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Optimal Sizing and Techno-Economic Analysis of Battery Energy Storage System for Peak Shaving and Voltage Profile Improvement on a Rural Distribution Network

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Abstract: Distribution networks are increasingly strained by peak load demands and voltage regulation problems. This paper benchmarks Particle Swarm Optimization, Boda-Boda Optimization, and Adaptive Boda-Boda Optimization Algorithm with Fuzzy Logic (ABBOA-Fuzzy) to size and site Battery Energy Storage System (BESS) as a Non-Wires Alternative for rural 11kV feeder support. Baseline analysis of the feeder indicated a peak load of 99.6%, and a voltage drop to 0.936 p.u. The optimization process demonstrated the superiority of the ABBOA-Fuzzy algorithm, which converged faster. The optimized solution guided the selection of a commercially available 400kW/1200kWh BESS which reduced peak demand by 15.5% and raised the minimum voltage to 0.952 p.u. A 15-year techno-economic analysis using the System Advisor Model, accounting for battery degradation confirmed the economic viability with a Net Present Value of $43,643 and an Internal Rate of Return of 15.54%. The study recommends this framework for utility BESS planning.

Keywords Battery Energy Storage System (BESS), Net Present Value (NPV), Non-Wires Alternative (NWA), System Advisor Model (SAM)

1. Introduction

The constant growth in electricity demand, with the increasing penetration of distributed sources, is causing severe stresses on the existing electrical distribution systems. This problem is severe in rural areas, where long radial distribution networks are subjected to two critical issues during peak load periods: end-of-line consumers experience poor power quality due to significant voltage drops, while substation transformers become overloaded (Loji et al., 2023; Pjevalica et al., 2023). Traditionally, utilities have responded to these challenges by investing in expensive physical infrastructure upgrades, such as installation of larger transformers and reinforcement of power lines (Zarei et al., 2024). This approach is inefficient because the newly installed equipment is required for only a few hours each day and therefore remains underutilized for much of the time (Nourollahi et al., 2022). To overcome these limitations, Battery Energy Storage

Systems (BESS) are emerging as flexible Non-Wires Alternative (NWA), offering a focused solution for managing peak loads, improving voltage profiles, and therefore modernizing overall power grid stability (Loji et al., 2023).

Various BESS grid applications have been explored in the literature, including frequency regulation (Parajuli et al., 2024), peak shaving (Arias et al., 2021), power quality enhancement (Prakash et al., 2022), and energy arbitrage. Among them, peak shaving and voltage support have drawn much interest because they could delay costly infrastructure investments (Galea et al., 2025). The successful deployment for these targeted services depends on the solution of the fundamental challenge relating to optimum placement and sizing of BESS. To address this challenge, significant literature has applied metaheuristic algorithms such as Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) for obtaining an optimum BESS configuration by minimizing multi-objective functions involving network losses, voltage deviations, and lifecycle costs (Boonluk et al., 2021; Mat Isa et al., 2023; Pompern et al., 2023). Newer metaheuristic algorithms are being developed to perform better than established methods. This study will employ Boda-Boda Optimization Algorithm (BBOA) and an enhanced Adaptive Boda-Boda Optimization Algorithm with Fuzzy logic (ABBOA-Fuzzy) in benchmarking the solution from PSO.

The interdependence between siting and sizing complicates the optimization problem: Optimal power and energy capacity are functions of the location of the BESS, while the optimal location is a function of its capacity, and co-optimization is thus necessary (Mat Isa et al., 2023). The degradation of batteries introduces one of the most important long-term constraints since it affects the operational reliability of the system and the financial return directly. These performance fades come from two main mechanisms: cycle degradation, which is the wear from charge/discharge operations, and calendar degradation, which is the natural aging of the battery over time (P et al., 2025; Rufino Júnior et al., 2024). For example, the aggressive cycles needed for peak shaving accelerate cycle degradation predominantly, which greatly undermines the economic performance of the project in the long run (Apribowo et al., 2022).

The main barrier to achieving a financially viable investment case for BESS, particularly in developing countries, is their high capital cost. This cost is determined by both the energy capacity of the battery cells, usually denominated in dollars per kilowatt-hour ($/kWh), and the power capacity of the Power Conversion System (PCS), denominated in dollars per kilowatt ($/kW) (Zhao et al., 2023). This large upfront investment creates a significant financial risk whereby an oversized system may not achieve a positive return on investment, while an undersized system fails to deliver the grid benefits required to justify its cost (Zhao et al., 2023). For this reason, optimization of BESS configuration is not an academic exercise but a commercial necessity needed to ensure that the deployed asset is cost-effective and provides a viable return (Zhao et al., 2023).

A review of existing methodologies reveals a clear division in the approaches to BESS sizing and siting. While theoretical optimization studies apply metaheuristic algorithms in order to effectively search the solution space, they often result in commercially unavailable BESS capacities. Conversely, simulation-based assessments of standard equipment sizes lack a guaranteed path to an optimal solution. Table 1 provides a comparative summary of these approaches and visually highlights the resulting gap in the literature. Few studies offer a complete framework that bridges theoretical optimization with practical validation using industry standard simulation tools. The literature specifically lacks a methodology that concludes with a bankable techno-economic analysis one that incorporates lifecycle costs (Capital Expenses (CAPEX), Operational Expenses (OPEX), Future equipment replacement cost, taxes and insurance) and realistic battery degradation.

Table 1 Comparative Analysis of Recent BESS Optimization Studies

Ref	Primary Method	Co-optimizes sizing and siting	Considers Practical Commercial Sizes	Uses Real-world Distribution System	Economic Analysis Method	Includes BESS Degradation	Considers Future Equipment Replacement
(Arias et al., 2021)	Enumerative Search		✔	✔	Payback Period	✔	
(Boonluk et al., 2021)	PSO	✔		✔	Daily Op. cost min.		
(Zhang et al., 2022)	Economic Dispatch opt.				Lifecycle (profit max.)	✔	✔
(Pompern et al., 2023)	PSO/Metaheuristic	✔			Payback Period.		✔
(Parajuli et al., 2024)	Metaheuristic	✔			None		
(Ngala et al., 2022)	Simulation-based Opt.	✔		✔	Benefit Calc.		
(Khunkitti et al., 2022)	Metaheuristic	✔			Daily Op. Cost min.		
(Wongdet et al., 2023)	PSO				Lifecycle (NPV)	✔	✔
(Apribowo et al., 2022)	MILP	✔			Op. Cost min.		
Proposed Method	Hybrid PSO, BBOA & ABBOA-Fuzzy-Simulation	✔	✔	✔	Lifecycle (NPV)	✔	✔

*opt.-Optimization, MILP- Mixed-Integer Linear Programming, Op.- Operational, min.- Minimization, max.- Maximization, Calc.- Calculation

This paper addresses this gap by presenting and applying a two-stage hybrid methodology on a real-world case study of the 11kV feeder in Kenya. The novel contributions of this study are:

- Benchmarking PSO algorithm against two novel, locally-inspired metaheuristics BBOA and ABBOA-Fuzzy to provide a cross-validated solution for optimal BESS sizing and siting.

