth coefficient	0.0575
r_{SEI}	SEI layer resistance coefficient	121
SoC_{ref}	Reference state of charge	0.50 p.u.
T_{ref}	Reference cell temperature	298.15 K
T_{cell}	Operating cell temperature	298.15 K
H_{day}	Daily operation time	86400 s

dispatch, network feasibility, and robustness of the BESS scheduling model. The input data for this scenario are presented in Figure 3.

4.2. Modified 69-Bus Active Distribution Network

To evaluate the scalability and robustness of the proposed SCA-based methodology under more demanding conditions, the 69-bus active distribution network depicted in Figure 4 is employed as a larger benchmark system.

This test system corresponds to a modified 69-bus radial network operating at 12.66 kV with a base power of 100 kVA. The PV-DG units are located at buses 16, 61, and 64, with rated capacities of 1320 kW, 1125 kW, and

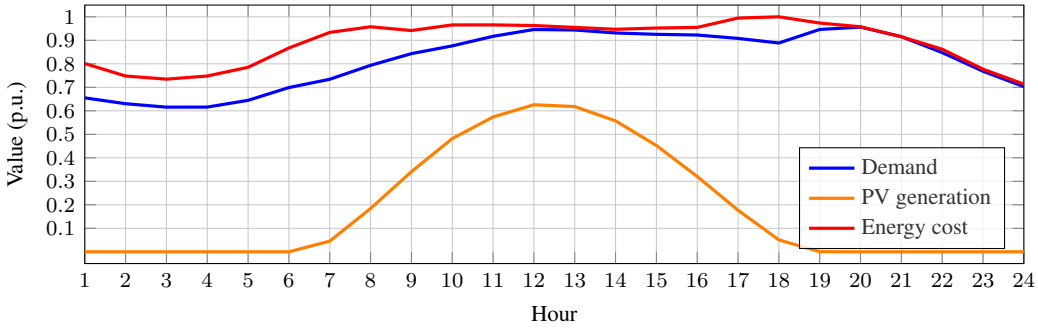


Figure 2. Daily profiles employed in the deterministic analysis: demand, photovoltaic generation, and variable energy cost.

