

**OPTIMAL SIZING AND TECHNO-ECONOMIC ANALYSIS OF A
BATTERY ENERGY STORAGE SYSTEM FOR AN 11 kV RURAL
DISTRIBUTION NETWORK**

Job Omambia Mwene

**A Thesis Submitted in Partial Fulfilment of the Requirements for the Degree of
Master of Technology in Electrical and Electronics Engineering of Murang'a
University of Technology**

August, 2026

DECLARATION

Student Declaration

I hereby declare that this thesis is my original work and, to the best of my knowledge, has not been presented for a degree award in this or any other university. I understand what plagiarism is, and I am aware of the university's policy on this. I understand that any false claim regarding this work shall result in disciplinary action in accordance with the University Anti-Plagiarism Policy.

Job Omambia Mwene
EN400/5135/2024

Date

Supervisor Approval

The undersigned certify that they have read and hereby recommend for acceptance of Murang'a University of Technology a thesis entitled "**Optimal Sizing and Techno-Economic Analysis of a Battery Energy Storage System for an 11 kV Rural Distribution Network**".

Prof. Eng. Christopher Maina Muriithi,
Department of Electrical and Electronics Engineering,
Murang'a University of Technology.

Date

Dr. Irene Ndunge Muisyo,
Department of Electronic and Computer Engineering,
Jomo Kenyatta University of Agriculture and Technology.

Date

DEDICATION

This thesis is dedicated to my mother, Sarah, my grandmother, Ruth and my sister, Naomi, whose unconditional love, prayers, sacrifices and unwavering support have been the foundation of my academic journey. Your strength, wisdom and belief in me have carried me through every challenge.

I also dedicate this work to my uncle, Isaac Motanya, for his guidance, encouragement and constant motivation throughout my studies.

Finally, this thesis is lovingly dedicated to my fiancée, Ndanu, for her patience, understanding, encouragement and support during this demanding journey. Your belief in me has been a constant source of strength and inspiration.

ACKNOWLEDGEMENT

I would like to express my gratitude to the Almighty God for the strength provided to complete this research.

I sincerely appreciate my supervisors, Prof. Eng. Christopher Maina Muriithi and Dr. Irene Ndunge Muisyo, for their expert guidance and mentorship. Their technical support was instrumental in shaping the objectives of this study and bringing this thesis to completion.

I also acknowledge my colleague, Amon, for the collaboration and encouragement shared during this research journey.

The practical foundation of this study was established through the collaboration between Murang'a University of Technology and the local utility. I am grateful for the provision of key network data, which served as the cornerstone of this analysis and helped address real-world industry challenges.

Finally, I acknowledge Murang'a University of Technology for the scholarship award that supported my Master's degree studies and research.

ABSTRACT

Distribution grids are currently facing operational stress due to peak load demands and voltage regulation problems, necessitating cost-effective grid modernization solutions. This study formulated an optimization framework benchmarking three metaheuristic algorithms: Particle Swarm Optimization (PSO), Boda-Boda Optimization algorithm (BBOA) and Adaptive Boda-Boda Optimization Algorithm with Fuzzy Logic (ABBOA-Fuzzy). The framework was employed to determine the optimal capacity and siting of a Battery Energy Storage System (BESS) for a real-world 11 kV rural feeder in Kenya comprising 158 buses. Baseline analysis of the feeder indicated a peak demand of 2.809 MW, loading the substation transformer to 99.6% and a voltage drop to 0.936 p.u. at the furthest buses. The optimization algorithms were implemented in a Python-based environment, where the ABBOA-Fuzzy algorithm demonstrated clear superiority by identifying a near-optimal solution from the first iteration and reaching full stability by iteration 7. The optimal solution was determined to be a 392.59 kW/1177.76 kWh BESS at Bus 117. Based on this, a commercially available 400 kW / 1200 kWh BESS was selected for validation. This configuration reduced peak demand by 15.5% and raised the minimum bus voltage to 0.952 p.u. A 15-year techno-economic simulation confirmed that the project is economically viable, yielding a positive NPV of \$43,643 and an IRR of 15.54%. Thus, this study recommended the adoption of the proposed framework as a planning tool by utilities in BESS projects. Future research could further enhance this framework by incorporating ‘value stacking’ of auxiliary services, such as energy arbitrage and frequency regulation, to potentially maximize the project’s net present value.

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ACRONYMS AND ABBREVIATIONS

ABBOA-Fuzzy	Adaptive Boda-Boda Optimization Algorithm with Fuzzy Logic
ACO	Ant Colony Optimization
BBOA	Boda-Boda Optimization Algorithm
BESS	Battery Energy Storage System
BFS	Backward-Forward Sweep
BoS	Balance of System
CAPEX	Capital Expenditures
CVR	Conservation Voltage Reduction
DoD	Depth of Discharge
DPP	Discounted Payback Period
DTR	Dynamic Thermal Rating
EA	Evolutionary Algorithm
EPRA	Energy and Petroleum Regulatory Authority
FIS	Fuzzy Inference System
GA	Genetic Algorithm
IRR	Internal Rate of Return
kV	Kilovolt
kW	Kilowatt
kWh	Kilowatt-hour
LCOE	Levelized Cost of Energy
LCOS	Levelized Cost of Storage
Li-Ion	Lithium-Ion
LP	Linear Programming
LPPA	Levelized Power Purchase Agreement
LSI	Loss Sensitivity Index
MILP	Mixed-Integer Linear Programming
MOO	Multi-Objective Optimization
MUT	Murang'a University of Technology
MVA	Megavolt-Ampere
MW	Megawatt
NaS	Sodium-Sulfur
NPV	Net Present Value
NREL	National Renewable Energy Laboratory
NWA	Non-Wires Alternative
O&M	Operation and Maintenance
OPEX	Operational Expenditures
p.u.	Per Unit
PCS	Power Conversion System

PSO	Particle Swarm Optimization
RFB	Redox Flow Battery
RT-Na/S	Room-Temperature Sodium-Sulfur
SA	Simulated Annealing
SAM	System Advisor Model
SI	Swarm Intelligence
SLD	Single-Line Diagram
TS	Tabu Search
VDI	Voltage Deviation Index
VRE	Variable Renewable Energy
VSI	Voltage Sensitivity Index
WACC	Weighted Average Cost of Capital

CHAPTER ONE

INTRODUCTION

1.1 Background

The global energy landscape is transitioning toward resilient grid modernization; a trend reflected in regional efforts to improve power reliability across Africa. The Kenyan power distribution system is currently facing severe operational strains due to the ever-increasing demand for electricity and the rising integration of distributed energy sources. These problems are more pronounced in rural areas, where long radial distribution networks are susceptible to two critical issues during peak periods. End-of-line consumers experience poor power quality due to significant voltage drops, while substation transformers become overloaded [1], [2].

According to the Energy and Petroleum Regulatory Authority (EPRA, 2023), Kenya's system peak demand reached a record 2,149 MW, reflecting the increasing load burden placed on the national distribution grid. Traditionally, utilities have responded to these challenges by investing in expensive physical infrastructure upgrades such as reinforcement of power lines and installation of larger transformers [3]. This approach is uneconomical since the newly installed equipment is needed for only a few hours each day and remains underutilized for the majority of the time [4]. To address these shortcomings, Battery Energy Storage Systems (BESSs) are gaining prominence as flexible Non-Wires Alternatives (NWA), presenting a targeted solution for managing peak loads, enhancing voltage profiles and thereby modernizing overall power grid stability [1], [5].

The efficient utilization of these targeted services depends on solving the major challenge of optimal sizing and siting of the BESS. The interdependence between siting and sizing adds complexity to this optimization problem. Optimal power capacity and energy capacity are dependent on the BESS location, while the optimal location is dependent on its capacity and co-optimization is therefore necessary [6], [7]. Battery degradation presents a critical long-term constraint that affects system reliability and economic performance directly. Such performance fades arise from two primary processes: cycle degradation, driven by repeated charge/discharge operations and calendar degradation, arising from natural ageing over time [7], [8]. Recent research underscores that incorporating capacity degradation functions and Depth of

Discharge (DoD) constraints is a necessary condition for realistic planning, whereas ignoring such factors can undermine the assumed economic viability of the project [9].

Although BESS is a viable NWA for rural distribution networks, utilities still face a fundamental planning challenge: identifying a configuration that is both technically effective and economically justified over the life of the project [1], [3]. Existing work tends to fall into two camps. Academic sizing studies emphasize mathematical optimization and often report theoretically optimal but non-commercial BESS ratings on standardized test systems [5], [10]. Utility-oriented studies, on the other hand, prioritize simplified techno-economic screening and frequently overlook practical requirements such as realistic battery degradation, future replacement costs and the use of commercially available equipment [6], [10]. This leaves a clear disconnect between the sizes produced by theoretical models and the configurations utilities can actually procure and finance.

