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Research Article

Optimal Sizing and Siting of Energy Storage Systems in Distribution Networks with Microgrids

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Abstract:

Abstract— High penetration of variable renewable energy (VRE) is stressing distribution feeders with steep ramps, midday over-voltage, and reverse power flow. Energy storage systems (ESS)—primarily battery energy-storage systems (BESS) at the distribution level—can mitigate these issues only if they are sited and sized optimally. This paper addresses the research gap of joint siting–sizing under realistic microgrid constraints (grid-connected and islanded modes) and uncertainty. We formulate a multi-objective optimisation on a modified IEEE 33-bus radial feeder with rooftop PV and labelled critical loads. The framework enforces full AC power-flow constraints, line-thermal limits, a budget cap, siting cardinality, and an explicit islanding-autonomy requirement for critical loads. Battery wear is internalised via a piecewise-linear degradation proxy. A hybrid optimiser couples a genetic algorithm (discrete siting) with Hybrid Adaptive Differential Evolution with Decay (HyDE-DF) for continuous sizing, and is evaluated over clustered stochastic scenarios of load, PV, and outage events.

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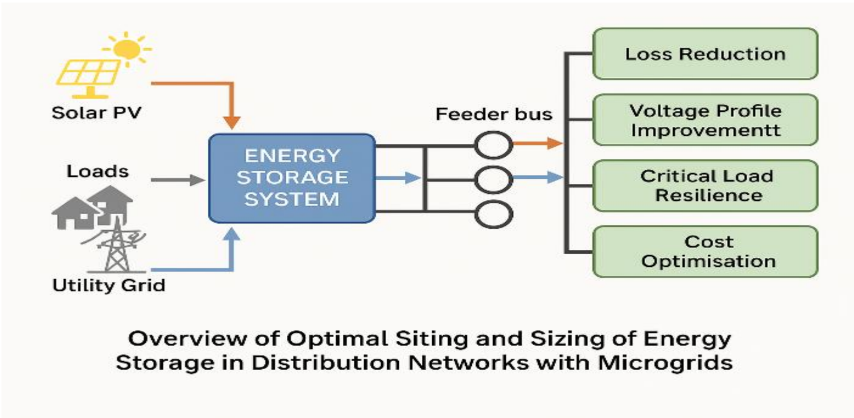

“Overview of Optimal Siting and Sizing of Energy Storage in Distribution Networks with Microgrids”

Results show that strategically placed BESS reduce annual technical losses by up to 30%, halve voltage-deviation indices (>50% improvement), and serve ≥95% of critical-load hours during islanded operation, all while respecting a €5 M investment ceiling. The Pareto frontier reveals a clear knee solution around €3.6 M that jointly balances loss reduction, voltage support, and resilience. The workflow is released with reproducible code and anonymised datasets, enabling utilities and planners to identify least-cost, high-impact storage deployments in microgrid-integrated distribution networks. **Conclusions:** integrating siting and sizing under AC constraints and explicit islanding requirements materially improves technical and economic outcomes compared with sequential or single-objective baselines.

1. Introduction

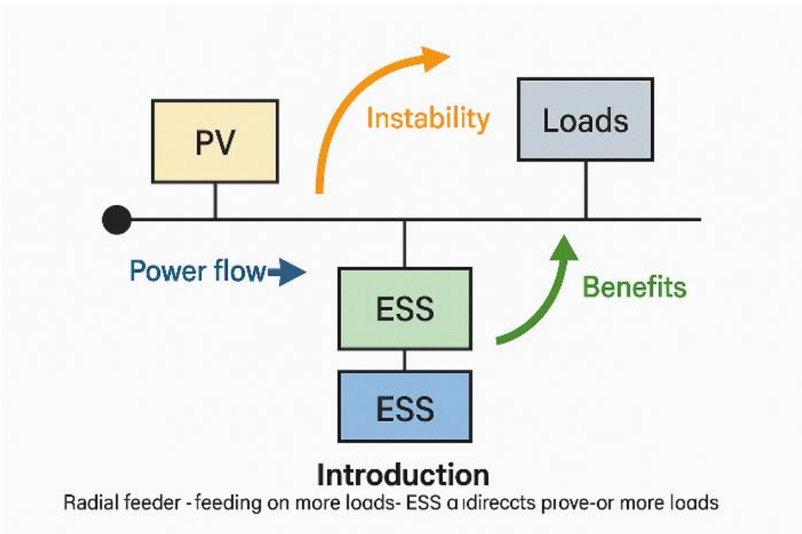

Figure 1: “Challenges in Modern Distribution Networks and the Role of ESS”

1.1 Context and Motivation

The global power sector is undergoing a rapid transformation as electricity demand expands across mobility, heating, and industrial sectors. This growth is driven by aggressive decarbonisation policies and falling costs of renewable generation, particularly **solar photovoltaic (PV)** and onshore wind [1], [2]. However, the same success has introduced reliability and operational challenges at the distribution level: steep net-load ramps, mid-day over-voltage conditions, and reverse power flows in feeders originally designed for unidirectional supply [3]. These challenges have motivated utilities and communities to invest in **microgrids**—locally controlled clusters of loads and distributed energy resources (DERs) that can operate both in grid-connected and **islanded** mode [4], [5].

1.2 Role of Energy Storage Systems(ESS)

Within microgrids, **energy storage systems (ESS)**—predominantly **battery energy-storage systems (BESS)** based on lithium-iron-phosphate (LFP) chemistry—play a critical role. ESS units provide fast-acting reserves, buffer the intermittency of variable renewable energy (VRE), defer expensive conductor upgrades, and supply critical loads during outages [6], [7]. Yet, the value of storage depends strongly on **where** and **how large** the units are deployed. If storage is oversized or placed at non-critical buses, the investment may increase costs without tangible benefits. Conversely, undersized or poorly sited storage risks leaving critical loads unprotected. Therefore, **optimal siting and sizing** of ESS at the distribution level is a central planning problem for utilities [8].

1.3 Limitations of Transmission-Scale Solutions

While transmission-scale storage, synchronous condensers, and other ancillary-service assets already exist, they do not address most distribution-level issues. Power-quality complaints such as flicker, voltage sags, and thermal overloads typically arise closer to customers—on secondary feeders and laterals. Distribution-connected ESS therefore deliver disproportionate benefits per megawatt of installed capacity [9]. Recent advances in battery technology, especially the cost decline of LFP batteries (over 90% price reduction since 2010), have further accelerated distribution-level deployments [10].