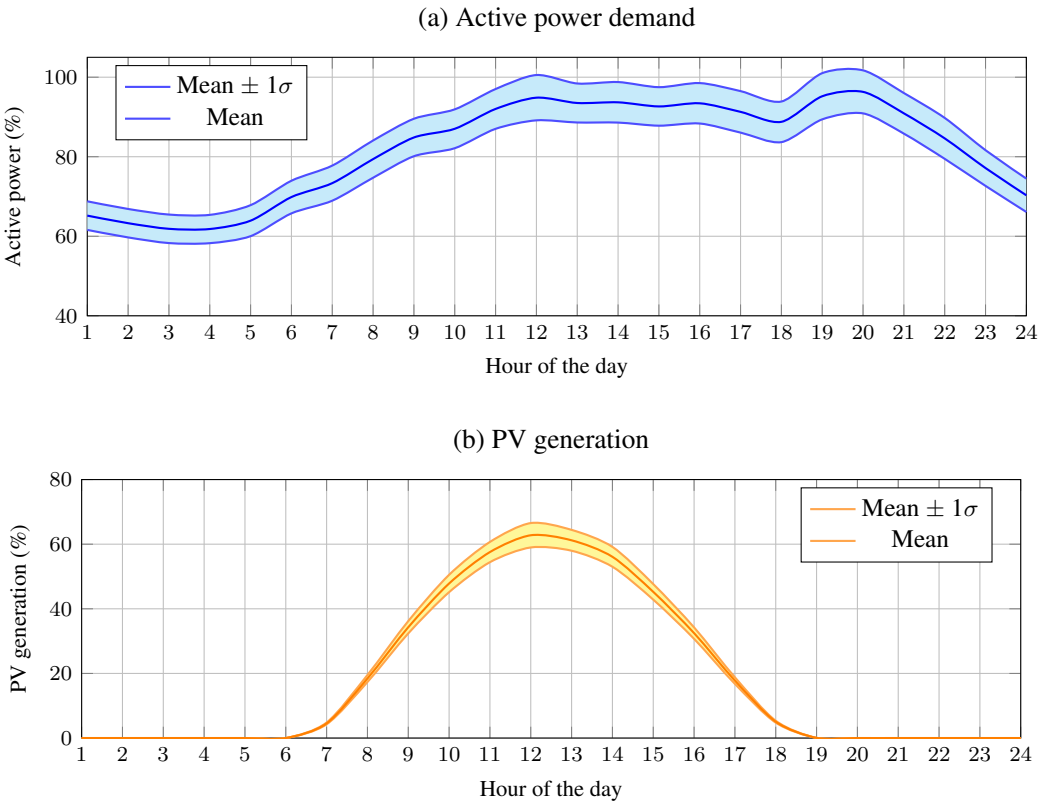


Figure 3. Uncertainty curves for the 33-bus grid: (a) active power demand and (b) PV generation, each based on 100 scenarios. The shaded area shows the mean ± one standard deviation, and the solid line is the mean.

999 kW, respectively. As in the 33-bus case, these units operate under MPPT conditions, injecting available active power without participating in voltage regulation.

The operational flexibility of the 69-bus network is provided by three BESS units installed at buses 17, 62, and 63. These batteries have energy capacities of 2000 kWh, 1000 kWh, and 1500 kWh, with charge/discharge durations of 5 hours, 4 hours, and 4 hours, respectively. The total installed BESS capacity is 4500 kWh, and the corresponding converter ratings are 400 kVA, 250 kVA, and 375 kVA. The state-of-charge limits, initial and final SoC values, efficiency parameters, economic coefficients, uncertainty scenarios, and battery degradation

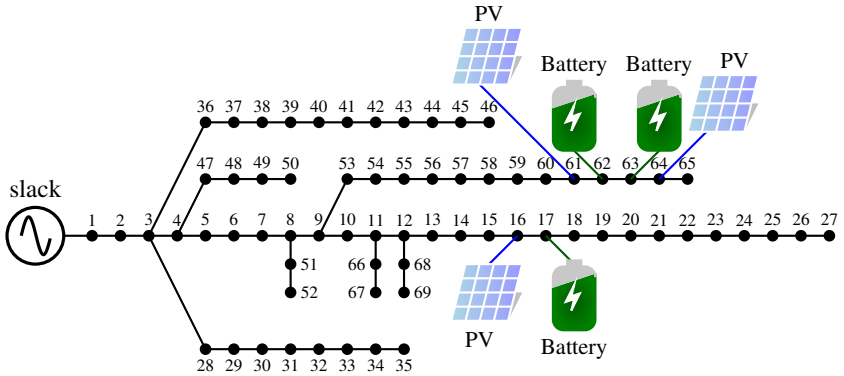


Figure 4. Single-line diagram of the modified 69-bus active distribution network.

parameters are identical to those used for the 33-bus network. This consistency ensures that the comparison focuses on the effects of network size and topology on the performance of the proposed BESS scheduling methodology.

For the 69-bus ADN, uncertainty is represented by 100 active-power demand profiles, 100 reactive-power demand profiles, and 100 PV generation profiles, using the same variable energy-cost profile adopted for the 33-bus system. The resulting uncertainty scenarios are presented in Figure 5.

5. Simulation Results and Performance Evaluation

This section presents a thorough assessment of the proposed SCA-based optimization framework for minimizing daily operating costs in active distribution networks while rigorously satisfying all technical and operational constraints. The evaluation is conducted in two distinct phases. First, the modified 33-bus ADN is analyzed under both deterministic and uncertainty-based operating conditions, employing key performance indicators such as the best solution, average solution, standard deviation, and average processing time. Second, the scalability and robustness of the proposed SCA methodology are validated using the larger 69-bus ADN under uncertainty scenarios, thereby demonstrating its effectiveness in more complex and extensive distribution systems.