From this disconnect, three specific limitations of current practice can be identified. First, theoretically optimal ratings are rarely mapped onto commercially available BESS modules, so the results are difficult to implement. Second, sizing and siting are often validated on generic test networks rather than on actual feeder data, which limits their practical relevance. Third, lifecycle costs are frequently simplified by ignoring battery degradation and mid-life replacement, which can overstate the economic case. Addressing these limitations is essential if BESS investments are to deliver measurable peak-load reduction, voltage support and long-term financial viability.

This research seeks to address these identified limitations by proposing a planning framework that incorporates theoretical optimization, simulation-based validation using real data and a techno-economic evaluation. The study contributes a novel comparative approach that benchmarks three algorithms: Particle Swarm Optimization (PSO), Boda-Boda Optimization Algorithm (BBOA) and Adaptive Boda-Boda Optimization Algorithm with Fuzzy Logic (ABBOA-Fuzzy), for determining an optimal BESS capacity and location. The framework proposed herein extends theoretical sizing to mapping optimized results onto commercial BESS configurations and further technically validating its performance in DIgSILENT PowerFactory on a real 11 kV feeder in Kenya. Additionally, detailed 15-year

lifecycle techno-economic analysis has been performed using the National Renewable Energy Laboratory's (NREL's) System Advisor Model (SAM) based on realistic battery degradation modelling and its replacement costs. This work, therefore presents an integrated approach, offering a practical methodology of selecting appropriate BESS solutions that are both technically effective and financially viable for the reinforcement of rural grids.

1.2 Problem Statement

High peak electricity demand is a severe operational issue for distribution networks, particularly in rapidly urbanizing regions where load growth often exceeds the thermal limits of existing infrastructure resulting in significant economic losses for utilities. This demand pattern initiates a cascade of technical issues, including transformer thermal overloads and poor voltage regulation for end-of-line consumers. Baseline analysis of the representative 11 kV feeder quantifies this severity, with a peak demand of 2.809 MW loading the substation transformer to 99.6%. In contrast to standard distribution planning criteria, which recommends that transformer loading should not exceed 85% of its rated capacity to prevent premature failure [11], this level of loading causes a significant voltage drop to 0.936 p.u. at the furthest nodes.

While BESS offer a flexible alternative to traditional grid reinforcement [12], utilities face a critical planning challenge. The root of this dilemma is the absence of a clear techno-economic framework to guide the optimal sizing and siting of the BESS, a choice central to resolving the underlying grid challenges [13]. An undersized system will fail to resolve technical constraints, while an oversized one represents an unwise use of capital with a low return on investment.

This study directly addresses this planning gap by utilizing advanced metaheuristic algorithms to develop a techno-economic framework for determining the optimal rated power capacity (kW), energy capacity (kWh) and placement for a BESS on an 11 kV feeder. By bridging this gap, the research provides a methodology to balance technical performance with financial viability establishing a financially justified framework for grid modernization.

1.3 Objectives

1.3.1 Main Objective

The main objective of this research was to perform an optimal sizing and techno-economic analysis of a BESS for peak shaving and voltage profile improvement on a rural distribution network.

1.3.2 Specific Objectives

- i.) Develop a DIgSILENT PowerFactory model of the 11 kV distribution feeder and establish a quantitative baseline of its technical performance.
- ii.) Formulate a constrained objective function and benchmark three metaheuristic algorithms (PSO, BBOA and ABBOA-Fuzzy) to determine the optimal rated power capacity (kW), energy capacity (kWh) and location of the BESS.
- iii.) Quantify the technical performance improvements (peak demand reduction and voltage profile improvement) of the optimally sized and sited BESS in DIgSILENT PowerFactory, and assess its long-term financial viability through a lifecycle cost analysis in NREL's SAM.

1.4 Research Questions

The research questions are formulated to address the specific objectives of the study. Question (i) corresponds to the baseline modelling in Objective (i); (ii) addresses the algorithmic optimization in Objective (ii); and (iii) investigates the techno-economic viability outlined in Objective (iii).

- i.) What are the key technical performance limitations of the 11 kV feeder under its current peak load conditions?
- ii.) What is the optimal rated power capacity (kW), energy capacity (kWh) and location for a BESS on the 11 kV feeder that minimizes capital investment while satisfying defined technical constraints for peak shaving and voltage profile improvement?
- iii.) Is the optimally configured BESS economically viable when evaluated over its project lifecycle, considering battery degradation, its technical benefits, operational costs and key financial indicators such as NPV and IRR?

1.5 Significance of the Study

Traditional grid reinforcement requires substantial capital expenditure for assets that remain underutilized outside peak periods. While BESS offer a flexible alternative, their deployment is hindered by high initial costs and the technical complexity of modelling long-term lifecycle performance [14]. Thus, there is a need to extend technical sizing methodologies into a techno-economic framework that incorporates battery degradation and equipment replacement costs to support investment decisions [15].

A second justification for this study is the use of real network data. The research is based on an actual 11 kV feeder using network parameters provided by the local utility, ensuring that the load profiles and operating constraints reflect real-world conditions rather than a generic test system. The study also quantifies key economic benefits, including deferred infrastructure investment valued at \$1,327,200 and reduced energy losses, against the full lifecycle cost of the BESS. This integrated approach provides a practical and replicable framework for assessing BESS feasibility in developing distribution networks.

1.6 Scope and Limitations of the Study

This study investigates the application of BESS as an NWA to defer traditional grid reinforcement on rural distribution networks. The research focuses specifically on two primary grid services: peak load reduction to relieve thermal stress on substation transformers and dynamic voltage support along the feeder. The scope is limited to distribution-level analysis and excludes transmission-level services and market-based participation, such as frequency regulation and energy arbitrage. The study utilizes a real Kenyan 11 kV feeder as the specific case study, a long radial network of 158 buses spanning approximately 69 km, using topology and load data supplied by the local utility to ground the analysis in real-world operating conditions.

The methodological scope encompasses an optimization framework implemented in Python to determine the optimal rated power capacity (kW), energy capacity (kWh) and location for a BESS. This analysis is performed under deterministic conditions using historical load data and does not account for variability in load growth or electricity tariffs. Furthermore, the optimization process is constrained to a population size of 20 and a maximum iteration count of 100 to ensure computational efficiency.

Technical validation is performed via 24-hour quasi-dynamic power flow simulations in DIgSILENT PowerFactory, while financial feasibility is assessed through a 15-year lifecycle analysis using NREL's SAM.

1.7 Contribution of the Thesis

This research contributes to the field of power systems planning by providing a framework for the integration of BESS in rural distribution networks. Specifically, this thesis contributes by:

- i.) **Demonstrating an adaptive metaheuristic approach, ABBOA-Fuzzy** that couples the Boda-Boda Optimization Algorithm with a fuzzy-logic controller to adjust the exploration and exploitation parameters at every iteration. This improves search efficiency and convergence speed over the standard PSO and BBOA solvers when applied to the non-linear BESS sizing and siting problem.
- ii.) **Establishing an integrated planning methodology** that translates the theoretical optimum into the nearest commercially available BESS rating and validates it on a real 11 kV Kenyan feeder in DIgSILENT PowerFactory, thereby linking academic sizing results to equipment that a utility can realistically procure.
- iii.) **Quantifying the 15-year lifecycle techno-economic viability of BESS as an NWA** on a rural feeder under realistic battery-degradation and replacement-cost assumptions, and reporting the resulting NPV, IRR, LCOS and upgrade-deferral value as financial evidence to support utility investment decisions.

1.8 Organization of the Thesis

The remainder of this thesis is organized into four chapters. Chapter Two reviews the operational challenges of rural distribution networks, the role of BESS as an NWA, the main methods used for optimal sizing and siting, and the techno-economic frameworks that inform the study, closing with the identified research gap. Chapter Three presents the methodology, covering the DIgSILENT PowerFactory model of the feeder, the baseline analysis, the formulation of the optimization problem, the three metaheuristic solvers and the techno-economic evaluation in NREL's SAM. Chapter Four reports and discusses the results, from the baseline feeder performance and the

algorithmic comparison to the technical validation of the optimized BESS and its 15-year financial assessment. Chapter Five draws the conclusions of the study against each objective and sets out the recommendations for adoption and for future work.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter begins by reviewing the operational challenges in modern distribution networks, such as peak load, voltage regulation and power losses. The discussion then shifts to the Battery Energy Storage System (BESS) as a Non-Wires Alternative (NWA), looking at its technical capabilities and applications. After that, this work evaluates optimization methods, ranging from standard techniques like Particle Swarm Optimization (PSO) to newer, locally-inspired approaches like the Boda-Boda Optimization Algorithm (BBOA) and Adaptive Boda-Boda Optimization Algorithm with Fuzzy Logic (ABBOA-Fuzzy). Finally, the review summarizes these points to identify the specific research gap regarding the integrated techno-economic optimization of BESS capacity and siting for rural grid modernization, laying the groundwork for this thesis.