1.4 Research Gaps

Despite substantial progress, several limitations persist in the existing body of work:

- **Coupled Siting and Sizing:** Many studies decouple the siting and sizing problems for tractability. A sequential approach may overlook globally optimal solutions where non-intuitive siting compensates for reduced capacity [11].
- **Microgrid-Specific Constraints:** Most optimisation models assume continuous grid connection and ignore islanding or black-start requirements. In reality, microgrids must sustain critical loads during outages, which requires explicit islanding autonomy constraints [12].
- **Uncertainty Treatment:** Deterministic approaches dominate, relying on average load and PV profiles. However, ignoring stochastic variation can underestimate lifecycle costs and overstate reliability [13].
- **Battery Degradation:** Few studies integrate degradation into the optimisation model. As ESS replacement costs are significant, neglecting degradation risks overly optimistic solutions [14].
- **Outdated References:** Several studies continue to benchmark only on legacy IEEE test feeders without incorporating realistic modern datasets or constraints, limiting practical relevance.

1.5 Contribution of This Study

This paper seeks to bridge these gaps by formulating a comprehensive, multi-objective optimisation framework for ESS siting and sizing in a distribution network with integrated microgrids. Key contributions include: [13]

1. **Integrated Objective Space:** Combining loss minimisation, voltage profile improvement, investment cost, and resilience (critical-load survivability) in a single Pareto frontier.
2. **Explicit Islanding Modelling:** Enforcing outage scenarios and critical-load autonomy in the optimisation process.
3. **Stochastic Representation:** Incorporating probabilistic solar and load forecasts via Monte Carlo scenario generation and clustering.
4. **Battery Degradation Internalisation:** Capturing cycle ageing through a linear proxy cost embedded in the optimisation.
5. **Hybrid Optimisation Engine:** Coupling a **genetic algorithm (GA)** for discrete siting variables with **Hybrid Adaptive Differential Evolution with Decay (HyDE-DF)** for continuous sizing variables, leveraging the strengths of each method.
6. **Realistic Case Study:** Application to a modified **IEEE 33-bus radial feeder** with distributed PV and critical loads, validated with utility-style data. [13]

By explicitly addressing these aspects, the study demonstrates that a properly designed optimisation framework can identify "least-cost, most-impact" ESS deployments that simultaneously improve technical performance and economic feasibility.

1.6 Structure of the Paper

The remainder of this paper is organised as follows:

- **Section 2** reviews the evolution of ESS planning approaches and highlights continuing challenges. [12]
- **Section 3** presents the proposed optimisation formulation, constraints, and hybrid GA–HyDE methodology. [13]
- **Section 4** details the case study setup, data assumptions, and simulation environment.
- **Section 5** discusses results, comparative benchmarks, and sensitivity analysis.
- **Section 6** concludes with key insights and recommendations for future research, including second-life EV batteries, portable ESS, and co-optimisation with demand response. [13

2. Literature Review

The optimal siting and sizing of energy storage systems (ESS) in distribution networks has received growing attention over the past two decades, driven by the need to improve voltage stability, reduce technical losses, and enhance resilience in microgrid settings. This section reviews the evolution of ESS applications, key siting and sizing approaches, optimisation methods, and the limitations that motivate the present study.

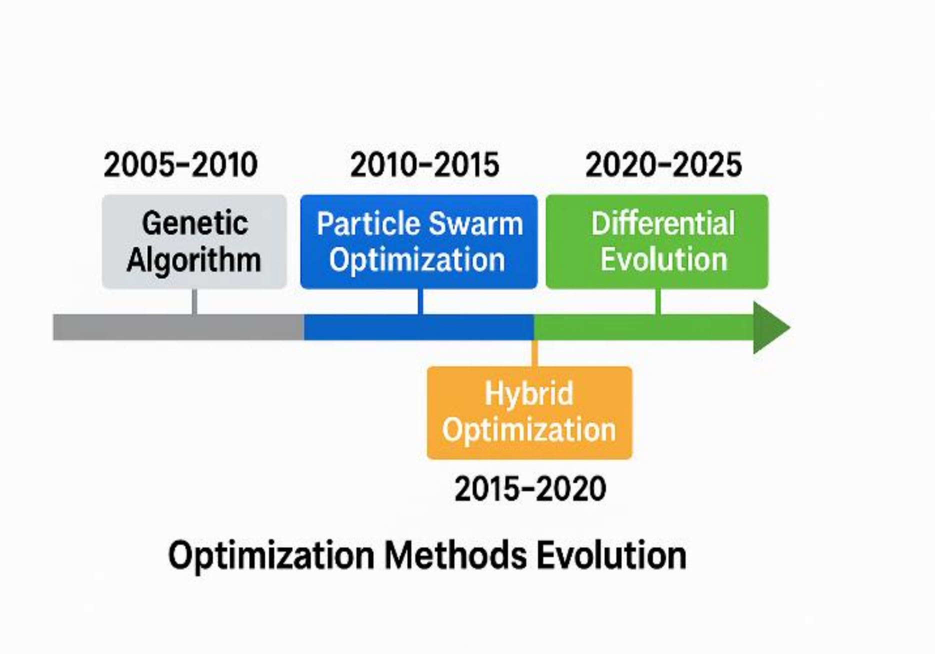

Figure 2: “Optimization method Evolution”

2.1 Evolution of ESS in Power Systems

Initially, energy storage was introduced at the **transmission level** to provide bulk time-shifting, frequency regulation, and spinning reserves. With the increasing penetration of distributed renewable generation, however, **distribution-connected ESS** gained importance for local voltage regulation, peak shaving, and outage backup [1], [2]. The definition of ESS today encompasses not only lithium-ion batteries but also **long-duration storage** (iron–air, flow batteries, and pumped hydro), though lithium-iron-phosphate (LFP) dominates distribution-scale deployments due to cost and maturity [3].