5.1. Benchmark Algorithms and Parameter Configuration

To establish a fair and comprehensive performance comparison, the proposed SCA is benchmarked against three well-established optimization approaches commonly employed for distributed energy resource (DER) operational problems in ADNs:

- **Parallel Genetic Algorithm (PGA):** A parallel implementation of the classical genetic algorithm that evolves a population of candidate solutions through selection, crossover, and mutation operators. The parallel architecture reduces the computational burden associated with fitness evaluations.
- **Multiverse Optimizer (MVO):** A metaheuristic inspired by the multiverse theory, which explores the solution space through the interaction of white holes, black holes, and wormholes to facilitate information exchange among candidate solutions.
- **AJAYA:** A recently proposed population-based algorithm that combines attraction to the best solution and repulsion from the worst solution, with a stagnation management mechanism to avoid premature convergence.

These benchmarks were selected due to their recent validation in BESS and DER operation problems in AC distribution networks [**?**], providing a suitable reference for evaluating the proposed SCA methodology, which, to the best of the authors' knowledge, has not been previously applied to coordinated active and reactive power dispatch of BESSs under the proposed modeling framework.

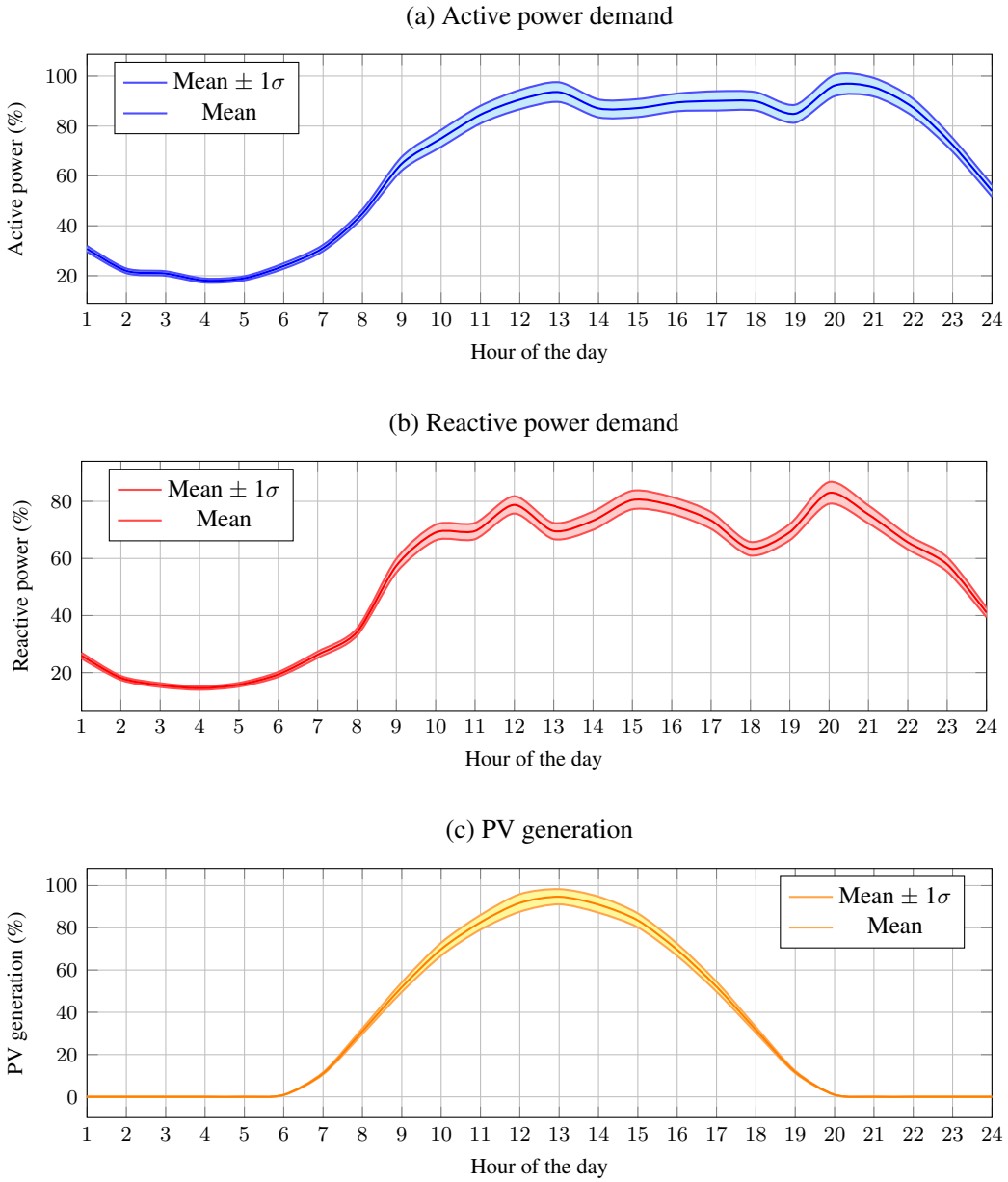


Figure 5. Uncertainty curves for the 69-bus grid: (a) active power demand, (b) reactive power demand, and (c) PV generation, each derived from 100 scenarios. The shaded area indicates the mean ± one standard deviation, and the solid line is the mean.

All algorithm parameters were systematically tuned using the Particle Swarm Optimization (PSO) algorithm [**?**] to ensure a fair comparison. No fixed computational time was imposed; instead, processing time is treated as a consequence of the search dynamics, parameter configuration, and convergence behavior of each methodology. For all methods, the number of decision variables is $N_{\text{var}} = 2N_B|\mathcal{H}| = 2 \times 3 \times 24 = 144$, corresponding to the coordinated