- The use of simulation-based performance verification, where the optimal theoretical solution is used to select a commercially available BESS whose technical performance is then confirmed in DIgSILENT PowerFactory.
- The development of a bankable techno-economic case that confirms financial viability by integrating a comprehensive lifecycle cost analysis with a realistic battery degradation model in NREL'S SAM.

Section 2 of the paper details the complete methodology, from system modeling and the formulation of the optimization algorithms to the techno-economic framework. Section 3 then presents and discusses the results, covering the baseline analysis, the comparative optimization, and the final technical and financial validation. The paper concludes in Section 4 with the conclusions and recommendations derived from the study's findings.

2. Methodology

Figure 1 presents the flowchart of the whole hybrid methodology, from initial system modeling to the final techno-economic validation. The suggested framework includes three major steps: system modeling and baseline analysis, theoretical optimization by PSO, BBOA and ABBOA-Fuzzy, and simulation-based validation.

2.1 Case Study

An 11 kV feeder in Kenya was selected for this study, where all network topology data, including overhead line parameters, transformer ratings, and historical load profiles, were provided by the local utility. The feeder has a long, radial topology, as depicted in Figure 2 of approximately 69 kilometers, with a mix of residential, small commercial, and agricultural loads. This composition of loads gives a pronounced daily load profile, normally peaking around 18:00 to 21:00 hours. A complete network was modeled in DIgSILENT PowerFactory to represent real-world operational conditions for the feeder.

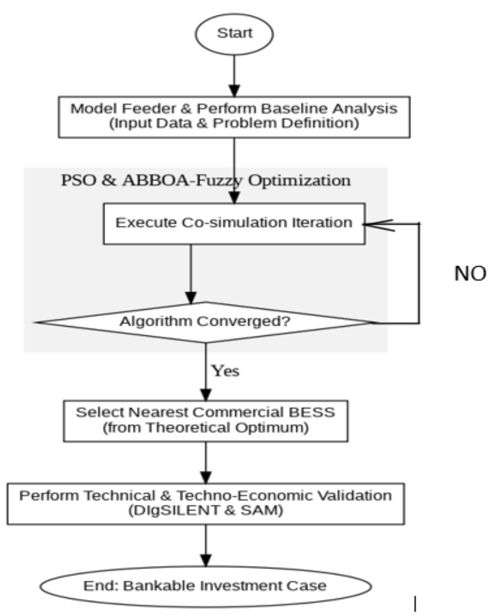

Figure 1 Flowchart of the proposed two-stage methodology

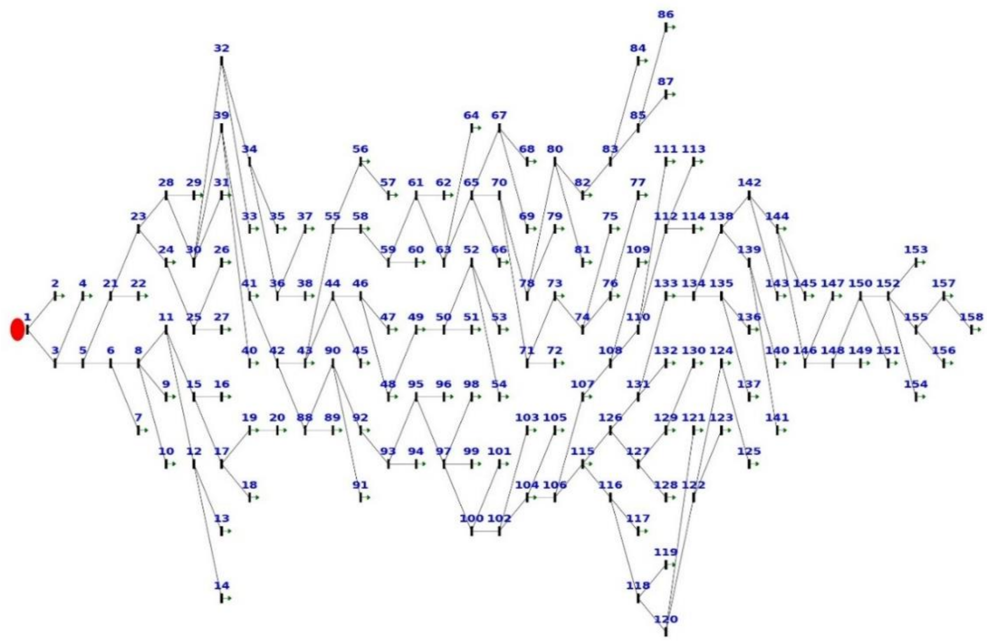

Figure 2 Single-line diagram of the 11kV distribution feeder

2.2 Baseline Analysis

Baseline analysis was conducted to quantify the performance of the feeder without a BESS. A quasi-dynamic load flow simulation was executed in DIgSILENT PowerFactory over a 24-hour period using the typical daily load profile of the feeder. This established the existing operational condition and determined the primary deficiencies of the system. Four key performance indicators were analyzed: Peak load, transformer loading, voltage profile and system losses. The baseline analysis confirmed that the feeder operates under significant stress, establishing a clear need for a grid support solution and providing the performance benchmarks against which the subsequent optimization would be evaluated.

2.3 Optimal Sizing and Siting of BESS Using Metaheuristic Algorithms

Following the base case analysis, the first step in the hybrid approach was the application of a metaheuristic optimization algorithms to identify the optimal size and location for BESS. This step aims to provide an unbiased benchmark to guide a subsequent practical choice of the system. Three different algorithms, PSO, BBOA and advanced ABBOA-Fuzzy, were used to arrive at an optimized solution. PSO has been chosen here because it has already proven effective in finding global optima of complex nonlinear problems of power systems, as demonstrated in (Boonluk et al., 2021; Pompern et al., 2023). Compared to other metaheuristic methods, such as Genetic Algorithms, PSO is more frequently selected for such applications because of its high computational efficiency (Khunkitti et al., 2022), fast convergence rate (Pompern et al., 2023), and easier implementation, all of which are crucial advantages when the evaluation of the fitness function involves complex power system simulations. The solution obtained with PSO was further benchmarked using BBOA and ABBOA-Fuzzy algorithms.

2.3.1 Objective Function

The metaheuristic algorithms were implemented within a Python-based environment to co-optimize BESS power capacity (P_{BESS}), energy capacity (E_{BESS}), and bus location. The optimization was formulated to minimize BESS CAPEX with two important operational constraints derived from baseline analysis: a reduction of at least 15% in peak demand of the feeder and the correction of the voltage drop identified. Therefore, the optimization was designed in order to impose a defined operational voltage target so that the minimum bus voltage lies above 0.94 p.u., providing a clear safety margin above the statutory lower limit at 0.90 p.u. Candidate solutions that failed to meet these constraints were set to a high penalty value within the algorithm to effectively guide the search towards a set of technically feasible and cost-effective configurations, a standard technique for handling constraints in metaheuristic optimization (Nassef et al., 2023). The complete objective function to be minimized is formulated as follows:

$$F(x) = C_{sys}(x) + w_p \cdot max\ (0, P_{peak}(x) - P_{target}) + w_v \cdot max\ (0, V_{limit} - V_{min}(x)) \quad (1)$$

Where $F(x)$ represents the fitness value of the candidate solution x; $C_{sys}(x)$ is the system Capital Expenditure (CAPEX) calculated as $(C_p \times P_{BESS}) + (C_e \times E_{BESS})$, with C_p and C_e representing the unit costs in \$/kW and \$/kWh, respectively. $P_{peak}(x)$ denotes the resulting feeder peak demand with the BESS in operation, while P_{target} is the target peak demand defined as $0.85 \times P_{base}$ (where P_{base} is the baseline peak load). $V_{min}(x)$ is the minimum bus voltage recorded during the simulation, and V_{limit} is the operational voltage target set at 0.94 p.u.