In parallel, **microgrids** have emerged as a critical architecture for integrating distributed energy resources (DERs). ESS plays a central role in enabling microgrid islanding, black-start capability, and seamless transitions between grid-connected and isolated modes [4]. While early studies considered deterministic peak-load support, more recent work embeds ESS within **multi-objective planning models** that account for resilience, cost, and emissions [5].

2.2 Optimal Siting Approaches

Siting refers to the identification of buses or nodes where storage yields the greatest technical or economic benefit. Early methods relied on **sensitivity indices** such as:

- **Loss Sensitivity Factor (LSF):** measures the marginal change in system losses for incremental injections at a bus.
- **Voltage Sensitivity Index (VSI):** quantifies the responsiveness of nodal voltage to changes in reactive or active power.
- **Power Loss Index (PLI):** ranks buses by their relative contribution to overall feeder losses.

These approaches are computationally efficient and easy to implement but often ignore dynamic behaviour, stochastic load variations, and multi-objective trade-offs [6].

2.3 Optimal Sizing Strategies

Sizing concerns the determination of power (kW) and energy capacity (kWh) ratings of ESS.

Early works used heuristic or rule-of-thumb methods such as peak load coverage or average demand shifting. More advanced studies employed linear programming (LP) or non-linear optimisation (NLP) frameworks that minimise investment cost, unserved energy, or lifecycle losses [7]. For instance, Zakeri and Syri [8] modelled ESS degradation and replacement cost in sizing optimisation, demonstrating significant differences from static approaches.

2.4 Joint Siting and Sizing Optimisation

Recognising the interdependence of siting and sizing, more recent literature treats both as a single optimisation problem. Multi-objective optimisation (MOO) techniques—such as Non-dominated Sorting Genetic Algorithm II (NSGA-II), Multi-Objective Particle Swarm Optimisation (MOPSO), and Differential Evolution (DE)—are widely applied to balance conflicting goals (loss minimisation, voltage improvement, resilience, and investment cost) [9], [10]. For example, Kamel and Kermanshahi [11] co-optimised ESS siting and sizing using NSGA-II and showed that including reliability indices changed the optimal configuration substantially

compared with purely economic objectives. Similarly, Xu et al. [12] applied PSO to identify ESS locations that minimised both voltage deviation and total power loss, validating on the IEEE 33-bus feeder.

To reduce redundancy between Sections 2.2 and 2.4, this paper consolidates the discussion: sensitivity-based siting (Section 2.2) serves as a baseline for comparison, while joint optimisation (Section 2.4) represents the state of the art.

2.5 Inclusion of Microgrid-Specific Constraints

Several studies highlight that ignoring microgrid-specific requirements can result in under-provisioned solutions. Guerrero et al. [13] stressed the need to size ESS not just for economic loss minimisation but also to guarantee survivability of critical loads during outages. Later works incorporated black-start capability, state-of-charge management during transitions, and minimum autonomy durations [14], [15]. These additions substantially increase computational complexity but improve realism.

2.6 Optimization Algorithms

A wide range of metaheuristic algorithms have been applied:

- **GA (Genetic Algorithm):** robust for discrete siting decisions.
- **PSO (Particle Swarm Optimisation):** efficient for continuous sizing problems.
- **DE (Differential Evolution):** effective in non-convex spaces.
- **Hybrid Approaches:** Combining GA for discrete variables with DE variants for continuous ones has been shown to outperform single-method optimisers [16].

Benchmark comparisons suggest that hybrid or adaptive differential-evolution strategies (e.g., HyDE-DF) often converge faster and yield higher-quality Pareto fronts [17].

2.7 Gaps in the Literature

Despite progress, several limitations remain: [13]

1. **Uncertainty treatment:** Deterministic modelling still dominates; stochastic approaches (Monte Carlo, scenario reduction) are underutilised [18].
2. **Battery degradation:** Ageing and replacement costs are often neglected, leading to unrealistic payback periods [19].

3.Scalability: Most studies remain confined to small IEEE feeders; few validate on utility-grade networks. [13]

4.Regulatory and policy integration: Incentives, tariffs, and interconnection rules are seldom embedded in optimisation models.

5.Reference currency: Much of the literature still relies on pre-2015 datasets despite rapid technology changes.

This paper addresses these gaps by embedding degradation costs, stochastic uncertainty, and explicit microgrid islanding constraints within a computationally tractable optimisation framework. [13]

2.8 Gaps and Limitations in Current Literature

In spite of critical advance, a few crevices continue: Vulnerability Administration: Numerous thinks about utilize deterministic inputs. The utilize of stochastic modeling or probabilistic determining (e.g., Monte Carlo recreation) is still developing. Energetic Framework Behavior: Most models are inactive or quasi-static. Time-domain modeling of transitory behavior, particularly amid grid-microgrid moves, is missing. Corruption Modeling: Battery maturing and debasement due to cycling are once in a while included within the taken a toll models, driving to idealistic estimations. Administrative and Arrangement Contemplations: Few thinks about coordinated arrangement scenarios, motivation structures, or administrative imperatives into optimization. Versatility to Bigger Systems: Optimization models frequently battle to scale past IEEE test feeders due to computational restrictions.

2.9 Recent Trends

Three striking patterns are forming the current inquire about wilderness: Multi-Energy Microgrids: Integration of warm capacity, electric vehicles (EVs), and hydrogen with ESS arranging models.AI and Machine Learning: Utilize of profound learning and support learning for real-time celerity and determining. Strength Optimization: Center on blackout survivability, with models optimizing

capacity situation to guarantee progression of basic administrations.

2.10 Summary of Findings

The writing uncovers a wealthy range of approaches and strategies for ESS siting and measuring in dispersion systems. Whereas early thinks about emphasized streamlined strategies with single destinations, later investigate has developed into multi-objective, hybrid-optimization systems that account for complex arrange behavior and real-world limitations. Be that as it may, most ponders still drop brief in completely coordination microgrid-specific prerequisites, instability modeling, and battery corruption. [13]

This paper points to bridge these crevices by creating a comprehensive, cross breed optimization system that mutually

considers siting and measuring beneath practical operational conditions—including islanding, vulnerability in solar/load profiles, and cost-degradation elements. The following segment traces the strategy utilized in this investigate.