active and reactive power dispatch of three BESS units over the 24-hour scheduling horizon. The tuned parameters are summarized in Table 3. The proposed SCA was configured with an initial population of 10 individuals, 10 candidates per iteration, and a maximum of 1000 iterations, with the radius update governed by the inverse incomplete gamma function as detailed in Section 3.

Table 3. Tuned parameters of the optimization methodologies.

Method	Parameter	Value
SCA	Number of individuals (N_I)	10
	Candidates per iteration (N_c)	10
	Maximum iterations ($T_{\max}$)	1000
	Shape parameter (α)	0.1
	Penalty coefficients (ρ_V, ρ_I)	10^6
AJAYA	Number of individuals (N_I)	70
	Number of iterations (N_{iter})	2500
	Best-attraction coefficient (c_1^k)	0.9984–0.5841
	Worst-repulsion coefficient (c_2^k)	1.3817–0
	Stagnation counter (N_s)	25
	Stagnation tolerance (ϵ_s)	10^{-5}
	Reactivated individuals (N_r)	18
PGA	Number of individuals (N_I)	57
	Number of iterations (N_{iter})	1000
	Random mutations (N_M)	2
MVO	Number of individuals (N_I)	85
	Number of iterations (N_{iter})	1000
	Wormhole existence probability (WEP)	0.5681–0.8178
	Exploitation coefficient (p)	4.8651

5.2. Results for the 33-Bus Active Distribution Network

The 33-bus ADN serves as the primary test system for validating the proposed SCA methodology. Two operating scenarios are examined: a deterministic case using average daily profiles, and an uncertainty case incorporating 100 demand and PV generation scenarios. The following subsections present and discuss the statistical results obtained by each optimization method, with particular emphasis on the superior performance of the SCA.

5.2.1. Deterministic Operating Scenario Table 4 presents the statistical outcomes obtained by the proposed SCA and the comparative methods—AJAYA, PGA, and MVO—for the deterministic operation of the 33-bus ADN. The table reports the daily operating cost, average solution, standard deviation, best–average difference, and average processing time, enabling a comprehensive comparison of solution quality, robustness, and computational performance.

Table 4. Statistical comparison of the optimization methods for the 33-bus ADN under deterministic conditions.