The penalty coefficients w_p and w_v were empirically set to 10^5 and 10^6, respectively. These magnitudes were chosen to be significantly larger than the typical CAPEX values, ensuring that any solution violating the voltage constraint or failing to meet the peak reduction target is assigned a high fitness score. This effectively excludes technically infeasible solutions from the search space during the optimization process. A sensitivity analysis was performed to validate these penalty magnitudes. When the penalty factors were set to lower values (10^4), the optimization converged to a trivial solution of 0 kW, indicating that the penalty cost was insufficient to outweigh the CAPEX savings of omitting the BESS. However, for penalty factors of 10^5 and above, the algorithm consistently converged to the feasible global optimum (392.6 kW).

2.3.2 Fitness Evaluation Procedure

Evaluation of the objective function F(x) required a power system model which could run rapid and repetitive simulations at every candidate solution that the metaheuristic algorithms would propose. For this purpose, a computationally efficient power flow model of the 11kV feeder was developed in Python. The Backward-Forward Sweep (BFS) algorithm was selected as a power flow solver since it has been proven to be fast and converges definitely in a radial topology network (Fang et al., 2023). This computational efficiency, which can give results with minimum resources, as stated by (Petridis et al., 2021), was essential for this study's optimization process. The Python-based BFS solver was benchmarked against DIgSILENT PowerFactory to verify its accuracy. The BFS model calculated a minimum voltage of 0.9360 p.u., matching the DIgSILENT result of 0.936 p.u. Additionally, the calculated active power losses (0.105 MW) were nearly identical to the DIgSILENT benchmark (0.10 MW). This confirms that the BFS engine provides the necessary accuracy for the optimization loop while remaining computationally efficient.

Figure 3 presents a flowchart of this evaluation process. This process is initiated when a metaheuristic algorithm (PSO, BBOA and ABBOA-Fuzzy) proposes a candidate solution. This configuration is then implemented in the Python model, and a 24-hour load flow simulation is executed to determine the feeder performance. The critical outputs of the simulation i.e., the new peak demand, P_peak (x) and minimum bus voltage V_min (x) are utilized in Equation (1) to compute the fitness value. This iterative co-simulation approach with the BFS algorithm playing the role of the embedded load flow engine has been determined as the better method of solving these types of optimization problems (Altaf et al., 2024).

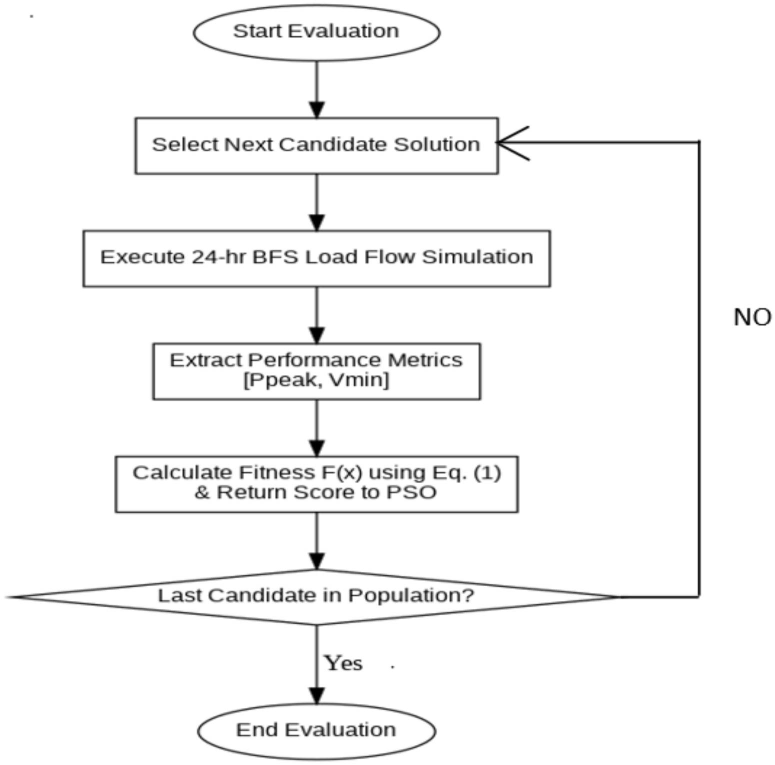

Figure 3 The fitness evaluation process for a single candidate solution

2.3.3 Boda-Boda Optimization Algorithm (BBOA)

The BBOA is a metaheuristic that takes inspiration from adaptive navigation strategies of Kenyan boda-boda (motorcycle taxi) riders. It extends a basic PSO structure with two new, specialized probabilistic operators to enhance a better balance between exploration and exploitation. These operators model real-world decision-making by the riders:

i. *Exploration (Shortcut):* The "exploration" factor, specified by a fixed probability α, simulates the rider's decision to take a risky but potentially faster shortcut. This can be achieved by adding a random vector to the agent's velocity.

ii. *Exploitation (Traffic):* An "exploitation" factor regulated by a fixed probability β simulates cautious reaction to traffic congestion by slowing down or braking. This is modeled by reducing the agent's velocity.

The velocity and position of each agent are updated according to the following equations:

$$v_i(t+1) = w \times v_i(t) + c_1 \times r_1\big(p_{best}(i) - x_i(t)\big) + c_2 \times r_2\big(g_{best} - x_i(t)\big) + v_{\{shortcut\}} - v_{\{traffic\}} \quad (2)$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \quad (3)$$

Where v_i is the agent velocity, x_i is the agent position, w is the inertia weight, c_1 and c_2 are the cognitive and social coefficients, and p_{best} and g_{best} are the personal and global best positions. The term $v_{\{shortcut\}}$ is a random vector applied with probability α, and $v_{\{traffic\}}$ represents a velocity reduction applied with probability β.

The main feature of the BBOA is that the parameters α and β are fixed constants defined at the initialization of the optimization. This offers a consistent but rigid search strategy because the trade-off between exploration and exploitation does not adapt to the advancement of the agent during the search.

2.3.4 Adaptive Boda-Boda Optimization Algorithm with Fuzzy Logic (ABBOA-Fuzzy)

The ABBOA-Fuzzy overcomes the limitation of fixed parameters in the BBOA. The adaptive algorithm elevates the model from fixed probabilistic rules to include a fuzzy logic controller that can simulate the context-aware judgment of a rider. Exploration factor α and exploitation factor β are instead varied dynamically within ABBOA-Fuzzy, rather than using fixed values.