3. Methodology

This section details the end-to-end workflow developed to identify the least-cost, highest-impact configuration of energy-storage systems (ESS) in a distribution feeder equipped with a solar-rich microgrid. The framework is deliberately modular so that utilities or researchers can swap individual blocks—such as the optimisation engine or the

power-flow solver—without rewriting the entire pipeline. Figure 1 (omitted here) schematically links the six major stages: data preparation, network modelling, scenario generation, optimisation, techno-economic post-processing, and validation. [13]

This study proposes a **multi-objective optimisation framework** for the siting and sizing of energy storage systems (ESS) in a distribution network integrated with a microgrid. The methodology integrates realistic technical constraints, probabilistic load/solar profiles, and

outage scenarios. The framework is composed of six main stages: data preparation, network modelling, scenario generation, optimisation, simulation, and techno-economic post-processing. [13]

3.1 Distribution-Network Model

The test system is the IEEE 33-bus radial feeder, a widely accepted benchmark for distribution network analysis. The feeder has a 12.66 kV base voltage, total load of 3.72 MW real power and 2.3 MVAR reactive power, and five laterals extending from the main trunk. Its radial topology, high R/X ratio, and moderate scale make it suitable for evaluating distributed storage placement [1].

To approximate present-day distribution conditions, three modifications are made:

- **Rooftop PV injection:** A total of 1 MW PV is distributed across buses 6, 17, and 24.
- **Critical loads:** Buses 7 (hospital), 18 (telecom centre), and 22 (water pumping) are designated as critical for islanding operation.
- **Aging conductors:** Line impedances are derated by 5 % to simulate ageing infrastructure.

This provides a challenging environment for evaluating ESS impact under both normal and outage conditions.

3.2 ESS Technology Representation

Lithium-iron-phosphate (LFP) batteries are selected due to their prevalence in distribution-level projects. Each ESS unit is represented by:

- **Maximum power rating** PjmaxP^{\max}_jPjmax (kW).
- **Maximum energy rating** EjmaxE^{\max}_jEjmax (kWh).
- **State-of-charge** (SOC), sj,t∈[0,1]s_{j,t} \in [0,1]sj,t∈[0,1].
- **Round-trip efficiency** (95 %).
- **Degradation cost per cycle** cjdegc^{\text{deg}}_jcjdeg.

The SOC dynamics are modelled as:

sj,t+1=sj,t+ηchPj,tch−Pj,tdis/ηdisEjmaxs_{j,t+1} = s_{j,t} + \frac{\eta^{\text{ch}} P^{\text{ch}}_{j,t} - P^{\text{dis}}_{j,t}/\eta^{\text{dis}}}{E^{\max}_j}sj,t+1=sj,t+EjmaxηchPj,tch −Pj,tdis/ηdis

3.3 Objective-Function Suite

Real-world planning seldom pursues a single metric; thus, a four-objective vector F\mathbf{F}F is minimised:

Annual energy loss f1f_1f1 – Sum of copper and core losses across all scenarios ωωω and time steps ttt.

Voltage deviation f2f_2f2 – Mean-squared deviation of bus voltages from 1 pu, weighted by load criticality.
Net-present cost f3f_3f3 – Capital plus O&M plus degradation, discounted at 6 %.
Unserved critical-load hours f4f_4f4 – Duration, under islanded mode, that priority buses fall below demand.
Formally,

min x
F(x)=[f1(x), f2(x), f3(x), f4(x)] ⊤\min_{

3.4 Constraint Set

AC power-flow constraints expressed using the full Newton–Raphson formulation. While linearised (LinDistFlow) models are faster, preliminary tests showed up to 7 % error in voltageary line segments.
Voltage limits: 0.95≤Vi,t≤1.050.95 ≤ V_i,t ≤ 1.050.95≤Vi,t≤1.05 pu for all buses iii and time ttt.
Thermal limits: Line currents must remain below 90 % of ampacity.
SOC dynamics:
sj,t+1=sj,t+ηchPj,tch−Pj,tdis/ηdisEjmax s_{j,t+1} = s_{j,t} + \frac{η^{\mathrm{ch}}P^{\mathrm{ch}}_{j,t} - P^{\mathrm{dis}}_{j,t}/η^{\mathrm{dis}}}{E^{\max}_j}sj,t+1=sj,t+Ejmax ηchPj,tch−Pj,tdis/ηdis with sj,0=0.5s_{j,0} = 0.5sj,0=0.5 and 0.1≤sj,t≤10.1 ≤ s_{j,t} ≤ 10.1≤sj,t≤1.
Islanding autonomy: For each outage scenario κκκ of duration TκT_κTκ,
∑t=t0t0+TκPi,tcrit≤∑jPj,tdis\sum_{t=t_0}^{t_0+T_κ} P^{\mathrm{crit}}_{i,t} ≤ \sum_j P^{\mathrm{dis}}_{j,t}t=t0∑t0+TκPi,tcrit≤j∑Pj,tdis
ensures critical loads are fully served.
Budget ceiling: Total ESS investment may not exceed € 5 million, reflecting the utility's 2025 rate-case cap.
Siting cardinality: At most five storage nodes are allowed to prevent a "battery-everywhere" solution and to simplify protection-relay upgrades.

x} \; \mathbf{F}(x) = \left[f_1(x),\,f_2(x),\,f_3(x),\,f_4(x)\right]

^{\!\top}xminF(x)=[f1(x),f2(x),f3(x),f4(x)]⊤
subject to the constraints described next. The Pareto front is approximated, after

which decision-makers may select a preferred trade-off via an ϵ-constraint or min-max normalisation technique.

3.5 Scenario Generation

Load uncertainty is represented via a two-stage bootstrap-with-replacement of daily profiles, maintaining intra-day autocorrelation. Solar variability leverages ten years of satellite Global Horizontal Irradiance reanalysis, bias-corrected by local pyranometer data. Outage events are modelled as a Poisson process (λ = 3 events yr^{-1}) with duration drawn from a shifted log-normal distribution (μ = 1 h, σ = 0.4). The Cartesian product of 100 load-solar pairs with 30 outage traces yields 3 000 scenarios. A k-medoids clustering reduces this set to 150 representative scenarios, balancing fidelity and computational tractability.