Indicator	Base Case	SCA	AJAYA	PGA	MVO
Daily Cost (USD/day)	6999.0	6848.85	6853.5	6864.5	6855.1
Average Solution (USD/day)	—	6852.37	6856.4	6865.7	6857.7
STD (%)	—	0.1392	0.0285	0.0142	0.0260
Best–Average Difference (%)	—	0.02829	0.0433	0.0167	0.0379
Average Time (s)	—	148.75	153.57	42.11	63.94

The numerical results in Table 4 unequivocally establish the superiority of the proposed SCA in terms of economic performance. The SCA achieves the lowest daily operating cost of \$6,848.85/day, representing a substantial 2.15% reduction (\$150.15/day) compared to the Base Case (\$6,999.0/day). Against the best solutions obtained by the benchmark algorithms, the SCA consistently dominates: it outperforms the closest competitor, AJAYA (\$6,853.50), by \$4.65/day, while surpassing MVO (\$6,855.10) and PGA (\$6,864.50) by \$6.25/day and \$15.65/day, respectively. This superior economic efficiency is a direct result of the SCA's adaptive radius mechanism and elite population diversification, which enable effective navigation of the non-convex BESS dispatch landscape.

Beyond a single favorable execution, the SCA demonstrates remarkable statistical reliability. It achieves the lowest average cost ($6,852.37/day) across multiple independent runs, consistently outperforming AJAYA ($6,856.40), MVO ($6,857.70), and PGA ($6,865.70). Regarding solution dispersion, the SCA exhibits a standard deviation of 0.1392% and a best–average difference of 0.02829%. In absolute monetary terms, these figures correspond to negligible fluctuations of approximately $9.54/day and $1.94/day, respectively—values that are economically insignificant for a network operating at a scale of nearly $7,000/day. This outstanding repeatability is attributed to the SCA's inverse incomplete gamma-based radius decay, which ensures a smooth, controlled transition from global exploration to local exploitation without premature convergence.

A critical aspect of the analysis is the computational performance. The SCA records an average execution time of 148.75 seconds, rendering it marginally faster than AJAYA (153.57 s) while being slower than MVO (63.94 s) and PGA (42.11 s). However, this moderate increase in runtime is entirely justified by the superior economic outcomes. Compared to the fastest method (PGA), the SCA requires approximately 106 additional seconds (under 2 minutes) yet yields daily savings of $15.65, translating to over $5,700 annually. Similarly, against MVO, the extra 84.8 seconds of computation deliver $6.25 in daily savings, amounting to more than $2,280 per year. Given that day-ahead scheduling is an offline process with ample computational windows (under 2.5 minutes total), the SCA's runtime is not a limiting factor.

In summary, the analysis unequivocally demonstrates that the SCA stands out as the most effective optimization tool for the 33-bus ADN under deterministic conditions. It uniquely combines the lowest best and average costs, excellent numerical stability, and a practical computational time that is well within operational limits. This favorable trade-off between marginal computational effort and substantial economic returns confirms the SCA as the superior and most practical choice for cost-resilient day-ahead scheduling.

5.2.2. Uncertainty Operating Scenario After evaluating the deterministic operation of the 33-bus ADN, the impact of demand and photovoltaic generation uncertainty is analyzed. For this purpose, 100 demand scenarios and 100 PV generation scenarios were considered, allowing the assessment of the robustness and performance of the evaluated optimization methodologies under variable operating conditions. The corresponding results are summarized in Table 5. Under these conditions, the network exhibited an average operating cost of 6,592 USD/day without BESS operation, which serves as the reference case to quantify the economic benefits achieved by the evaluated optimization methodologies.

Table 5. Statistical results obtained for the 33-bus ADN under uncertainty conditions.