The core of this enhancement is a fuzzy inference system that modulates α and β depending on a single intuitive input: the normalized distance of an agent x_i from the current global best solution, g_{best}. The fuzzy inference system utilizes Triangular Membership Functions (trimf) for both the input variable (Normalized Distance, D) and the output variables (Exploration α, Exploitation β). The input D represents the Euclidean distance of an agent from the global best solution, normalized to the range $[0, 1]$. The membership functions are defined with the following ranges derived from the algorithm's tuning: "Near/Low" $[0.0, 0.0, 0.3]$, "Medium" $[0.2, 0.5, 0.8]$, and "Far/High" $[0.7, 1.0, 1.0]$. The Mamdani inference method is employed with a centroid defuzzification strategy. The fuzzy rule base, presented in Table 2, was designed to dynamically adjust the search behavior based on the agent's proximity to the optimum.

Table 2 Fuzzy Rule Base for ABBOA-Fuzzy

Rule No.	IF Normalized Distance	THEN (α) (Exploration)	THEN (β) (Exploitation)
1	Far	High	Low
2	Medium	Medium	Medium
3	Near	Low	High

This adaptive mechanism enables the algorithm to gradually shift from a globally exploratory search in the early stages to a locally exploitative search toward the later iterations. The position-velocity update equation for ABBOA-Fuzzy remains similar to that for BBOA; however, in the update mechanism, dynamically adjusted values of α and β from the fuzzy controller at every iteration are utilized. This intelligent adaptive strategy enhances the capability of the algorithm for exploring complex nonlinear search spaces while preventing fast convergence toward any local optimum, thereby giving a major advantage over the methods with fixed parameters of search. The specific hyperparameters configured for each algorithm are detailed in Table 3.

2.4 Practical BESS selection and Techno-Economic Analysis

The output of the algorithms is a precise, mathematically optimal solution that serves as an unbiased benchmark. This theoretical optimum solution may not correspond to a standard commercially available BESS module. Therefore, the framework transitions from theoretical optimization to practical validation. This process involves identifying the converged theoretical power and energy capacities from the algorithms, then choosing the nearest equivalent, commercially available BESS. This selected practical system is then modelled in DigSILENT PowerFactory and NREL's SAM for technical and economic assessment.

To investigate the long-term financial viability of the chosen practical BESS configuration, a lifecycle analysis was executed using the NREL's SAM. SAM was adopted because it is an industry-standard, advanced model capable of projecting project cash flows in detail over several years. The analysis was set up to establish the project's NPV over an operational lifetime of 15 years.

Table 3 Optimization Algorithm Hyperparameters

Category	Parameter	Symbol	Value	Description
General Settings	Population Size	N	20	Number of search agents
	Maximum Iterations	$T_{\max}$	30	Stopping criterion
PSO Parameters	Inertia Weight	w	0.5	Controls exploration–exploitation balance
	Cognitive Coefficient	c_1	1.5	Influence of personal best position
	Social Coefficient	c_2	1.5	Influence of global best position
BBOA / ABBOA Parameters	Inertia Weight	w	0.7	Velocity retention factor
	Acceleration Coefficients	c_1, c_2	1.5	Acceleration factors
Fuzzy Controller (ABBOA)	Input Variable	Normalized Distance	$[0, 1]$	Distance to global best (g_{best})
	Output Variables	α, β	$[0, 1]$	Adaptive probability parameters

NPV was the preferred primary financial metric because, as opposed to the simple payback, it considered the time value of money by discounting all future revenues and costs to their present-day value, therefore offering a much better indication of overall profitability (Mohamed et al., 2022).

A key aspect of this modeling was the use of a realistic battery degradation model in SAM. This ensures that the financial projections accurately account for the battery's performance fade and the associated replacement costs, as simplistic degradation approaches can lead to unreliable conclusions (Shamarova et al., 2022). The model simulates the decline in capacity and efficiency due to both cycle degradation i.e., charge/discharge operations and calendar degradation i.e., aging over time (Collath et al., 2023). The detailed financial assumptions that form the basis of this techno-economic model, including capital costs, operational costs, and the calculations for the total upgrade deferral benefit, are provided in Table 4 and Table 5.

The techno-economic parameters were selected based on standard industry benchmarks and regional economic conditions. The nominal discount rate of 10% aligns with recent optimization studies for renewable energy systems in Kenya, such as the off-grid hybrid assessments by (Adem & Otara, 2023). The battery cost projections and performance metrics, including variable operations and maintenance (O&M) costs, were derived from the NREL Annual Technology Baseline (Cole & Karmakar, 2023). Furthermore, the inclusion of a realistic 1.5% annual degradation rate and an 80% Depth of Discharge (DoD) limit address the critical importance of accurate battery modeling in techno-economic assessments, as simplified assumptions can significantly bias lifecycle costs (Shabani et al., 2022).

2.5 BESS Dispatch Strategy and Degradation Modelling

The technical and financial performance of the BESS is entirely dependent on its operational or "dispatch" strategy. This strategy dictates when the BESS charges and discharges to meet its primary objectives of peak shaving and voltage support. As these operational decisions directly govern the rate of battery degradation and, consequently, the project's profitability, they must be realistically modeled. The following subsections detail the dispatch logic and the degradation model used in this analysis.

Table 4 Key assumptions for the techno-economic analysis

Parameter Category	Parameter	Value	Description
Project and Financial assumptions	Analysis period	15 years	BESS project lifetime
	Nominal discount rate	10%/year	The minimum acceptable rate of return
	Inflation rate	2.5%/year	Standard assumption for future cost increases
	Income tax rate	30%/year	Based on Kenyan corporate tax
Battery System Specifications	Battery type	Lithium ion	
	Rated Power (AC)	400kW	Deliverable power to the grid.
	Usable Capacity (AC)	1200kWh	The total Energy the BESS can deliver
	Round Trip-Efficiency	85%	
	Annual degradation	1.5%/year	Model's the battery's loss of capacity over time
	System Availability	98%/year	2% accounts for annual downtime for maintenance
Capital costs (CAPEX)	Direct Costs	$252/kWh $383/kW	Total installed project cost, including all hardware, engineering, and construction costs (Cole & Karmakar, 2023)
	All-in Installed Cost	$637,825	
Operating costs (OPEX)	Annual O&M basis	1.5% of CAPEX	Standard industry estimates for O&M (Lazard, 2023)
	O&M (year 1)	$9,637	
	O&M Escalating rate	2%/year	Accounts for inflation of operating costs
	Inverter replacement cost	$0.15/W (DC)	Cost to replace the inverter in year 12
Primary Financial Benefits	Total upgrade deferral	$1,327,200	Core benefit.

2.5.1 BESS Dispatch Strategy

A peak shaving strategy based on time was developed to control the operation of the BESS using SAM's Manual dispatch controller. This controller follows a user-defined 24-hour schedule that ensures holding the battery's capacity for the peak periods. Figure 4 presents the resulting operational profile, which follows a single deep charge/discharge cycle per day, timed to coincide with the feeder's load pattern. As illustrated, the BESS charges from the grid at its full 400 kW rated power during early morning off-peak hours, remains idle all day, and then discharges to feed power into the network during the evening peak, commencing at 18:00 hours. This simple dispatch strategy ensures that the energy stored in the BESS is used to maximum effect in addressing the evening peak constraint directly identified in the baseline analysis.