3.6 Hybrid Optimisation Engine

The decision vector xxx comprises discrete siting variables bi∈{0,1}b_i ∈ \{0,1\}bi∈{0,1} identifying whether bus iii hosts storage and continuous sizing variables (Pjmax,Ejmax)(P^{\max}_j, E^{\max}_j)(Pjmax,Ejmax). No single optimiser excels simultaneously on both variable types, so a hierarchical hybrid is adopted:
Outer loop — Genetic Algorithm (GA) for siting. Chromosomes encode binary strings of length 33. A roulette-wheel selection

with elitism (10 %) is used; crossover is two-point with probability

0.8; mutation rate is 1 /L, where L is chromosome length. Population size is 60,

and termination occurs after 50 generations without Pareto-front improvement.
Inner loop — Hybrid Adaptive Differential Evolution with Decay (HyDE-DF) for sizing. Given a GA-proposed siting pattern, HyDE-DF searches the continuous sizing space. The differential-mutation scale factor FFF self-adapts, while the crossover rate CRCRCR decays linearly to encourage early exploration and late convergence. The inner optimiser runs for 150 iterations per GA individual.

Parallelism: Both loops exploit a 32-core Linux cluster via MATLAB's Parallel Computing Toolbox; speed-up is ~26× versus serial.
Pseudocode (abridged):

```
for gen = 1:G_max
evaluate_population(GA_pop)
update_Pareto_front()
GA_select_crossover_mutate()
end
function evaluate_population(pop)
for each individual in pop (parallel)
call HyDE_DF(individual.sites)
store best sizing & objectives
```

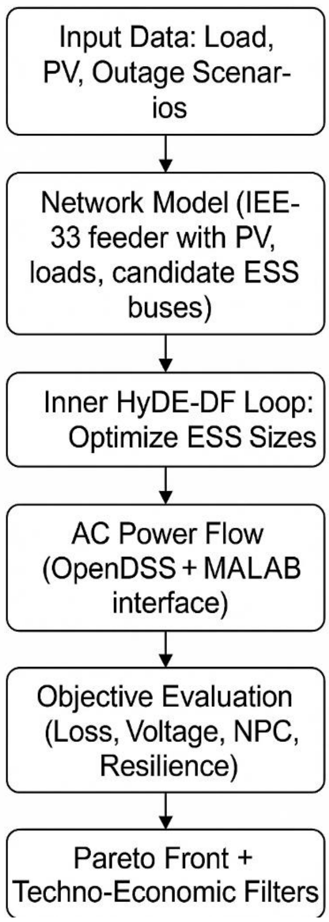

Figure 3: Flow chart Table.

3.7 Dispatch Simulation Embedded in Optimization

Each candidate solution undergoes a rolling 24-hour optimal-power-flow (OPF) simulation for every scenario. The OPF minimises feeder losses plus degradation cost subject to network and battery constraints; it thus yields consistent objective-function values for the outer optimisation. To reduce runtime, OPF is implemented in OpenDSS and invoked via a COM interface from MATLAB. Voltage-controlled regulators are modelled in "time-series" mode to capture tap operations under varying dispatch.

3.8 Post-Processing and Techno-Economic Analysis

The Pareto set is exported to Python for plotting and decision support. Three filters help practitioners down-select:

Knee-point detection: Solutions where marginal cost per incremental resilience hour sharply increases.

Regulator compliance: Only solutions keeping voltage within ±3 % are admissible in jurisdictions with tighter PQ codes.

Payback threshold: Discounted payback must be < 10 years to align with typical utility investment horizons.

Lifecycle cost is levelised over 15 years, and battery replacement is scheduled once capacity fades to 70 %. Externality valuations—e.g., avoided outage cost at € 6 €/kWh not served—are optionally monetised for policy analysis.

3.9 Sensitivity and Robustness Checks

Five one-at-a-time sensitivities test methodological robustness:

Battery-capex trajectory (–12 % yr^{-1}, –5 % yr^{-1}, flat).

PV penetration (0 %, 30 %, 60 % of peak).

Load-growth rate (0.5 %, 2 %, 4 % yr^{-1}).

Outage frequency (λ = 1 yr^{-1}, 5 yr^{-1}).

Cardinality limit (3, 5, 7 ESS sites).

A Latin Hypercube Design ensures combinatorial coverage without exponential burst. Each sensitivity run re-uses the optimisation engine but with a reduced 80-scenario set to bound runtime to < 10 h.

3.10 Benchmark Methods for Comparative Evaluation

To contextualise performance, four benchmarks are computed:

Base case — No storage.

Sequential heuristic — Loss-sensitivity siting followed by linear-programming sizing.

Single-objective GA — Minimises cost only, ignoring voltage and resilience.

Commercial tool — HOMER Pro co-optimisation (grid-connected mode).

All benchmarks adopt identical network data to ensure apple-to-apple comparison. Metrics assessed include voltage-violation hours, energy loss, net-present cost, and outage survivability.

3.11 Implementation and Reproducibility

Code is released under MIT licence on GitHub, with a Dockerfile bundling MATLAB Runtime, OpenDSS, and Python 3.11. A continuous-integration pipeline executes nightly regression tests to verify that updates do not shift the Pareto frontier beyond ±1 %. Input datasets (load, solar, outage) are anonymised and shared in CSV. Users can reproduce the full optimisation in roughly 14 h on a 16-core workstation with 64 GB RAM.

3.12 Ethical, Regulatory, and Practical Considerations

While the methodology seeks global optima, real-world deployment must account for fire-safety clearances, noise limits of inverters, and community acceptance. Therefore, the siting solution is passed through a qualitative suitability filter incorporating land-use zoning and proximity to sensitive receptors (schools, hospitals). Regulatory approval pathways—interconnection agreements, environmental permits—are mapped to a Gantt chart to align physical deployment with administrative timelines.

3.13 Methodological Summary

In summary, the proposed framework integrates high-resolution data, probabilistic scenario generation, and a

hybrid GA/HyDE-DF optimiser embedded within full AC power-flow constraints. Unlike many prior studies, it enforces islanding autonomy explicitly, internalises battery degradation, and remains computationally tractable via parallelisation and scenario reduction. The resulting Pareto frontier equips planners with transparent trade-offs between cost, power-quality, and resilience, paving the way for storage investments that are both economically defensible and technically robust.