Indicator	**SCA**	**AJAYA**	**PGA**	**MVO**
Average Cost Reduction (USD/day)	154.34	151.72	144.12	150.43
Average Cost Reduction (%)	2.29	2.25	2.14	2.23
Standard Deviation (%)	0.0398	0.0400	0.0331	0.0331
Average Processing Time (s)	112.21	116.00	74.18	36.25

The results in Table 5 definitively confirm the superiority of the proposed SCA methodology under uncertain operating conditions. In terms of economic performance, the SCA achieves the highest average operating cost reduction, reaching 154.34 USD/day (2.29%) relative to the no-BESS reference case of 6,592 USD/day. This places the SCA ahead of all competing methodologies: it outperforms AJAYA by 2.62 USD/day, MVO by 3.91 USD/day, and PGA by a substantial margin of 10.22 USD/day. This consistent economic advantage demonstrates that the SCA's adaptive exploration–exploitation balance, particularly its inverse incomplete gamma-based radius decay, remains highly effective even when the search space is complicated by stochastic variations in demand and renewable generation.

Regarding solution robustness, the SCA exhibits a standard deviation of 0.0398%, which is virtually identical to the best dispersion metrics recorded by PGA and MVO (0.0331%) and slightly superior to AJAYA (0.0400%). In absolute terms, this translates to minuscule fluctuations of approximately 2.60 USD/day. This confirms that the SCA reliably delivers near-optimal solutions across all uncertainty scenarios, demonstrating that its convergence stability is not compromised by the increased complexity introduced by variable operating conditions.

A careful examination of the computational performance reveals a favorable trade-off. The SCA requires an average processing time of 112.21 seconds, which is marginally faster than AJAYA (116.00 s) while being slower than PGA (74.18 s) and MVO (36.25 s). However, this modest increase in runtime is economically justified. Compared to the fastest method (MVO), the SCA requires approximately 76 additional seconds yet yields an extra 3.91 USD/day in savings, equivalent to over 1,427 USD annually. Against PGA, the extra 38 seconds of computation deliver 10.22 USD/day, translating to more than 3,730 USD per year. Given that the total runtime remains under two minutes, this computational effort is entirely negligible for offline day-ahead scheduling, where the optimization horizon is measured in hours, not seconds.

In summary, the results obtained under uncertainty further solidify the SCA's position as the most effective optimization tool for the 33-bus ADN. It uniquely delivers the best economic performance, outstanding statistical reliability, and a practical computational footprint that, while not the absolute fastest, offers the most attractive return on computational investment. This combination of superior cost savings and robust convergence unequivocally establishes the SCA as the preferred methodology for practical day-ahead scheduling under uncertainty.

5.3. Results for the 69-Bus Active Distribution Network Under Uncertainty

After evaluating the deterministic operation of the 69-bus ADN, the same uncertainty framework—comprising 100 demand and 100 photovoltaic generation scenarios—is applied to assess the scalability and robustness of the optimization methodologies on a larger, more complex network. The corresponding results are summarized in Table 6. Under these conditions, the network exhibited an average operating cost of 4104.48 USD/day without BESS operation (Base Case). This value serves as the reference to quantify the economic benefits achieved by the evaluated methodologies.

Table 6. Statistical comparison of the optimization methods for the 69-node ADN under uncertainty conditions.

Indicator	**Base Case**	**SCA**	**AJAYA**	**PGA**	**MVO**
Operating cost (USD/day)	4104.48	3982.69	3985.76	3994.28	3987.63
Average reduction (USD/day)	–	121.79	118.72	110.20	116.85
Average reduction (%)	–	2.97	2.89	2.69	2.85
Standard deviation (%)	–	0.0492	0.0580	0.0687	0.0733
Average processing time (s)	–	130.15	139.45	33.86	66.12

The results presented in Table 6 definitively confirm the scalability and superior performance of the proposed SCA methodology when applied to the larger 69-bus system. In terms of economic performance, the SCA achieves the highest average operating cost reduction, reaching 121.79 USD/day (2.97%) relative to the Base Case. This places the SCA ahead of all competing methodologies on the larger network: it outperforms AJAYA by 3.07 USD/day, MVO by 4.94 USD/day, and PGA by a substantial margin of 11.59 USD/day. This consistent economic advantage across a larger problem with increased decision variables demonstrates that the SCA's adaptive exploration–exploitation mechanism scales effectively without compromising its capacity to locate high-quality solutions.