2.2 Challenges in Modern Rural Distribution Networks

The operating pattern of distribution networks is being transformed by the pressures of increasing electricity loads and Variable Renewable Energy (VRE) penetration. Radial topologies designed for single-direction power flow in conventional networks are often unsuitable to meet these new dynamic challenges [1]. A set of recurring operating issues has therefore been found in the literature. This work categorizes these concerns into three high-priority categories: thermal limitations due to peak load, power quality degradation and voltage regulation deterioration and the economic impact of technical power losses.

2.2.1 Peak Load and Thermal Constraints on Assets

Peak load management in distribution networks presents significant challenges as utilities must size infrastructure to handle intermittent peaks while assets remain underutilized for the majority of the time. The complexity of this management is intensifying with increasing renewable energy penetration, requiring more sophisticated planning approaches [16]. The severity of this constraint is evident in recent projections showing that without effective intervention, transformer violations could reach as high as 81% by 2050 [17]. However, such projections often rely on aggressive growth models that may not fully account for localized demand-side

management. This operational strain is compounded by the intermittent nature of renewable sources, which induces additional thermal stress on transformers, accelerating ageing and necessitating enhanced analytical frameworks to predict remaining useful life [18]. Although advanced strategies combining conservation voltage reduction (CVR) with dynamic thermal rating (DTR) have demonstrated potential cost savings [19], the fundamental limitation remains the thermal capacity of assets under sustained peak stress.

2.2.2 Voltage Regulation and Power Quality Issues

Maintaining voltage profiles within regulatory limits is a critical operating requirement of distribution systems. However, this stability is severely compromised during periods of peak demand. On long radial feeders, the combination of high line impedance and maximum load currents results in significant voltage decay ($I \cdot Z$ drop) toward the end of the line. This operational strain creates severe under-voltage conditions for remote consumers, leading to the malfunction of sensitive electronic equipment and instability in industrial loads [20]. While distributed generation can induce opposing overvoltage issues during light load periods [21], the primary challenge on rural feeders remains the deep voltage sags during evening peaks. These reliability issues render traditional, static grid reinforcement measures inadequate, driving the urgent need for flexible, fast-acting interventions capable of providing dynamic voltage support.

2.2.3 Technical Power Losses and Economic Impacts

Technical losses in distribution networks are predominantly resistive (I^2R) in nature and represent a direct financial leakage for utilities. Because these losses are proportional to the square of the current, they increase exponentially during peak load periods, meaning a disproportionate amount of energy is wasted during a few hours of maximum demand [1]. This creates a dual economic penalty: the utility loses revenue on energy generated but not sold and simultaneously faces potential regulatory fines for failing to maintain system efficiency standards. Consequently, loss minimization is not merely an engineering objective but a financial imperative. Strategies that reduce peak currents, such as demand profile reshaping via BESS, are therefore critical for improving the overall economic performance of the grid.

2.3 BESS as a Non-Wires Alternative (NWA)

2.3.1 The Concept of a Non-Wires Alternative (NWA)

Non-Wires Alternatives (NWAs) represent a strategic approach to defer or eliminate traditional grid infrastructure upgrades by leveraging distributed energy resources and demand management technologies [22], [23]. García-Santacruz et al. in [22] highlighted that NWAs offer a versatile solution for mitigating voltage violations and thermal overloads caused by network congestion, providing distinct advantages over single-technology solutions from both utility and investor perspectives. This approach has evolved into dynamic planning models that optimally combine traditional wire reinforcements with non-wire assets, thereby enabling distribution system operators to maximize overall operational flexibility and participation in ancillary services markets [24], [25].

2.3.2 BESS for Peak Shaving and Load Levelling

BESS provides effective peak shaving and load-levelling solutions for distribution networks by charging during off-peak periods and discharging during peak periods. BESS deployment significantly reduces thermal stress on substation transformers by managing overloading conditions, which extends insulation life and defers costly equipment replacements [26]. While evening peak surges are common to both urban and rural distribution networks, this technical capability is particularly valuable for rural feeders where long radial configurations create a wide disparity between base and peak loads. In contrast, traditional grid reinforcement techniques, such as transformer and conductor upgrades, are often limited by high capital intensity and the underutilization of these assets during off-peak hours. Practical implementations indicate that rule-based control algorithms, when paired with load forecasting, manage these peaks effectively even under real-time conditions [27].

From an economic perspective, this operational relief translates into tangible capital savings. Recent analyses show that BESS deployment can defer network upgrades for up to six years while maintaining a positive Net Present Value, even after accounting for variable battery costs [28]. However, it must be noted that these long-term deferral claims are highly sensitive to load growth and discount rate assumptions, which can vary significantly in developing economies. Further investment modelling confirms that applying BESS for peak shaving and maintenance deferral yields positive returns

and acceptable payback periods, validating the technology as a viable option within a broader grid reinforcement case [29].

2.3.3 BESS for Dynamic Voltage Support

BESS can also provide critical dynamic voltage support through their advanced power conversion systems, which can rapidly inject or absorb reactive power for voltage regulation and power factor correction [30]. The power electronics inverters in BESS enable ultra-fast, millisecond-scale responses that are superior to traditional mechanical voltage regulation systems like capacitor banks and on-load tap changers [30]. Fedayi et al. [31] validated that this capability effectively maintains system voltages within the standard acceptable range of 0.9 to 1.1 p.u., ensuring stability indices remain above critical thresholds even under operational stress. Additionally, the integration of active and reactive power controllers allows for simultaneous power smoothing, establishing these systems as essential assets for managing ancillary services in distribution networks with high renewable energy penetration [12], [32].

2.3.4 Interplay Between BESS Services and Value Stacking

The financial viability of a BESS investment often relies on its ability to deliver multiple services from a single asset, a concept termed ‘value stacking’ [33]. For distribution networks, this means using a BESS to solve multiple problems at the same time. For instance, a BESS deployed primarily for peak shaving also provides a secondary benefit by reducing technical losses. Since resistive losses (I^2R) are proportional to the square of the current, reducing the peak current lowers distribution losses, creating a direct operational saving without requiring additional infrastructure [34].

Existing literature suggests that adding market-based services, such as energy arbitrage or frequency regulation can further enhance financial metrics, with some studies indicating revenue increases of up to 129% [33]. However, the feasibility of these specific stacks is highly context-dependent, relying on the local regulatory architecture and market existence. In many rural distribution contexts, the most significant value stack remains the combination of infrastructure deferral and technical energy loss reduction. Therefore, techno-economic evaluation must focus on these locational benefits to build a bankable case for utilities where market participation

may not yet be viable. Table 2.1 summarizes the services a BESS can deliver as they have been conceptualized in the literature.

Table 2.1: Summary of Key BESS Grid Services

Service	Primary Technical Objective	Primary Value Driver(s)	Typical Timescale	Citation
1. Peak shaving	Reduce peak demand on grid assets (transformers, conductors).	Deferred capital expenditure for upgrades Reduced demand charges.	Minutes to Hours	[35] [36]
2. Voltage support	Maintain local voltage within statutory limits by injecting/absorbing VARs.	Improved power quality Avoidance of penalties Enabling more DER hosting.	Milliseconds to Seconds	[30] [36]
3. Energy loss reduction	Minimize system I ² R losses by reducing peak current.	Reduced operational cost from saved energy (kWh).	Minutes to Hours	[37]
4. Energy Arbitrage	Charge when energy prices are low and discharge when they are high.	Revenue from price differentials in electricity markets.	Revenue from price differentials	[34]
5. Frequency Regulation	Inject/absorb real power to stabilize grid frequency around nominal value.	Revenue from providing ancillary services to the grid operator.	Seconds to Minutes	[12] [38]

As summarized in Table 2.1, the services a BESS can provide are complementary rather than mutually exclusive: peak shaving and load levelling relieve thermal stress on assets, dynamic voltage support corrects power-quality problems, and the associated reduction in peak current lowers technical losses. For a constrained rural feeder, the table shows that the two services with the clearest and most bankable local value are infrastructure-upgrade deferral and technical-loss reduction, which is why the techno-economic assessment in this study concentrates on these benefits.