Table 5 Supporting Calculations for the Total Deferred Upgrade Cost

Parameter	Value	Source
Feeder length requiring upgrade	10.35 km	Assumed 15% of the total 69 km feeder length.
Distribution network construction cost	$100,000 / km	Based on regional utility costs (Ondigo & Wekesa, 2024).
Subtotal (Line Reinforcement)	$1,035,000	Calculated as $10.35km \times \$100{,}000/km$
Required transformer capacity upgrade	5 MVA	From existing 3 MVA to a proposed 5 MVA.
Transformer unit cost	$30 / kVA	Estimated from manufacturer data, Taishan transformers, 2024
Subtotal (Transformer Upgrade)	$150,000	Calculated as $5MVA \times 1000kVA \times \$30/kVA$
Network construction and transformer cost	$1,185,000	$1,035,000+$150,000
Ancillary costs (installation, etc.)	12% of 1,185,000 $142,200	Estimated as a small percentage for labor and materials.
Total Deferred Upgrade Cost	$1,327,200	Sum of all component costs.

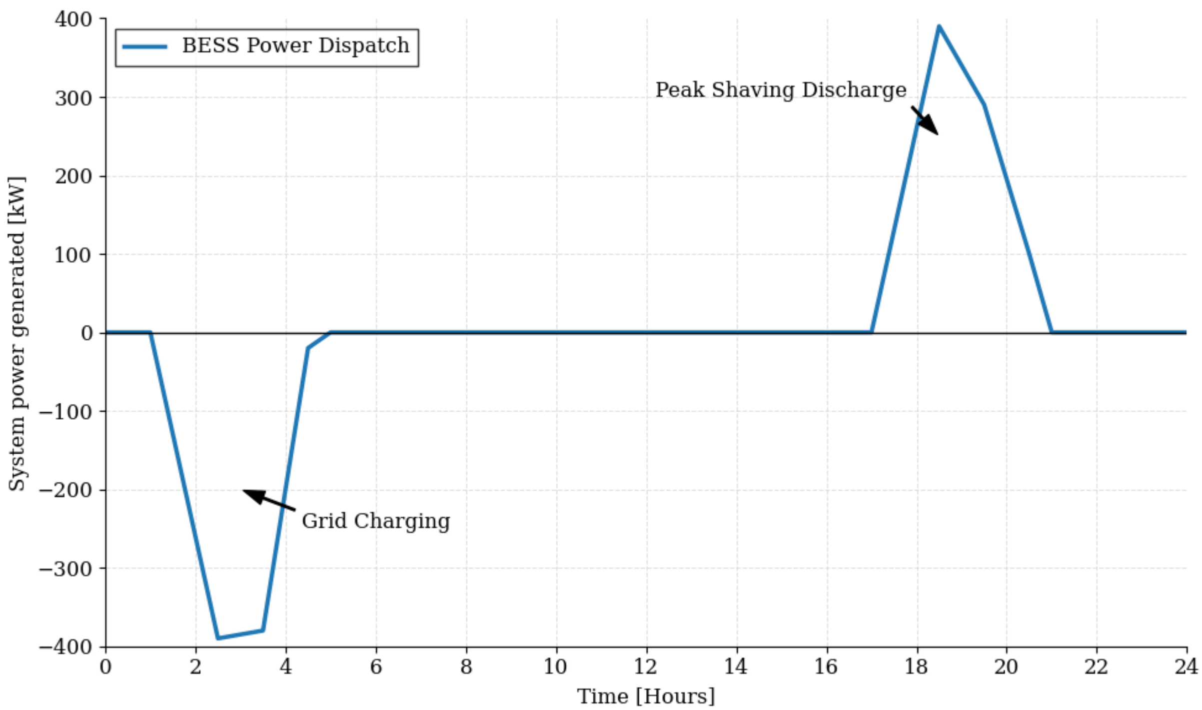

Figure 4 Daily BESS dispatch profile, showing grid charging (negative power) and peak shaving discharge (positive power)

2.5.2 Degradation Modelling in SAM

The SAM analysis included a realistic battery degradation model to obtain an accurate financial forecast. This is important since degradation affects both the battery's performance and its total cost over the project's life. The model includes the two major causes of battery wear, which are cycling degradation due to charge and discharge cycles, and calendar degradation due to normal aging over time. A critical determinant of how quickly a battery wears out is its DoD in each cycle. Deeper cycles are harder on the battery, which makes it lose capacity faster and shortens its life. Figure 5 from NREL's SAM illustrates this relationship by comparing the health of a battery over its lifetime for deep 100% DoD cycles versus shallower 80% DoD cycles. As can be seen from Figure 5, limiting the discharge to 80% slows down the wear and extends the time when the battery would need to be replaced considerably. In order to take advantage of this, a maximum 80% DoD limit was imposed in the simulation for this study. This strategy helps to extend the life of the battery, reduce future replacement costs, and will be one of the important strategies to make the project economically successful.

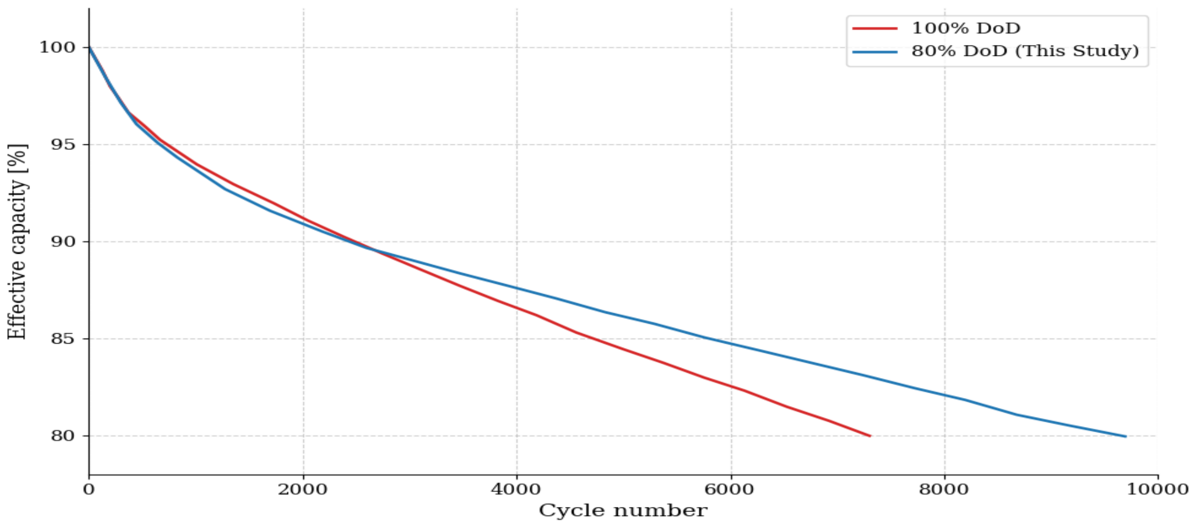

Figure 5 Impact of Depth of Discharge (DoD) on BESS Cycle Life

3. Results and Discussion

The proposed methodology was applied to an 11kV feeder in Kenya, Figure 2 to determine a technically effective and financially viable BESS solution. The findings are presented in the order that follows from the methodological framework: first, the outcomes of the baseline analysis are detailed to establish initial performance benchmarks for the feeder. This is followed by the results of the theoretical optimization as conducted by the metaheuristic algorithms. The section concludes with the validated technical performance and techno-economic results from NREL's SAM for the selected practical BESS configuration.