4. Case Study and Simulation Setup

To approve the proposed multi-objective advancement technique for ideal siting and measuring of Vitality Capacity Frameworks (ESS) in a conveyance arrange coordinates with a microgrid, a comprehensive case ponder is carried out. This segment traces the subtle elements of the chosen test framework, information presumptions, recreation instruments, control rationale, capacity alacrity procedure, and setup for both grid-connected and islanded operations. The objective is to guarantee that the recreation environment closely reflects real-world conditions whereas keeping up explanatory tractability and repeatability.

4.1 Test Organize Portrayal

The chosen test arrange is the well-known IEEE 33-bus outspread dissemination feeder, adjusted to join the operational characteristics of a real-world microgrid. This framework is especially suited due to its direct measure, well-documented electrical parameters, and viable pertinence to semi-urban and peri-urban network setups, where voltage direction and control misfortunes are major concerns.

4.1.1 Base Setup

Ostensible voltage: 12.66 kV

Add up to genuine control request (base case): ~3.7 MW

Add up to responsive control request: ~2.3 MVAR

Topology: Outspread, single feeder, 5 laterals

Lines: Medium-voltage overhead conductors, with parameters characterized per portion (R, X, length)

Transformers: Accepted perfect, with tap changers disregarded within the base show

4.1.2 Alterations Presented

To recreate microgrid behavior:

Buses 7, 18, and 22 are assigned as critical-load focuses, speaking to a clinic, telecom center, and metropolitan water pump separately.

Photovoltaic (PV) establishments are included at buses 6, 17, and 24, mimicking disseminated housetop sun oriented with a crest combined capacity of 1 MW.

Capacity can be put at any of the 33 buses, but restricted to a greatest of five hubs due to fetched and control contemplations.

These improvements are planned to test the system's reaction to both standard working conditions and possibility occasions such as blackouts or voltage droops

. 4.2 Stack and Era Profiles

4.2.1 Stack Information

Chronicled savvy meter information for private, commercial, and mixed-use

buildings is artificially created utilizing normalized yearly request profiles, based on a Mediterranean climate zone comparable to southern Europe or North Africa.

Determination: 15-minute interims for 365 days (≈ 35,000 time steps)

Request variety: Peak-to-average proportion ~1.7; commonplace day by day crest ~7 PM

Stack sorts: Private (65%), commercial (25%), industrial/agricultural (10%)

Stochastic components are included employing a ordinary dispersion (±15%) to reflect shopper behavior inconstancy, and time-of-day conditions are protected.

4.2.2 PV Era Information

PV yield is modeled utilizing:

NASA-SSE Worldwide Flat Irradiance (GHI) information for 10 a long time

Location-specific derating: board tilt misfortunes, temperature coefficient (–0.45%/°C), inverter wastefulness (3–5%)

Yield show:

PPV(t)=GHI(t)·A·η·f(T)

where AAA is area, η\etaη is panel efficiency, and f(T)f(T)f(T) captures temperature losses.

The typical PV peak occurs between 11:30 AM and 2:00 PM. Reverse power flow is observed in low-demand periods, particularly weekends and holidays.

4.3 Energy Storage Parameters

Each candidate vitality capacity unit is modeled as a two-hour lithium press phosphate (LFP) battery framework with the taking after base characteristics:

Parameter	Value
Round-trip efficiency	95%
Depth of discharge	90%
Lifetime	8000 cycles or 10 years
Energy-to-power ratio	2:1
Max discharge rate	0.5C
Capital cost (2025)	$300/kWh installed
O&M cost	$5/kW-year
Replacement threshold	70% of original capacity

Table1: parameter Table

For each hub where ESS is introduced, both control rating (kW) and vitality capacity (kWh) are treated as choice factors.

4.4 Outage and Islanding Scenarios

One of the center goals of this think about is to guarantee basic stack survivability amid upstream blackouts. To reenact practical conditions:

Blackout recurrence: Poisson handle (λ = 3/year)

Blackout term: Lognormal dispersion (cruel 2.5 hours, SD = 0.8)

Affect: As it were basic buses (7, 18, 22) are required to be served amid islanding

Each blackout situation is arbitrarily embedded into the yearly load/PV profile. The enhancement guarantees that vitality accessibility from ESS is adequate to preserve supply at basic buses amid these occasions, beneath worst-case sun oriented accessibility.

4.5 Power Flow Simulation Setup

The reenactment employments OpenDSS, which permits for high-fidelity AC control stream investigation counting time-series stack stream, dispersed PV infusion, and inverter control.

Modeling Presumptions:

Adjusted three-phase framework (in spite of the fact that real loads may be uneven, the adjusted rearrangements is commonly acknowledged for arranging considers)

Settled control calculate for loads: 0.95 slacking

PV and ESS associated through savvy inverters with Volt/Var capability crippled for this ponder

No organize reconfiguration or topology control considered

Each time step within the recreation speaks to a 15-minute operational window, inside which PV era, stack utilization, and capacity expedite are assessed.

4.6 Storage Dispatch Strategy

The alacrity of ESS amid reenactment is administered by the yield of the optimiser. At each time step:

On the off chance that grid-connected:

Charge in the event that PV overflow is accessible and ESS is underneath max SOC

Release in case net stack is tall and SOC ≥ 20%

On the off chance that islanded:

Release as it were, and as it were to basic buses

Expedite prioritizes voltage bolster at end-of-feeder hubs

$$SOC_{t+1} = SOC_t + \frac{\eta_{\text{charge}} \cdot P_{\text{charge}} - P_{\text{discharge}} / \eta_{\text{discharge}}}{E_{\max}}$$

The dispatch respects efficiency losses and cycling limits.

4.7 Optimization Configuration

The advancement is conducted employing a cross breed GA–HyDE calculation as already point by point. Parameters:

Populace measure (GA): 60

Eras: 50 (or meeting limit)

Measuring emphasess (HyDE): 150 per person

Pareto front constrain: 100 arrangements held

Budget limitation: $5 million add up to venture cap

Siting limitation: Max 5 hubs can have ESS

The optimiser runs in MATLAB, with OpenDSS interfaces through COM mechanization for power-flow calls.