2.4 Battery Energy Storage Technologies

Energy storage technologies are essential for addressing renewable energy integration challenges and grid stability issues. These systems are broadly categorized into electrical, electrochemical, mechanical, thermal and chemical forms, with no single

technology capable of addressing all power system applications due to varying power ranges and discharge characteristics [39], [40]. While pumped hydro storage currently dominates global energy storage capacity, constituting 96% of currently operational storage systems [40], BESS have become particularly valuable for distribution networks due to their flexible configurations, fast response times and high control levels [41]. The literature identifies several distinct electrochemical technologies suitable for grid support, which are critically analyzed in the following subsections. Beyond these contemporary sources, the foundational reviews of battery energy storage for power-system applications established the comparative technology characteristics that continue to inform modern technology selection [42], [43], [44].

2.4.1 Lead-Acid Batteries

Lead-acid batteries represent the most commercially established storage technology, having been utilized in power systems for over a century. They are primarily characterized by their low upfront capital cost, typically ranging between 50 and 600 USD/kWh and high reliability in backup applications [45]. However, their application in modern grid support is limited by significant technical constraints. Lead-acid batteries exhibit a low energy density of approximately 20–30 Wh/kg and a relatively short cycle life, particularly when subjected to the deep daily discharges required for peak shaving. Furthermore, to maintain a reasonable operational lifespan, these systems typically require a Depth of Discharge (DoD) limitation of around 50%, which effectively necessitates oversizing the installed capacity to achieve the same usable energy as newer technologies [46].

2.4.2 Sodium-Sulfur (NaS) Batteries

Sodium-sulfur (Na-S) batteries are recognized for their high energy density and efficiency, utilizing earth-abundant materials that make them cost-effective candidates for grid-scale applications [47]. However, conventional Na-S batteries face significant operational challenges, particularly their requirement for high operating temperatures of approximately 300°C to maintain electrodes in a molten state [47]. This characteristic necessitates complex thermal management systems to regulate behaviour, which can complicate deployment and impact energy throughput [48]. While recent research has explored Room-Temperature Na-S (RT-Na/S) variants to overcome these thermal limitations, these technologies currently face practical

implementation hurdles regarding sulfur loading and electrolyte management, limiting their immediate utility in standard distribution networks [49].

2.4.3 Redox Flow Batteries (RFBs)

Redox Flow Batteries (RFBs) have a unique architecture where energy is stored in external electrolyte tanks, allowing for the independent scaling of power and energy capacities. This flexibility, combined with an extended cycling life, makes them particularly suitable for long-duration grid-scale applications [10], [50]. However, RFBs face a critical limitation regarding energy density due to the restricted solubility of active materials in conventional solvents. This constraint necessitates large tank volumes and extensive physical floor space to achieve the same capacity as solid-state alternatives [51]. While innovative solid-liquid storage concepts are being developed to potentially increase energy density by over four-fold [51], the current spatial footprint and balance-of-system complexity present significant challenges for deployment in standard distribution substations.

2.4.4 Lithium-Ion Batteries (Li-Ion)

Lithium-ion batteries have emerged as the preferred technology for grid-scale energy storage applications due to their superior technical and economic characteristics. These batteries offer high energy and power density, flexible installation and long-life cycles, making them particularly promising for utility-scale deployment [52]. Comparative studies demonstrate that lithium-ion technology outperforms traditional alternatives. Specific configurations achieved renewable energy shares up to 70% at competitive levelized costs of approximately \$0.1334/kWh [53].

From an environmental perspective, lifecycle assessments reveal that lithium-ion batteries have significantly lower environmental impacts than lead-acid batteries across multiple categories, including approximately 45% less climate change impact for nickel cobalt aluminium variants [54]. Furthermore, cost projections indicate continued price reductions, with utility-scale lithium-ion storage costs expected to reach \$245–403/kWh by 2030 and potentially drop to \$159–348/kWh by 2050 [55].

Due to this combination of economic viability, technical performance and environmental superiority, Lithium-Ion was adopted as the reference battery technology for the optimization and techno-economic analysis in this study.

2.4.5 Hybrid Energy Storage Systems

Beyond the single-technology chemistries discussed above, the classification of storage for grid support also includes Hybrid Energy Storage Systems (HESS), which combine two complementary technologies to overcome the limitations of any one device. A common arrangement pairs a high-energy source, such as a lithium-ion battery, with a high-power source, such as a supercapacitor, so that the battery supplies the sustained energy for peak shaving while the supercapacitor absorbs the fast transients that would otherwise accelerate battery degradation [39], [40]. Such configurations can extend battery life and improve dynamic response, but they add control complexity and cost. They are noted here for completeness; the present study adopts a single lithium-ion BESS, which offers the most mature and cost-effective option for the sustained daily cycling required on the study feeder.

2.5 Methodologies for Optimal Sizing and Siting of BESS

The selection of the most appropriate size (Kw/kWh) and location of a BESS is a critical planning task extensively debated in the scientific literature. A proper sizing method is driven by the technical and economic objectives of the BESS project, ranging from market participation revenue maximization to investment cost minimization for distribution support [13]. Many optimization-based and analytical techniques have been developed to address this complex issue. These techniques can be collectively categorized into mathematical programming (linear and mixed-integer programming) and metaheuristic algorithms.

Within the framework of metaheuristics, a number of nature-inspired algorithms have been applied to address the BESS sizing and siting problem [56], [57]. These include evolutionary algorithms like Genetic Algorithms (GA) [58], swarm intelligence-based algorithms like Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO). They also include physics-inspired algorithms like Simulated Annealing (SA) [59] and human-inspired algorithms like Tabu Search (TS) [60]. Metaheuristic methodologies are favoured in research primarily because they are able to traverse the expansive, non-linear and generally non-convex solution spaces characteristic of BESS optimization. This section will critically assess these various methodological classes, evaluating their effectiveness in determining the best BESS configuration to meet targets like peak shaving and voltage support.

2.5.1 Mathematical Programming and Analytical Approaches

Mathematical programming techniques such as Linear Programming (LP) and Mixed-Integer Linear Programming (MILP) are foundational to BESS sizing as they guarantee global optimality for convex problems. These deterministic methods are highly effective for minimizing total system costs and optimizing dispatch schedules. As highlighted in the review by [61], the integration of economic analysis with technical optimization is increasingly critical for the successful deployment of BESS in renewable energy systems. However, these methods often require the simplification of complex power system constraints. To address this, Zhang et al. in [62] introduced an improved cycle ageing cost model using piece-wise linearization, which enhances accuracy in estimating battery life degradation while maintaining the computational benefits of linear programming.

In addition to these formal programming methods, analytical and heuristic approaches serve as useful shortcuts to limit the search area for BESS sizing especially when full optimization is computationally costly. While these methods do not always guarantee absolute optimality, they offer simplicity and rapid execution for initial planning stages [63]. For BESS deployment on distribution feeders, two of the most widely used analytical tools are the Loss Sensitivity Index (LSI) and the Voltage Sensitivity Index (VSI).

The Loss Sensitivity Index (LSI) is used to identify the feeder nodes at which the injection of real power produces the greatest reduction in total system active-power loss. It expresses the marginal change in system losses with respect to the real-power injection at each bus, so that the buses offering the largest loss reduction are ranked highest for siting; the formal expression is provided in [64].

The Voltage Sensitivity Index (VSI) identifies the weakest electrical points on the feeder from a voltage-stability perspective, and installing a BESS at such locations yields the greatest voltage support. It measures the change in bus voltage magnitude produced by a small real- or reactive-power injection, as formulated in [65].

The VSI identifies the most sensitive electrical nodes where small power injections yield the greatest improvement in the local voltage profile. While these sensitivity-based methods are effective tools for pre-screening potential locations and reducing

the complexity of the siting problem, they are fundamentally static as they are solved at a single operating point such as peak load. Consequently, they cannot account for the optimal energy capacity (kWh) or the dynamic operating strategy required to manage a varying 24-hour load profile. This limitation necessitates the use of more robust optimization techniques, as discussed in the following section.

2.5.2 Metaheuristic Algorithms

Mathematical programming and analytical approaches establish a theoretical basis for BESS sizing. However, their application is often limited by the requirement for problem linearity and static representations. Deterministic methods face limitations in handling the uncertain, nonlinear and multi-objective scenarios characteristic of modern distribution networks [66]. The complexity of the BESS sizing problem, defined by non-linear power system interactions and competing goals, necessitates more flexible optimization-based methods. Determining BESS capacity involves a complex trade-off between minimizing lifecycle cost, maximizing technical performance and maintaining battery health [67].