3.1 Baseline Analysis Results

This baseline analysis, conducted in the absence of any BESS, established that the feeder always operates under significant operational stress, particularly during peak periods. A 24-hour quasi-dynamic simulation performed in DIgSILENT PowerFactory quantified the key feeder performance benchmarks, and the resultant daily load profile is presented in Figure 6. The outcome of the simulation showed a system peak load of 2.809 MW, which loaded the main 3 MVA substation transformer to 99.6% of its rated capacity. Simultaneously, the feeder also suffered a voltage drop, with the minimum voltage at the electrically furthest bus falling to 0.936 p.u. The energy losses were estimated to be 989 kWh for the period of 24 hours.

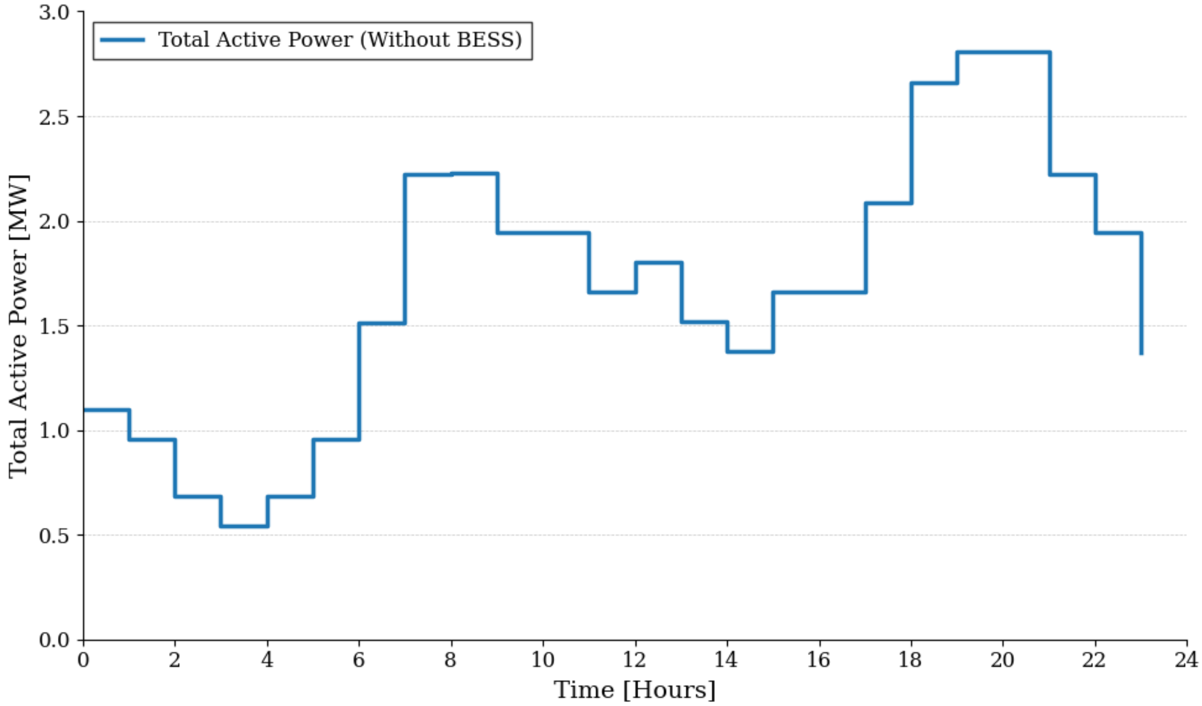

Figure 6 Baseline daily load profile for the 11kV feeder without a BESS

These findings build a quantitative profile of a feeder operating at full technical capacity. The high transformer loading threatens asset health and reliability, leaving no room for future load growth. Similarly, although the minimum voltage of 0.936 p.u. is technically in compliance with the statutory 0.90 p.u. limit, this condition represents significant voltage stress. Therefore, these baseline values provide the critical performance benchmarks for the subsequent optimization. The major technical objectives for the BESS are accordingly to reduce the peak load by at least 15% and to raise the minimum voltage to achieve an operational target of 0.94 p.u.

3.2 Optimization Results and Comparative Algorithm Performance

The hybrid methodology involved the application of three metaheuristic algorithms (PSO, BBOA, and ABBOA-Fuzzy) to identify the optimal BESS capacity and location. This multi-algorithm approach was chosen to ensure a comprehensive search of the solution space and to perform a comparative analysis, which was essential for cross-validating the results and identifying the most effective algorithm for this complex optimization problem.

3.2.1 Algorithm Convergence and Efficiency Analysis

Figure 7 presents the convergence characteristics of the three algorithms evaluated. The plot clearly demonstrates the superior performance of the ABBOA-Fuzzy algorithm. From the first iteration, ABBOA-Fuzzy identified a solution within the near-optimal search space with a much lower fitness score compared to the other two algorithms. Then, the algorithm proceeds with stable, incremental improvements until it converges to the global optimum.

In contrast, both PSO and BBOA are initialized with highly suboptimal solutions and take many iterations to converge across the vast search space. Convergence curves from these two algorithms exhibit distinct plateaus, especially for the early iterations in BBOA. These plateaus reflect how the algorithms were temporarily trapped in local optima-a common phenomenon in complex optimization and indicative of a less effective exploration strategy. All algorithms eventually converge toward similar fitness values, but ABBOA-Fuzzy is demonstrably much more efficient and faster in convergence.

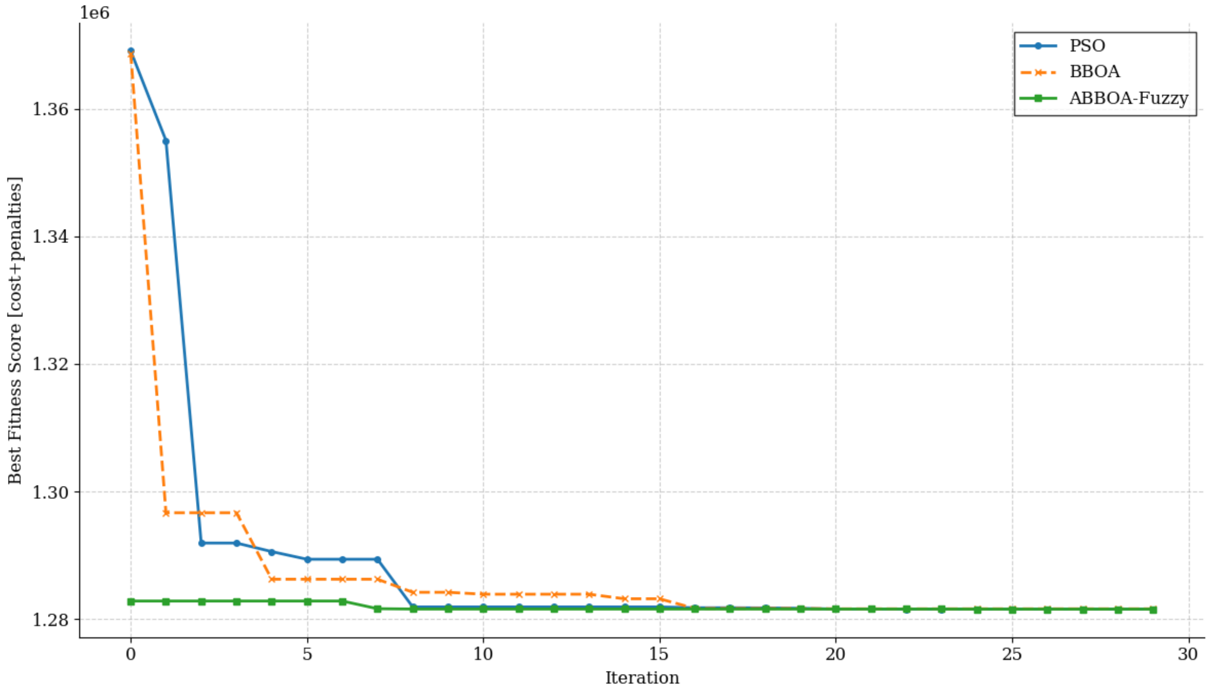

Figure 7 best fitness score, comparing the performance of PSO, BBOA, and ABBOA-Fuzzy