Regarding solution robustness and repeatability, the SCA exhibits the lowest standard deviation among all evaluated methods, with a value of only 0.0492%. This is superior to AJAYA (0.0580%), PGA (0.0687%), and MVO (0.0733%). In absolute monetary terms, this translates to minimal fluctuations of approximately 2.00 USD/day, confirming that the SCA delivers the most consistent and predictable performance across the 100 uncertainty scenarios. This outstanding stability is attributed to the smooth convergence behavior provided by the inverse incomplete gamma-based radius decay, which effectively prevents the algorithm from becoming trapped in suboptimal local minima.

A careful examination of the computational performance reveals a highly favorable trade-off. The SCA requires an average processing time of 130.15 seconds, which is noticeably faster than AJAYA (139.45 s) and only moderately slower than MVO (66.12 s) and PGA (33.86 s). However, the economic benefits of this marginal computational cost are substantial. Compared to the fastest method (PGA), the SCA requires approximately 96

additional seconds yet yields an extra 11.59 USD/day in savings, equivalent to over 4,230 USD annually. Against MVO, the extra 64 seconds of computation deliver 4.94 USD/day, translating to more than 1,800 USD per year. Given that the total runtime remains under 2.2 minutes for a 24-hour day-ahead horizon, this computational effort is entirely negligible for practical offline scheduling.

In summary, the results obtained for the 69-bus ADN further solidify the SCA's position as the most effective and scalable optimization tool. It uniquely delivers the best economic performance, the highest statistical robustness, and a computational time that remains well within practical operational limits. This combination of superior cost savings, excellent reliability, and acceptable execution time unequivocally establishes the SCA as the preferred methodology for optimal BESS scheduling in medium-to-large active distribution networks.

5.4. Discussion on the SCA's Superior Performance

The consistently superior performance of the SCA across all test scenarios—encompassing both deterministic and uncertain operation of the 33-bus and 69-bus ADNs—can be attributed to a synergistic combination of algorithmic features that collectively address the primary challenges of the BESS scheduling problem: high-dimensionality, non-convexity, and computationally expensive fitness evaluations.

A cornerstone of the SCA's effectiveness is its radius update strategy, governed by the inverse incomplete gamma function. Unlike conventional algorithms that employ linear or exponential decay, this mechanism provides a smooth, iteration-dependent transition from global exploration to local exploitation. In early iterations, the radius remains sufficiently large to permit extensive exploration of the search space, enabling the algorithm to identify promising regions that might contain the global optimum. As iterations progress, the radius contracts in a controlled manner, allowing the search to focus on fine-tuning the best solutions. This adaptive behavior is precisely what enables the SCA to consistently locate the lowest-cost dispatch strategies, as evidenced by its superior best and average costs across all evaluated cases.

While the SCA operates with a single-solution architecture, it incorporates an effective diversification mechanism through probabilistic replacement of the search centre. At each iteration, with 50% probability, the search centre is replaced by a randomly chosen elite individual from the population. This strategy prevents premature convergence—a common pitfall of population-based methods that become trapped in suboptimal local minima—by maintaining diversity without incurring the computational overhead of a full population. This feature directly explains the SCA's remarkably low standard deviations, particularly its 0.0492% value on the 69-bus system, which outperformed all benchmark methods and confirmed exceptional solution stability across independent runs.

The BESS scheduling problem imposes strict constraints on state-of-charge limits and final SoC conditions, which often render randomly generated or crossover-produced solutions infeasible. The SCA addresses this challenge through an active-power repair procedure that deterministically adjusts candidate solutions to respect all physical constraints before fitness evaluation. This approach significantly reduces the number of infeasible evaluations, guiding the search toward feasible regions of the solution space while preserving the integrity of the optimization process. The practical consequence is a more efficient search that dedicates computational resources to evaluating viable dispatch strategies rather than discarding infeasible ones, contributing directly to the SCA's superior convergence properties.