Metaheuristic algorithms have emerged as a powerful alternative to address these non-linear challenges. These approaches offer high adaptability for complex optimization problems without requiring the strict linearization of power system constraints [6], [66]. These methods are particularly valuable for addressing the increasing penetration of renewable energy sources, where BESS provides the flexibility and controllability required to mitigate intermittency. Furthermore, advanced optimization planning must incorporate battery degradation factors, such as ambient temperature effects, to ensure BESS performance remains robust over the project lifetime [8]. The subsequent subsections provide an examination of these metaheuristic approaches, evaluating their principles and specific applications in determining the best BESS configuration to meet targets such as peak shaving and voltage support.

2.5.2.1 Evolutionary Algorithms (EA)

Evolutionary Algorithms operate on a population of potential solutions inspired by the principles of evolutionary biology. The most widely known is the Genetic Algorithm (GA). GA represents potential solutions as ‘chromosomes’ and uses selection mechanisms, crossover and mutation to evolve iteratively in the population to an optimum solution [68]. These algorithms are robust for non-differentiable

complicated problems and possess excellent global search ability. In direct comparisons in power system issues, GA has exhibited good precision, even if this is occasionally at the expense of a more intensive computational load compared to other methods [69].

2.5.2.2 Swarm Intelligence (SI) Algorithms

Swarm Intelligence (SI) algorithms are founded upon the collective social behaviour of decentralized, self-organized systems. Particle Swarm Optimization (PSO) initializes a swarm of particles, each representing a candidate solution [70]. The particles move through the solution space by adjusting their trajectory according to two update rules. The velocity of each particle is updated by combining its current velocity, scaled by an inertia weight that balances exploration and exploitation, with an attraction toward its own best-known position (the cognitive term) and toward the best position found by the whole swarm (the social term). The particle position is then advanced by adding the updated velocity, as formulated in [71].

PSO is distinguished by its simplicity of concept, ease of implementation and low computational burden, leading to faster convergence times. However, this efficiency often comes at the expense of a lower solution quality compared to more detailed search methods like GA [69].

2.5.2.3 Emerging Adaptive and Hybrid Algorithms

Recent research has prioritized the development of adaptive metaheuristics to address the stagnation and premature convergence issues common in standard algorithms. These adaptive search strategies have demonstrated significant performance gains, achieving up to a 50% reduction in computational overhead and a 30% increase in solution accuracy compared to traditional static approaches [72]. Examples of these methodologies include Fuzzy-controlled Particle Swarm Optimization (FCPSO), which utilizes stagnation counters and fuzzy logic to tune inertia weights based on population diversity [73]. Another example is Velocity Pausing Adaptive PSO (VASPSO), which incorporates time-varying inertia coefficients to balance exploration and exploitation [74]. Furthermore, Roy et al. in [75] introduced a systematic framework for fuzzy feedback control, demonstrating that fuzzy-logic-enhanced algorithms consistently outperform traditional parameter control variants in complex search spaces.

The integration of hybrid metaheuristics represents a parallel advancement in BESS optimization. For instance, Nguyen et al. in [76] developed a hybrid PSO-Grey Wolf Optimization (PSO-GWO) approach that achieved substantial power loss reductions while maintaining voltage profiles within statutory limits during peak demand periods. Similarly, mutation-improved variants such as Mutation-Improved Grey Wolf Optimizer (MIGWO) have shown superior convergence rates when coordinating BESS scheduling with renewable energy sources in active distribution networks [77]. These advancements are particularly critical for BESS placement and sizing; as demonstrated by [78], the application of optimized hybrid techniques can achieve operational cost reductions exceeding 64% while simultaneously improving grid voltage stability. Collectively, these logic-enhanced and hybrid strategies represent the current state-of-the-art, providing the theoretical justification for the ABBOA-Fuzzy framework proposed in this work. Table 2.2 provides a comparative summary of these optimization methodologies, highlighting the specific limitations that drive the need for the adaptive approach proposed in this study.

Table 2.2: Comparison of Optimization Methodologies for BESS Sizing

Category	Algorithm	Core Principle	Strengths	Weaknesses
Classical	MILP	Mathematical optimization	Guarantees global optimum for linear problems [79].	Requires problem linearization, can be computationally slow [7].
Evolutionary	GA	Natural selection	Robust for complex, non-linear problems, good global search [69].	Slow convergence, requires parameter tuning [69].
Swarm	PSO	Social behaviour of flocks	Fast convergence, simple implementation, few parameters [69].	Can converge prematurely to local optima [69].
Swarm	ACO	Ant foraging	Effective for discrete optimization problems [80].	Prone to premature convergence (local optima).
Adaptive	Logic-Enhanced Swarms	Dynamic parameter adjustment	Superior balance of exploration/exploitation.	Higher implementation complexity [81].

2.6 Techno-Economic Analysis Frameworks for BESS Projects

The significant capital expenditure required for a BESS necessitates a comprehensive techno-economic evaluation to translate technical performance into a viable business

case. The literature establishes that technical feasibility alone is not an appropriate investment criterion; an explicit methodology must be used to connect engineering design to financial justification.

Modern techno-economic frameworks have advanced significantly, now incorporating critical drivers such as battery ageing models to accurately determine the system's real lifecycle cost and energy throughput [82]. The economic viability of a BESS is highly context-dependent, relying heavily on the specific application and prevailing local conditions, such as energy markets and grid load profiles [61]. Furthermore, value stacking is frequently cited as a primary driver of profitability, as combining multiple revenue streams can dramatically increase financial returns compared to single-service applications [33].

This section discusses the conceptual frameworks for this analysis, delineating the methodologies found in the literature for quantifying lifecycle costs, valuing operational benefits and utilizing key financial metrics to ascertain project viability.

2.6.1 BESS Lifecycle Cost Quantification

A comprehensive techno-economic study requires an integrated accounting of all costs incurred over the project lifecycle. The literature consistently categorizes these costs into two primary components: initial Capital Expenditures (CAPEX) and subsequent Operational Expenditures (OPEX).

2.6.1.1 Capital Expenditures (CAPEX)

Capital Expenditures (CAPEX) refer to the total initial investment required to purchase and install the BESS, driven by the technical ratings set by the optimization process. The CAPEX principally comprises the Power Conversion System (PCS), the battery pack and the Balance of System (BoS), including control systems and installation [33], [55]. It is obtained by adding the product of the rated power and the per-unit power cost to the product of the rated energy and the per-unit energy cost, as expressed in [55].

2.6.1.2 Operational Expenditures (OPEX)

Operational Expenditures (OPEX) encompass all ongoing costs required to sustain BESS operation. These typically include a fixed annual component for routine

maintenance, insurance and labour; often estimated as a percentage of the initial capital cost [55]. However, the most critical variable component of OPEX for a daily-cycling BESS is battery degradation, which depends directly on the depth of discharge (DoD) and the charge/discharge cycle rate [62].

The literature documents various advanced methods for modelling this cost, such as ‘Wh-throughput’ models and refined cycle ageing models, to accurately capture the impact of operational stress on battery lifespan [83]. These degradation models are essential for determining the optimal balance between aggressive grid service provision and long-term asset health. This characterizes OPEX not merely as a fixed yearly fee, but as a dynamic cost that correlates directly with the operational duty cycle of the system [62].

2.6.2 BESS Benefits Quantification

The financial viability of a BESS depends on whether its value streams can cover its lifecycle costs. Literature often identifies value stacking as a key enabler of profitability, with some studies showing that combining services can increase revenue by up to 129% [33]. However, for a BESS located on a distribution network, the most prominent value streams are often direct operational and planning benefits for the utility [12]. Therefore, this study concentrates on the two most significant value sources: savings from reduced energy losses and the value of deferred infrastructure upgrades.

2.6.2.1 Value of Deferred Infrastructure Upgrades

The most significant value stream for a BESS on a constrained distribution feeder is the deferral of traditional infrastructure upgrades. This function is a fundamental tenet of the BESS as an NWA. The benefit is realized through peak shaving, which reduces the peak load on assets like transformers and conductors. By relieving thermal stress, the BESS postpones the need for capital-intensive equipment replacement. This has a pronounced impact in developing economies, where the tactical placement of BESS can lead to significant reductions in capital expenditure [14], [28]. The economic value of this deferral is taken as the present value of the avoided capital cost of the grid upgrade, obtained by discounting that cost over the number of years by which the upgrade is postponed at the utility discount rate [84].

2.6.2.2 Value of Decreased Energy Losses

A second, inherent value stream is the reduction of technical energy losses [33], [37]. This co-benefit arises because peak shaving reduces the feeder current (I) and resistive losses are a function of the square of the current (I^2R). The energy saved represents a direct reduction in operational costs for the utility, as it corresponds to energy that does not need to be generated or transmitted. The annual value of these savings is calculated as expressed in [85].