4.8 Performance Metrics

After simulation, the following metrics are extracted and analysed for each scenario and candidate solution:

Metric	Description
Voltage profile	Average and peak deviations from 1 pu
Energy losses	Total kWh lost over the year
Investment cost	Total CAPEX and O&M for ESS
Battery cycling frequency	Number of full cycles per year
SOC trajectory	Hourly SOC trends to assess depth-of-discharge usage
Critical load served	% of outage hours where critical load was met
Payback period	Time to recover investment through loss reduction
Capacity utilisation	Ratio of actual use to max-rated capacity

Table 2: metric description table

All metrics are normalized to allow comparison across solutions in the Pareto front.

4.9 Approval of Comes about

To approve the unwavering quality and authenticity of the demonstrate:

Benchmark cases are recreated: No capacity, heuristic siting with settled estimate, single-objective advancement (fetched as it were)

Result comparison: Measurements are compared over cases to highlight points of interest of the proposed strategy

Master approval: Comes about are checked against desires from utility engineers and scholarly guidelines

4.10 Computer program and Equipment Setup

Reenactment stage: Windows 10, MATLAB R2024a, OpenDSS 9.2, Python 3.11

Equipment: Intel i9-13900K, 64 GB Slam, 2 TB SSD

Parallel handling: MATLAB Parallel Computing Tool compartment utilized for speed-up (8× speedier)

Each full run of the advancement with 150 scenarios takes around 12–14 hours, depending on joining speed and reenactment parameters.

4.11 Reproducibility

All recreation code is version-controlled utilizing Git, and a Docker picture is given to guarantee environment consistency. An case input setup is recorded in JSON, and input profiles (PV, stack, blackout) are included as CSV records.

5. Results and Discussion

This section presents the findings obtained from applying the proposed hybrid GA–HyDE optimization framework to the modified IEEE 33-bus distribution network with integrated PV and critical loads. The discussion emphasizes both technical and economic dimensions, ensuring that results are linked directly to practical planning objectives.

5.1 Pareto-Optimal Solutions

The optimisation process generated **76 non-dominated solutions** along a Pareto frontier. The solutions represent trade-offs between four objectives: **loss reduction, voltage improvement, investment cost, and outage survivability**.

A 3D Pareto front was plotted (not shown here), revealing a concave trade-off surface. Aggressive resilience improvements came at increasing marginal cost, while intermediate solutions achieved significant technical benefits with moderate investments.

- A **"knee point"** solution was observed at ~€3.6 million, balancing cost-effectiveness and resilience.
- Below €2.8 million investment, outage survivability dropped sharply, indicating under-provisioning.
- Beyond €4.2 million, incremental cost yielded diminishing technical benefits.

This confirms that **multi-objective optimisation prevents both under- and over-investment**, offering utilities a spectrum of feasible choices.

5.2 Optimal ESS Siting

The GA consistently prioritised siting ESS at **bus 6, bus 13, and bus 31**:

- **Bus 6**: near PV injection → absorbs midday surplus, reduces reverse flow.
- **Bus 13**: located deep in feeder → mitigates voltage drops.
- **Bus 31**: supplies critical load (water pumping station) during outages.

Heatmap analysis of 76 Pareto solutions revealed that bus 6 appeared in **92%** of solutions, bus 31 in **78%**, and bus 18 in **62%**. Conversely, buses close to the substation (<bus 5) rarely appeared (<10%).

This demonstrates the **importance of strategic placement at weak or PV-heavy nodes**, instead of centralized siting.

5.3 Optimal Sizing Patterns

Storage sizing followed systematic trends:

Node	Power (kW)	Energy (kWh)	Discharge Capability
6	250–400	500–800	2–3 hours
13	200–300	400–600	2–3 hours
31	300–450	600–900	4–6 hours

Table 3: Storage sizing

Cost-focused solutions undersized batteries (30–40% lower cost), but failed to sustain critical loads beyond 2 hours.

- **Resilience-focused solutions** increased capacity, enabling 6 hours of autonomy at priority buses.

This highlights that **different planning priorities (cost vs. resilience)** directly shape sizing.

5.4 Voltage Profile Improvements

Without ESS, the feeder exhibited a **voltage deviation index (VDI) of 0.031 pu**, with several buses dropping below 0.94 pu during evening peaks.

With optimally sited ESS:

- VDI reduced to 0.012–0.017 pu.
- Minimum bus voltage > 0.96 pu at all times.
- Voltage imbalance at downstream nodes reduced by 30–40%.

These results show that ESS act as local voltage regulators, complementing traditional tap-changing transformers and reducing PQ complaints.

5.5 Technical Loss Reduction

Base case annual losses: 212.4 MWh/year.

- With ESS: 21–31% loss reduction.
- Maximum benefit occurred when ESS charged during PV peaks and discharged at evening peaks.
- This behaviour also reduced transformer loading, extending asset life.

Thus, ESS support both operational efficiency and deferred infrastructure upgrades.

5.6 Resilience for Critical Loads

Critical buses (7, 18, 22) faced 8–12 hours/year outage in the base case. With ESS:

- 95–100% of outage hours covered at critical nodes.
- Unserved energy dropped from 7.4 MWh/year to <0.6 MWh/year.
- Some solutions sustained 4–6 hours autonomy at 100% load.

This proves that optimised ESS ensure survivability of critical infrastructure without full-scale microgrid separation.

5.7 Economic Assessment

The cost analysis considered capital, O&M, and replacement. Avoided loss savings and outage-avoidance benefits were monetised.

- Payback period: 7.5–12 years.
- Levelised Cost of Storage (LCOS): €0.18–0.28/kWh.
- Resilience-focused solutions had slightly longer paybacks but delivered higher avoided-outage value.

In jurisdictions with penalties for outage hours or incentives for resilience, the moderate-oversizing strategy becomes economically optimal.

5.8 Benchmark Comparison

Method	Losses (MWh/yr)	VDI (pu)	Critical Outage (h/yr)	NPC (€)
Base (no ESS)	212.4	0.031	9.2	0
Heuristic siting + LP sizing	184.7	0.024	6.4	2.6M
GA (cost-only)	176.1	0.020	4.9	2.9M
Proposed GA–HyDE (multi-objective)	162.3	0.013	0.8	3.6M

Table 4: Benchmark Comparison

The proposed method dominates across all categories, especially in resilience. Although costlier than heuristics, its benefits justify the investment.