3.2.2 Determination of the Optimal BESS Solution

The final optimized parameters obtained from each of the three algorithms are summarized in Table 6. This comparative analysis found consistent results, with all three algorithms independently converging to a single optimal solution of a 392.6 kW / 1177.76 kWh BESS at Bus 117. This convergence by different search strategies provides a cross-validated configuration of the global optimum. While the final solution was identical, the efficiency in reaching it was not. As shown by its faster convergence in Figure 7, the ABBOA-Fuzzy algorithm proved to be the most efficient method, confirming that the choice of algorithm significantly impacts the computational effort required.

Table 6 Converged Optimal Solution Parameters from All Algorithms

Performance Metric	Optimized (PSO)	Optimized (BBOA)	Optimized (ABBOA-Fuzzy)
Optimal BESS Size	392.59 kW/ 1177.76 kWh	392.64kW / 1177.79 kWh	392.60 kW / 1177.76 kWh
Optimal Location	Bus 117	Bus 117	Bus 117
Final Estimated CAPEX	$455075	$455127	$455079
Best Fitness Score	1,281,575.17	1,281,627.94	1,281,579.94

3.2.3 Grid Performance with the Optimized BESS

The simulation-based validation of the optimized BESS configuration was performed in DigSILENT PowerFactory. Based on the results from the metaheuristic algorithms, a commercially available 400kW/1200kWh BESS was modelled at its optimal location (Bus 117). Table 7 summarizes the substantial grid improvements achieved, directly comparing the key performance indicators against the baseline. The installation of BESS reduced the peak load from 2.809 MW to 2.374 MW, which is a very significant reduction of 15.5%. This intervention reduced the peak loading of the main substation transformer from a critical 99.6% down to a much safer 83.9%.

Table 7 Technical Performance of the feeder with Optimized BESS

Performance Metric	Baseline BESS)	With Optimized BESS	% Improvement
Peak Load (MW)	2.809	2.374	-15.5%
Transformer Loading (%)	99.6	83.9	-15.8%
Minimum Voltage (p.u.)	0.936	0.952	+1.71%

Figure 8 compares the daily load profile of the feeder before and after the BESS installation. It clearly illustrates the peak shaving effect of the BESS, which discharges during the evening peak (18:00-21:00) and clips the peak to provide a flatter, more manageable load profile for the utility.

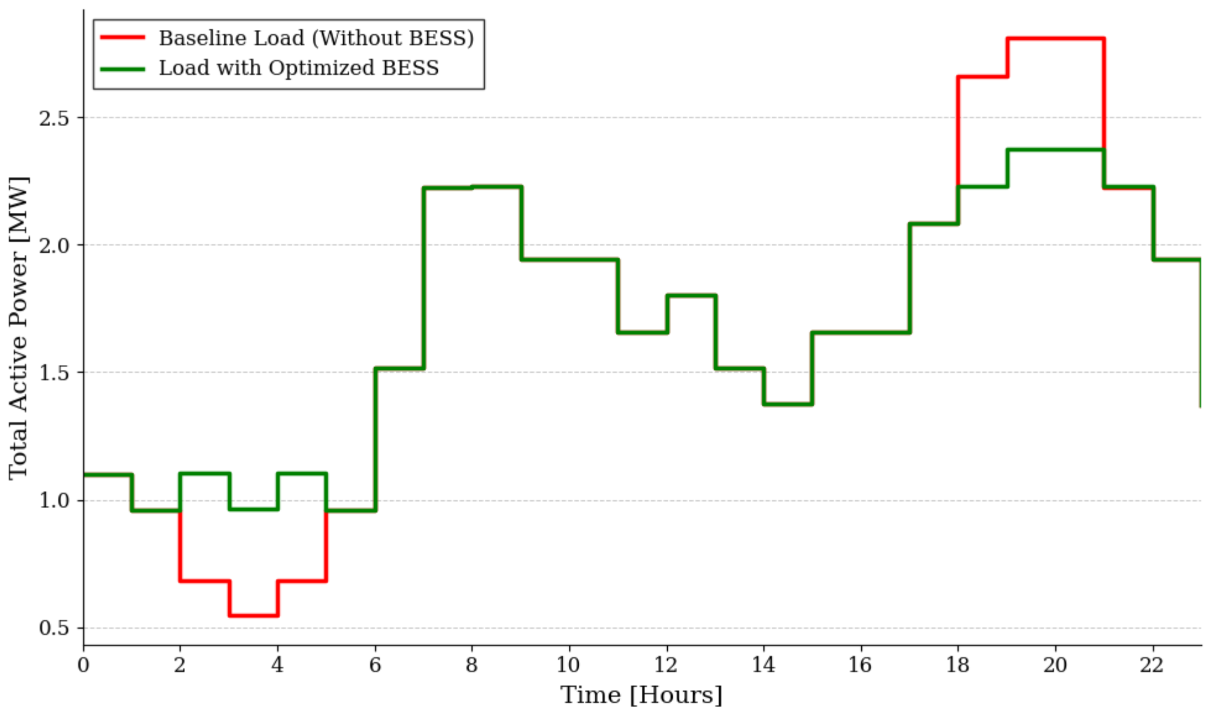

Figure 8 Comparison of the 24-hour feeder load profile with and without the optimized BESS.

The optimized BESS also mitigates the voltage issues of the network effectively. From Table 5, it is observed that the minimum bus voltage was elevated from 0.936 p.u. in the base case to 0.952 p.u., which is an improvement of 1.71%. Voltage improvement at the electrically weakest bus (Bus 158) is depicted for a 24-hour period in Figure 9. This figure clearly demonstrates that the voltage sag occurring in peak hours can be fully avoided, and the voltage of the feeder is always above the operational target of 0.94 p.u. throughout the day.