2.6.3 Important Financial Evaluation Indicators

The final stage of a techno-economic analysis involves applying standardized financial metrics to synthesize quantified costs and benefits into a clear investment decision. The economic viability of a BESS is relative rather than absolute, depending heavily on the specific application and regional economic context, such as prevailing battery prices and market structures [86]. This study evaluates the financial feasibility of the BESS project using three primary indicators: Net Present Value (NPV) to measure absolute profitability, Discounted Payback Period (DPP) to assess investment recovery time and Levelized Cost of Storage (LCOS) to determine the unit cost of energy throughput. These three indicators are selected because they answer complementary investment questions: NPV establishes whether the project creates value in absolute terms, DPP reflects how quickly the capital is recovered and therefore the exposure to risk, and LCOS expresses the cost per unit of energy delivered so that the BESS can be compared on a like-for-like basis with alternative solutions.

2.6.3.1 Net Present Value (NPV)

Optimization models are frequently formulated specifically to maximize the NPV of BESS investments [33]. The NPV is obtained by discounting each year's net cash flow to its present value and subtracting the initial capital expenditure [87].

2.6.3.2 Discounted Payback Period (DPP)

The Discounted Payback Period (DPP) quantifies the liquidity and risk of an investment by determining the time required for the project's discounted cumulative cash flows to recover the initial investment. It is defined as the smallest number of years for which the discounted cumulative cash flows equal or exceed the initial investment [88].

Recent studies indicate the utility of the payback period not only as a post-optimization analysis tool but also as an explicit constraint within BESS sizing algorithms, balanced against other technical and financial factors [13].

2.6.3.3 Levelized Cost of Storage (LCOS)

Levelized Cost of Storage (LCOS) is a normalized unit discharge price of energy (e.g., \$/kWh), allowing for the direct cross-comparison of the BESS with other energy supply or grid support technologies. It is calculated by dividing the total discounted lifecycle cost by the total discounted energy discharged over the life of the project. A competitive LCOS is typically realized through stacking multiple value streams to maximize the economic output of the system [34].

It is obtained by dividing the total discounted lifecycle cost by the total discounted energy discharged over the life of the project [89].

2.7 Analysis of Related Works, Research Gap and Contribution

2.7.1 Review of Related Studies

Recent studies regarding BESS integration focus on two primary areas: mathematical sizing optimization and financial feasibility assessment. Some studies demonstrate advanced optimization methodologies on standardized test systems [57], while others prioritize economic analysis but often utilize simplified technical capacities [28]. This divergence in research creates a disconnect between theoretical grid support such as technical loss minimization, peak load reduction and voltage profile improvement and the actual financial viability required for utility adoption [56]. To contextualize the research gap addressed in this study, this subsection synthesizes representative works categorized in Table 2.3 according to their optimization methodologies, reported grid impacts and technical limitations. This comparison highlights specific modelling constraints in existing literature and justifies the necessity for the integrated techno-economic approach developed in this research.

Table 2.3: Summary of Recent Related Studies

Reference	Methodology	Key Findings	Technical Limitations
[74]	VASPSO Algorithm (Enhanced PSO with Velocity Pausing)	Achieved number one rank in convergence accuracy and stability across 29	Lacks implementation in real- world power grids; theoretical foundations are still limited.

		complex optimization functions.	
[57]	Metaheuristic Comparison (PSO, AVOA, SSA) on IEEE 33/69-bus	Confirmed PSO as the best for cost-minimization; AVOA achieved the fastest payback period.	Does not consider BESS degradation; focuses on standard IEEE models rather than real world systems.
[90]	Linear Optimization with Life Cycle Assessment (LCA) on a real 33 Kv grid	Identified LFP batteries as the most eco-friendly; achieved \$0.367M annual savings with a 1% reliability target.	Focuses on sizing only (omits siting/placement); linear modelling may oversimplify complex non-linear grid dynamics.
[91]	Mixed Integer Linear Programming (MILP)	Demonstrated effective cost reduction and voltage profile improvement on IEEE test systems.	Restricted to standard IEEE test systems; lacks validation on real-world rural high-impedance feeders.
[92]	Deep Sleep Optimizer Algorithm	Achieved 20% voltage deviation mitigation and reduced power loss from 65.3 MW to 59.68 MW.	Tested on IEEE 39-bus systems; lacks the specific economic lifecycle analysis (NPV/Payback) included in this study.

2.8 Conceptual Framework

The study is guided by a conceptual framework that links the network problem to a validated technical and economic solution through three connected stages. The inputs are the measured characteristics of the 11 kV feeder, namely its topology, line and transformer parameters, the 24-hour load profiles and the prevailing cost and financial data. These inputs feed a process that first establishes a quantitative performance baseline, then screens the feasible search region through sensitivity analysis, co-optimizes the BESS size and location using metaheuristic algorithms, maps the theoretical optimum to a commercially available module, and finally subjects that configuration to a full lifecycle techno-economic assessment. The outputs are the optimal rated power, energy capacity and bus location of the BESS, the resulting technical improvements in peak demand and voltage profile, and the financial indicators that determine viability. The operational realization of this framework is presented as the Input-Process-Output architecture in Figure 2.1.

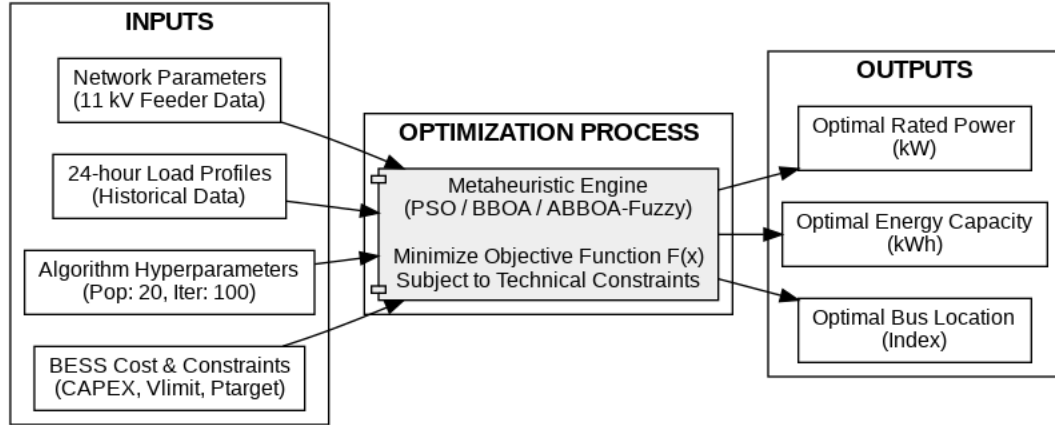


Figure 2.1: Input-Process-Output (IPO) architecture of the BESS optimization framework

2.9 Research Gap Identification

Analysis of the literature summarized in Table 2.3 demonstrates that a complete methodology for BESS optimization is absent from existing studies. The primary research gap identified is the absence of an integrated framework that simultaneously co-optimizes BESS size and location on a real-world feeder, considering commercially available BESS configurations and incorporating a full lifecycle assessment that accounts for battery degradation and future equipment replacement costs.

Existing models often oversimplify these complexities by utilizing standardized test systems or omitting the long-term financial impacts of battery performance fade. Consequently, a disconnect persists between theoretical optimization and the practical requirements for utility-scale deployment on long, radial rural feeders. This research addresses these identified limitations by developing an integrated techno-economic framework that determines the optimal rated power capacity (Kw), energy capacity (kWh) and placement for a BESS on an actual 11 Kv feeder. By bridging the gap between mathematical optimization and real-world utility data, this study establishes a replicable methodology for rural grid modernization. Specifically, the gap concerning commercial realism is addressed by mapping the optimized rating to a commercially available BESS; the gap concerning test-system validity is addressed by using measured data from an actual 11 Kv feeder; and the gap concerning simplified lifecycle costing is addressed by including battery degradation and mid-life

replacement in the 15-year economic assessment. The scope of the gap is therefore not limited to electrical performance alone but extends to the economic and practical dimensions that govern utility adoption.