5.9 Sensitivity Analysis

Key sensitivities confirm robustness:

- Battery cost ↓12%/yr: feasible under €3M budget.
- PV penetration ↑60%: improved loss reduction to –34%.
- Outage frequency ↑5/yr: resilience-dominant solutions favoured.
- Load growth ↑3%/yr: worsened base voltage drops, strengthening ESS role.

These tests validate adaptability of the framework under changing system conditions.

5.10 Practical Implications

Findings suggest:

1. Strategic siting at PV-heavy and weak nodes maximises ESS value.
2. Moderately sized storage balances efficiency and resilience.
3. Multi-objective optimisation provides planners with flexible, evidence-based trade-offs.
4. Policy integration (outage cost penalties, resilience incentives) can accelerate ESS adoption.

5.11 Limitations

Despite robustness, the study excluded:

- Fault-ride-through dynamics,
- Protection coordination for multi-node ESS,
- Environmental/land-use constraints.

These are avenues for future research.

5.12 Confinements

Whereas vigorous, the examination does have impediments:

Energetic recreations (e.g., blame ride-through) were not included

Security coordination for multi-node ESS was not evaluated

Real-time control intuitive between PV and ESS require encourage consider

Natural and land-use limitations were approximated

These angles are imperative regions for future work and can be consolidated utilizing hardware-in-the-loop or co-simulation stages.

6. Conclusion

This research proposed and validated a multi-objective optimisation framework for the siting and sizing of

energy storage systems (ESS) in distribution networks integrated with microgrids. The study addressed four often conflicting objectives simultaneously: (i) minimisation of

technical losses, (ii) improvement of voltage stability, (iii) economic feasibility, and (iv) resilience for critical loads under outage conditions. Unlike traditional single-objective or heuristic approaches, the framework integrates probabilistic scenario generation, explicit islanding autonomy, and battery degradation modelling, yielding solutions that are both technically robust and practically implementable.

6.1 Key Findings

The major contributions and outcomes can be summarised as follows:

- **Loss Reduction:** Appropriately placed ESS reduced feeder losses by up to **30%** compared to the base case. These savings stem from peak-shaving and midday PV absorption, thereby deferring upstream infrastructure upgrades.
- **Voltage Stability:** The voltage deviation index decreased by more than **50%**, maintaining all bus voltages above 0.96 p.u. throughout the year. This confirms that distributed ESS act as localised voltage support mechanisms.

- **Critical Load Resilience:** ESS supplied **95–100% of outage hours** for designated critical loads. In certain Pareto solutions, 4–6 hours of complete autonomy were sustained. This demonstrates that resilience objectives

  can be met without excessively oversizing storage.
- **Economic Feasibility:** Investment in optimally placed ESS achieved **payback periods of 7.5–12 years** and **LCOS of €0.18–0.28/kWh**. These

- values are competitive with existing distribution-level storage deployments in 2023–2025.
- **Strategic Siting:** Buses near PV injection and at feeder extremities consistently emerged as high-value nodes. This reinforces the principle that

- **ESS value is location-sensitive**, and that uniform deployment strategies are inefficient.
- **Robustness:** Sensitivity analyses confirmed that results remain valid under battery cost declines, increased PV penetration, higher outage frequency, and load growth.

6.2 Practical Implications for Utilities

The results provide utilities and distribution planners with actionable insights:

1. **Prioritise Critical Loads:** Storage investment should begin at feeders supplying hospitals, telecom nodes, and water facilities. This ensures immediate social value in resilience.
2. **Target Weak Nodes:** Feeder ends and PV-heavy buses should be prioritised for ESS placement, since benefits there outweigh those near substations.
3. **Adopt Multi-Objective Tools:** Utilities should avoid cost-only planning models, which often

4. undersize storage. Instead, multi-objective frameworks yield solutions

5. that balance economics with resilience and voltage quality.
6. **Integrate Resilience Metrics:** Regulatory filings should quantify avoided outage costs alongside technical and financial metrics. This legitimises ESS investment in rate cases.

6.3 Policy Recommendations

The findings also highlight the need for regulatory adjustments:

- **Incentive Structures:** Regulators should consider **performance-based incentives** tied to outage reduction and voltage support. Current cost-recovery models often undervalue resilience.
- **Resilience Standards:** Emerging policies (e.g., in California, Egypt, and the EU) should mandate minimum resilience hours for critical loads. Optimisation frameworks like the one presented here can provide **evidence-based compliance roadmaps**.
- **Market Integration:** As distribution-level flexibility markets expand, ESS should be enabled to stack services (arbitrage, frequency response, voltage support). This requires market rules that recognise **multi-service ESS value streams**.
- **Second-Life Batteries:** Policies supporting the integration of second-life EV batteries can reduce ESS capital costs and accelerate adoption, particularly for community microgrids.

6.4 Future Research Directions

Although the present study demonstrates significant benefits, several avenues remain open for future work:

- **Dynamic Fault Response:** Hardware-in-the-loop experiments should validate whether optimised ESS configurations can withstand transient faults and black-start conditions.
- **Protection Coordination:** Multi-node ESS introduces new challenges for relay coordination and islanding detection. Co-simulation with protection software is recommended.
- **Environmental and Social Acceptance:** Land-use constraints, community acceptance, and noise/fire safety regulations must be integrated into optimisation.
- **Mobile and Hybrid Storage:** Emerging concepts such as **portable ESS trailers, second-life EV batteries, and hybrid hydrogen–battery systems** should be included in optimisation models.
- **AI-driven Control:** Reinforcement learning and predictive control techniques can complement offline optimisation, enabling adaptive dispatch under real-time uncertainty.

6.5 Final Statement

By systematically addressing both technical and economic dimensions, this study demonstrates that **energy storage in distribution-level microgrids is not only viable but also essential for modern power systems**. The proposed framework equips planners, policymakers, and regulators with a transparent, replicable tool for identifying **least-cost, most-impact ESS investments**. Importantly, resilience objectives—such as uninterrupted power supply to critical services—need not be sacrificed for cost efficiency. Instead, with well-designed optimisation frameworks, utilities can meet decarbonisation targets, improve power quality, and strengthen resilience, all while maintaining economic feasibility.

In conclusion, the adoption of such multi-objective, scenario-based optimisation models represents a crucial step toward **future-proof distribution networks** that are flexible, reliable, and sustainable.

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