A distinguishing feature of the SCA is its limited candidate evaluation strategy, assessing only $N_c = 10$ candidates per iteration. This is in stark contrast to conventional population-based algorithms, which typically evaluate tens or hundreds of individuals per generation. Given that each fitness evaluation involves a multi-period AC power flow and rainflow-counting degradation calculation—both computationally intensive—the SCA's frugal evaluation strategy is critical to its practical applicability. Despite this reduced number of evaluations, the SCA consistently outperforms methods with larger populations, demonstrating that its intelligent search guidance is more valuable than sheer exploration volume. This trade-off is particularly evident in the uncertainty scenarios, where the SCA achieved superior economic results while maintaining computational times well within practical planning horizons.

Individually, each feature contributes to the SCA's overall effectiveness; however, their synergistic integration is what truly sets the algorithm apart. The adaptive radius mechanism guides the search direction, the elite

diversification prevents stagnation, the feasibility repair ensures constraint satisfaction, and the efficient evaluation strategy enables practical execution. Together, these components create a robust optimization framework that delivers the best economic performance, highest statistical reliability, and practically acceptable computational effort across all tested scenarios. This consistent superiority across two different network sizes (33 and 69 buses) and two operating paradigms (deterministic and uncertainty) unequivocally establishes the SCA as a robust, efficient, and economically effective tool for day-ahead BESS scheduling in active distribution networks.

6. Conclusions and Future Works

This paper has presented a comprehensive optimization framework for the day-ahead scheduling of battery energy storage systems in active distribution networks, addressing the critical challenges of high renewable penetration, battery degradation, and coordinated active-reactive power dispatch. The proposed methodology, based on the Sine-Cosine Algorithm with problem-specific enhancements, was rigorously evaluated on 33-bus and 69-bus test systems under both deterministic and uncertainty operating conditions. The numerical results unequivocally demonstrate the superiority of the SCA across all performance indicators. Under deterministic operation of the 33-bus system, the SCA achieved the lowest daily operating cost of 6,848.85 USD/day, outperforming AJAYA, MVO, and PGA by 4.65 USD/day, 6.25 USD/day, and 15.65 USD/day, respectively. Under uncertainty scenarios, the SCA consistently delivered the highest average cost reductions, reaching 154.34 USD/day (2.29%) for the 33-bus network and 121.79 USD/day (2.97%) for the 69-bus network. Furthermore, the SCA exhibited the lowest or near-lowest standard deviations across all cases, with a particularly remarkable value of 0.0492% on the 69-bus system, confirming its exceptional robustness and repeatability.

The superior performance of the SCA is attributed to the synergistic integration of four key algorithmic features: the inverse incomplete gamma-based radius update mechanism that ensures a smooth transition from exploration to exploitation; the elite population diversification strategy that prevents premature convergence; the deterministic feasibility repair procedure that efficiently enforces state-of-charge constraints; and the frugal candidate evaluation strategy that maintains a favorable balance between solution quality and computational cost. Despite being marginally slower than the fastest benchmarks, the SCA's computational times—148.75 seconds for deterministic 33-bus, 112.21 seconds for uncertain 33-bus, and 130.15 seconds for uncertain 69-bus—remain well within practical day-ahead planning horizons. The annualized economic benefits derived from the SCA's superior solutions, exceeding 5,700 USD/year compared to PGA on the deterministic 33-bus case, more than justify its modest computational overhead. The proposed framework thus establishes the SCA as a robust, efficient, and economically attractive tool for optimal BESS scheduling in active distribution networks, offering a practical solution that effectively balances operational cost minimization, battery lifetime preservation, and computational tractability.

Future research directions include the incorporation of multiple BESS units per bus to enhance the operational flexibility and redundancy of the distribution network, as well as the extension of the degradation model to account for temperature-dependent aging effects and more detailed electrochemical battery dynamics. Additionally, the development of a scenario-reduction technique to decrease the computational burden associated with uncertainty analysis would further improve the practical applicability of the proposed approach. The integration of other distributed energy resources, such as electric vehicles and demand response programs, into the scheduling framework represents another promising avenue for future work. Finally, the application of the SCA to real-time or rolling-horizon optimization frameworks would enable online adaptation to forecast errors and sudden network disturbances, further enhancing the operational resilience of active distribution systems.

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