2.10 Summary

This chapter reviewed the operational challenges of rural distribution networks, the role of the BESS as an NWA, the principal battery technologies, the methods used for optimal sizing and siting, and the techno-economic frameworks that translate technical performance into an investment decision. The review established that peak loading, voltage decay on long radial feeders and resistive losses are the dominant technical problems, and that a BESS can address all three while deferring costly infrastructure upgrades. It further showed that metaheuristic methods are better suited than deterministic programming to the non-linear, multi-objective nature of the sizing and siting problem, and that adaptive and fuzzy-enhanced variants offer the most promising search performance. Finally, the review identified the central research gap: the absence of an integrated framework that co-optimizes BESS size and location on a real feeder using commercially available equipment and a full lifecycle cost assessment. The methodology developed to close this gap is presented in the next chapter.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

This chapter details the systematic methodology developed to determine the optimal rated power capacity (kW), energy capacity (kWh) and placement of a BESS for peak shaving and voltage profile improvement on a rural distribution network. The process began with modelling the 11 kV feeder in DIgSILENT PowerFactory to establish a quantitative technical performance baseline. Next, a hybrid framework combining discrete sensitivity analysis and metaheuristic optimization is developed to identify the global optimal BESS configuration based on operational grid constraints. This optimization phase evaluates the performance of three algorithms: Particle Swarm Optimization (PSO), Boda-Boda Optimization Algorithm (BBOA) and Adaptive Boda-Boda Optimization Algorithm with Fuzzy Logic (ABBOA-Fuzzy) to determine the most efficient search strategy for identifying the precise global optimum. Finally, the methodology concludes with a techno-economic assessment using National Renewable Energy Laboratory's System Advisor Model (NREL's SAM). This stage subjects the optimized results to a 15-year lifecycle analysis, incorporating battery degradation models to derive key financial metrics, including NPV and Levelized Cost of Storage (LCOS).

3.2 Test System Modelling and Baseline Analysis

The first step of the methodology involved developing a model of the 11 kV feeder in Kenya using DIgSILENT PowerFactory. This model was used to quantify the network's baseline performance, establishing a benchmark against which the BESS intervention could be measured.

3.2.1 Case Study Description

An 11 kV feeder in Kenya was selected for this study. All network topology data, including overhead line parameters, transformer ratings and historical load profiles were provided by the local utility. The feeder features a long, radial topology spanning approximately 69 km as depicted in Figure 3.1 with a mix of residential, small commercial and agricultural loads. This load composition results in a pronounced daily load profile, typically peaking between 18:00 and 21:00 hours. A complete

network model was developed in DIgSILENT PowerFactory to represent the real-world operational conditions of the feeder.

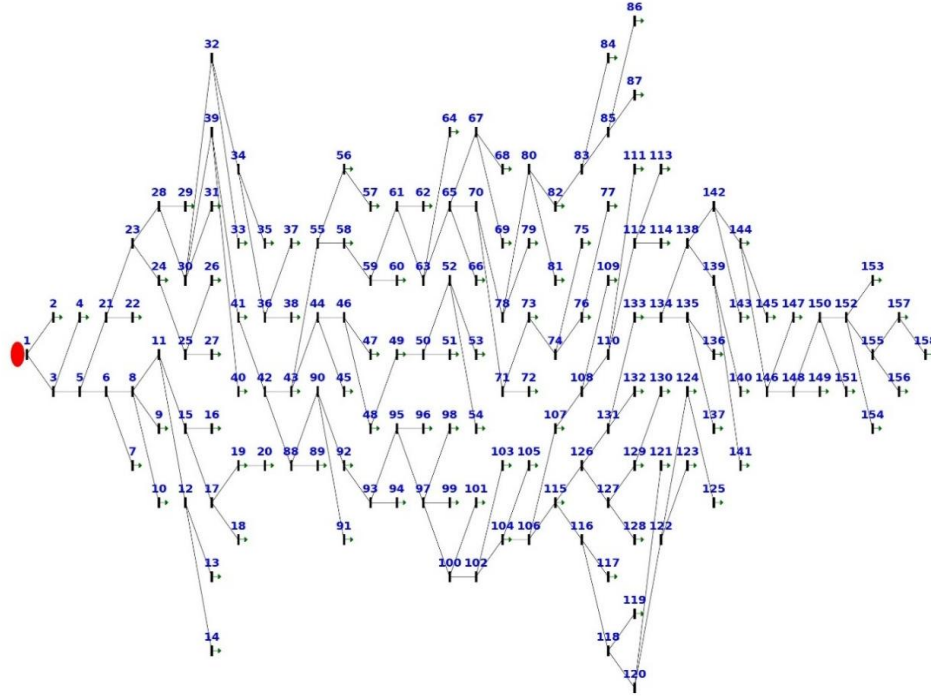


Figure 3.1: Single-line diagram of the 11 kV distribution feeder [93]

3.2.2 Network Data Required

The specific data sets utilized in the DIgSILENT PowerFactory model included:

- i.) *Topological Information:* Figure 3.1 displays the Single-Line Diagram (SLD) of the feeder, showing the connectivity of buses, lines and switching equipment.
- ii.) *Line Parameters:* Technical specifications of the overhead lines, including conductor type, cross-sectional area, and segment lengths, were incorporated to accurately determine line impedance (resistance and reactance) and thermal current limits.
- iii.) *Transformer Parameters:* Nameplate details of the main substation transformer were incorporated, specifically the MVA rating, primary and secondary voltage levels and the percentage impedance (%Z).

- iv.) *Dynamic Load Data*: Representative 24-hour time-series active and reactive power load profiles were integrated into the model to capture the critical evening peak duration.

3.2.3 Baseline Performance Quantification

The baseline performance of the feeder was quantified using three primary metrics to identify existing operational deficiencies:

i.) *Substation Peak Loading*

The peak apparent power drawn from the substation was calculated and compared against the transformer's nominal rating. This metric determines the loading factor, which is a direct indicator of thermal stress on the equipment [94].

$$\text{Loading Factor}(\%) = \frac{S_{sub,peak}}{S_{rated}} \times 100 \quad (3.1)$$

In Equation (3.1), the loading factor is expressed as a percentage and is obtained as the ratio of $S_{sub,peak}$, the peak apparent power drawn by the feeder from the substation, to S_{rated} , the rated nominal capacity of the transformer, with the result multiplied by one hundred. A loading factor approaching one hundred percent therefore indicates that the transformer is operating close to its thermal limit and has little headroom to accommodate additional load.

ii.) *Voltage Profile Deviation*

The voltage magnitude at every bus was monitored throughout the simulation period to identify the minimum bus voltage (V_{min}) and assess the proximity to statutory limits. The overall voltage quality was quantified using the Voltage Deviation Index (VDI):

$$VDI_{base} = \sum_{t=1}^{24} \sum_{i=1}^N (V_{nom} - V_i(t))^2 \quad (3.2)$$

In Equation (3.2), VDI_{base} denotes the baseline voltage deviation index, V_{nom} is the nominal system voltage taken as 1.0 p.u., $V_i(t)$ is the actual voltage magnitude at bus i at time step t , and N is the total number of buses in the distribution network. The index accumulates the squared deviation of every bus voltage from the nominal value across all N buses and over the twenty-four hourly time steps, so that a larger value corresponds to a poorer overall voltage profile.

iii.) *Total Energy Losses*

The total active power losses across all feeder branches were integrated over the 24-hour period. This metric represents the technical active power losses, which corresponds to a direct operational cost for the utility.

$$E_{loss,base} = \sum_{t=1}^{24} P_{loss}(t) \times \Delta t \quad (3.3)$$

In Equation (3.3), $E_{loss,base}$ represents the baseline energy loss, $P_{loss}(t)$ is the total real power loss in the network at time t , and Δt is the simulation time step of one hour. Summing the hourly power losses over the complete twenty-four-hour period yields the daily energy dissipated in the feeder branches, which corresponds to a direct operational cost to the utility.

3.3 BESS Optimization Methodology

This section details the optimization framework developed to determine the optimal BESS rated power capacity (kW), energy capacity (kWh) and placement on the 11 kV feeder. The methodology follows a sequential approach, beginning with a discrete sensitivity analysis to establish search boundaries for the optimization variables. This is followed by the mathematical formulation of the objective function and the benchmarking of three metaheuristic algorithms (PSO, BBOA and ABBOA-Fuzzy). This process identifies the efficient search strategy for locating the global optimum while ensuring all operational grid constraints are satisfied.

The choice of a metaheuristic approach follows directly from the review in Chapter Two. Deterministic programming methods such as linear and mixed-integer linear programming guarantee optimality for convex problems but require the sizing problem to be linearized, which does not hold for the non-convex interaction between BESS power, energy and location on a high-impedance radial feeder. Analytical sensitivity indices are fast but static, and cannot determine the energy capacity or the dispatch strategy. Population-based metaheuristics were therefore selected because they search the non-linear solution space without such simplifications.

The three algorithms benchmarked in this study, PSO, BBOA and ABBOA-Fuzzy, are compared on a common basis: each optimizes the same decision variables (rated power, energy capacity and bus location), uses the same objective function, population

size and iteration limit, and is evaluated with the same Backward-Forward Sweep power-flow engine. They differ only in their internal composition; PSO uses fixed inertia and acceleration coefficients, BBOA adds fixed probabilistic exploration and exploitation operators, and ABBOA-Fuzzy replaces those fixed operators with a fuzzy controller that adapts them at every iteration. This isolates the effect of the search mechanism on the resulting BESS parameters.