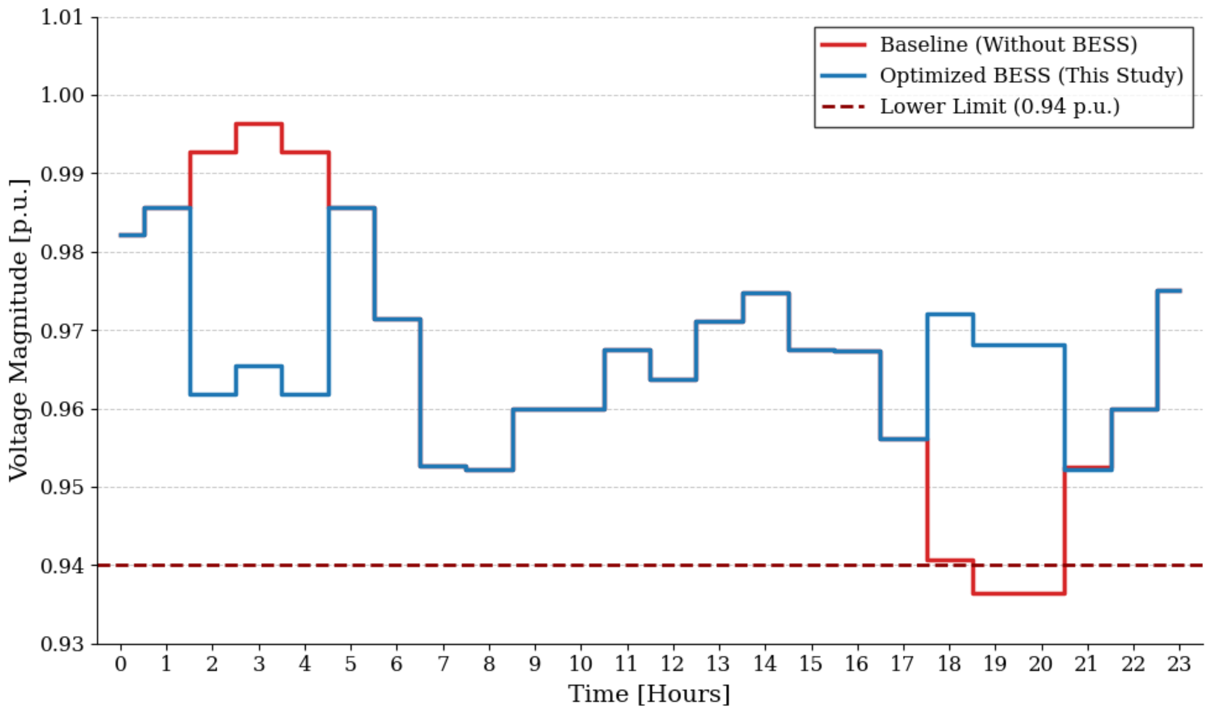

Figure 9 24-Hour Voltage Profile at Weakest Bus (Bus 158)

3.2.4 Validation of Results Against Existing Literature

To validate the findings, the performance of the optimized BESS design has been compared with similar research work that is available in the literature. A key performance objective of this study was peak demand reduction, where the final configuration achieved a 15.5% reduction. This result is in agreement with published findings; for instance, (Arias et al., 2021) achieved a similar peak reduction of approximately 16.7% in a peak-shaving application on a real distribution network, while (Pompern et al., 2023) reported a comparable reduction of 18% using a similar PSO methodology on the IEEE 33-bus system. Furthermore, the BESS-to-peak-load power ratio from this study, which is approximately 14% (392.60 kW BESS for a 2.809 MW peak), is consistent with the ratios found in these other works. The ratio from (Pompern et al., 2023) was about 20% (0.94 MW BESS for a 4.65 MW peak), while the ratio from (Arias et al., 2021) was about 25% (0.3 MW BESS for a 1.2 MW peak). The small discrepancies of these results are as expected because of the different network topologies and load profiles in each study. This correspondence of both technical performance and sizing ratio with various relevant studies validates the results of the optimization framework in this paper.

3.3. Techno-Economic Viability

The 15-year lifecycle analysis in NREL's SAM validated the long-term financial viability of the BESS project. All the lifecycle costs were included in the analysis, as shown in Table 4, including battery degradation and replacement costs. Financial outputs are summarised in Table 8.

This produced a positive NPV of $43,643, which demonstrates the profitability of the project, with returns in excess of the 10% nominal discount rate. An IRR of 15.54% is also calculated by the model, representing a strong return for a utility infrastructure asset. Comparison of LCOE and LPPA price gives further justification for project profitability, where the lifetime revenue per unit energy (71.09 ¢/kWh) is more than the lifetime cost (69.31 ¢/kWh).

Table 8 Key Financial Metrics from SAM Analysis

Metric	Value
NPV (Net Present Value)	$43,643
IRR (Internal Rate of Return)	15.54%
Year IRR is achieved	15
Levelized Cost of Energy (LCOE)	69.31 ¢/kWh
Levelized Power Purchase Agreement (LPPA)	71.09 ¢/kWh

These financial indicators have been validated through benchmarking the results against similar regional studies. One of the major outcomes of this study is the IRR of the project, which is 15.54%. The outcome represents a very sound and financially viable investment opportunity, especially when compared with a large-scale BESS project in a similar regional context with an IRR of 11% reported by (Mamphogoro et al., 2022).

The payback period of 15 years further falls within the same timeframe as that considered acceptable in the study by (Mamphogoro et al., 2022), hence indicating that the project timeline for return on investment is in line with regional expectations. While the NPV of the project is positive, valued at $43,643, it is smaller in scale than the multi-million-dollar returns reported in studies on larger systems such as by (Fida et al., 2023), however, it confirms the same underlying principle of positive financial returns for optimally sized BESS. This correspondence of key financial indicators with relevant studies validates the project as a bankable investment case and a cost-effective alternative to traditional network reinforcement.

4. Conclusion and Recommendations

This paper addressed the challenge of integrating a BESS into a constrained rural distribution network by introducing a two-stage hybrid methodology for its optimal sizing and siting. The first stage of the methodology was a comparative analysis that benchmarked three metaheuristic algorithms: PSO, BBOA, and the enhanced ABBOA-Fuzzy. The analysis showed that the ABBOA-Fuzzy algorithm outperforms others in converging to the optimal solution with the highest speed and efficiency. In turn, the optimization process yielded a consistent optimum solution of a 392.60 kW / 1177.76 kWh BESS at Bus 117. The second stage of the methodology validated this solution by confirming that a commercially equivalent 400 kW / 1200 kWh system is both technically effective and economically viable. Simulation results confirmed that this configuration reduces peak demand by 15.5% and raises the minimum bus voltage from 0.936 p.u. to 0.952 p.u., meeting all technical objectives. Additionally, a 15-year lifecycle analysis confirmed that this project is a bankable investment, yielding a positive NPV of $43,643 and an IRR of 15.54%. These findings demonstrate that an optimally sized and sited BESS offers a cost-effective NWA to enhance grid reliability in rural feeders. Based on these findings, utilities are encouraged to consider this hybrid optimization framework for practical planning. The work can be extended in the future by analyzing the economic benefit of stacking multiple BESS services, such as energy arbitrage and frequency regulation, besides testing the applicability of the framework across feeders with different load profiles and network topologies.

Declaration of Ethical Standards

As the authors of this study, we declare that we comply with all ethical standards.

Credit Authorship Contribution Statement

Job Omambia Mwene**:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Writing Original Draft, Visualization.

Christopher Maina Muriithi: Conceptualization, Methodology, Writing – Review & Editing, Supervision.
Irene Ndunge Muisyo: Methodology, Validation, Writing – Review & Editing, Supervision.

Declaration of Competing Interest

The authors declared that they have no conflict of interest.

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Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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