3.3.1 Preliminary Sizing via Discrete Sensitivity Analysis

A preliminary technical screening was conducted using Discrete Sensitivity Analysis in DIgSILENT PowerFactory. This step involved simulating specific commercial BESS configurations at Bus 158 which was identified during the baseline analysis as the feeder's weakest node. Three distinct scenarios were evaluated, representing 200 kW / 600 kWh, 400 kW / 1200 kWh and 600 kW / 1800 kWh systems. The process flow for this preliminary analysis is illustrated in Figure 3.2.

As illustrated, the process begins with the integration of the feeder model into the simulation environment. Discrete commercial BESS sizes are iteratively tested to identify the point of diminishing technical returns. In this context, diminishing returns refer to the stage where further increasing the BESS rated power capacity (kW) no longer yields proportional improvements in voltage stability or peak load reduction. Identifying this threshold allows for the establishment of a validated search region which defines the upper and lower bounds for the optimization variables. By narrowing the search space to a technically feasible range, the computational efficiency of the subsequent metaheuristic optimization is significantly enhanced.

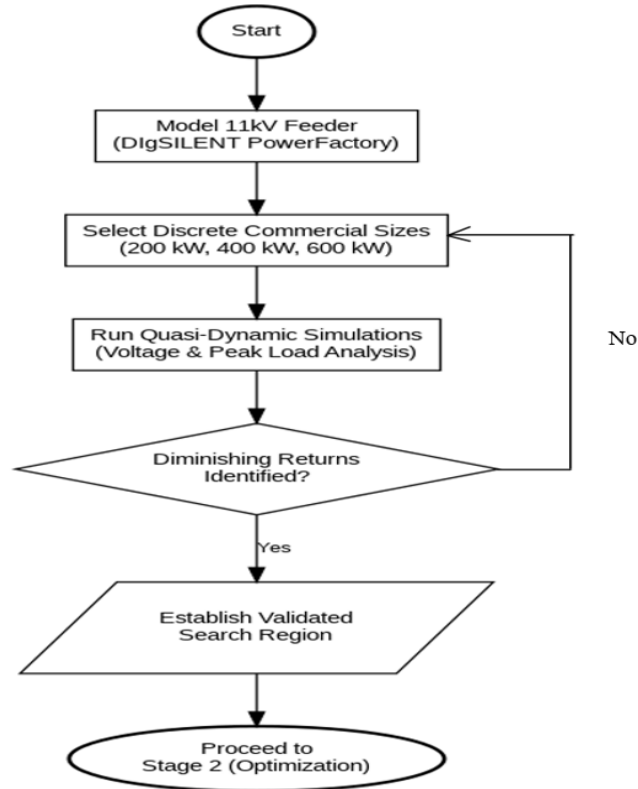


Figure 3.2: Process flow for the preliminary discrete sensitivity analysis

3.3.2 Mathematical Problem Formulation

3.3.2.1 Objective Function

The search boundaries established during the technical screening define the solution space for the optimization problem. This mathematical formulation is designed to simultaneously determine the optimal rated power capacity (P_{BESS}), energy capacity (E_{BESS}) and bus location. The objective function is formulated to minimize BESS CAPEX with two 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 [95]. The complete objective function to be minimized is formulated as follows:

$$F(x) = C_{sys}(x) + w_p \cdot \max(0, P_{peak}(x) - P_{target}) + w_v \cdot \max(0, V_{limit} - V_{min}(x)) \quad (3.4)$$

$$C_{sys}(x) = (C_p \times P_{BESS}) + (C_e \times E_{BESS}) \quad (3.5)$$

In Equation (3.4), $F(x)$ is the fitness value of a candidate solution x , while $C_{sys}(x)$ is the system capital expenditure obtained from Equation (3.5). The second term applies a penalty, scaled by the coefficient w_p , whenever the resulting feeder peak demand $P_{peak}(x)$ exceeds the target peak demand P_{target} , which is defined as $0.85 \times P_{base}$, where P_{base} is the baseline peak load. The third term applies a further penalty, scaled by w_v , whenever the minimum bus voltage $V_{min}(x)$ recorded during the simulation falls below the operational voltage target V_{limit} , set at 0.94 p.u. In Equation (3.5), C_p and C_e are the unit costs of power and energy capacity expressed in dollars per kilowatt and dollars per kilowatt-hour respectively, while P_{BESS} and E_{BESS} are the rated power capacity and energy capacity of the battery energy storage system.

The penalty coefficients w_p and w_v were set to 10^5 and 10^6 , respectively, following the parameter selection methodology described by [96]. 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 approach ensures that technically infeasible solutions are excluded from the search space during the optimization process. A sensitivity analysis was performed to validate the selection of these penalty magnitudes, ensuring that the coefficients are sufficiently large to prioritize technical constraints over cost minimization without inducing numerical instability.

3.3.3 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 11 kV 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 [97]. This computational efficiency, which can give results with minimum resources, as stated by [98], was essential for this study's optimization process. To ensure the reliability of the optimization results, the Python-based BFS solver was benchmarked against

DIGSILENT PowerFactory. The accuracy of the custom solver was validated by comparing calculated bus voltages and active power losses. This confirms that the BFS engine provides the necessary accuracy for the optimization loop while remaining computationally efficient.

Figure 3.3 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, $P_{\text{peak}}(x)$ and minimum bus voltage $V_{\text{min}}(x)$, are utilized in Equation 3.4 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 [99].

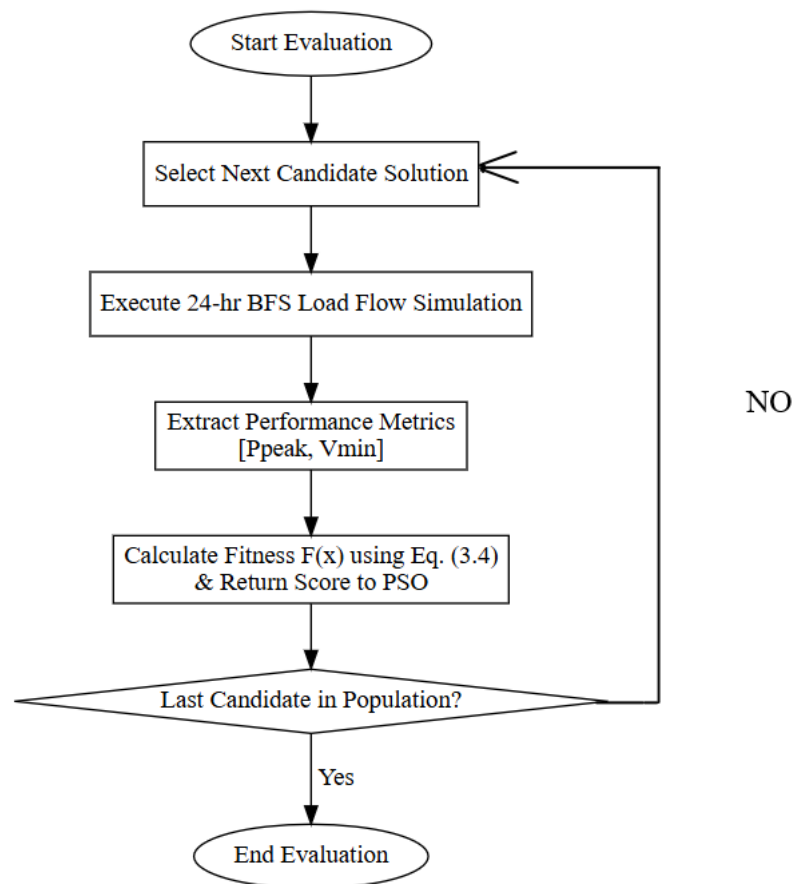


Figure 3.3: The fitness evaluation process for a single candidate solution

3.3.3.1 Boda-Boda Optimization Algorithm (BBOA)

The Boda-Boda Optimization Algorithm (BBOA) is a metaheuristic developed by [100] which draws inspiration from the adaptive navigation strategies of Kenyan motorcycle taxi (boda-boda) riders. This algorithm was selected for this study to address the limitations of standard PSO, specifically its tendency to converge prematurely in non-convex search spaces. 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 modelled by reducing the agent’s velocity.

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

$$v_i(t + 1) = w \times v_i(t) + c_1 \times r_1(p_{best}(i) - x_i(t)) + c_2 \times r_2(g_{best} - x_i(t)) + v_{\{shortcut\}} - v_{\{traffic\}} \quad (3.6)$$

$$x_i(t + 1) = x_i(t) + v_i(t + 1) \quad (3.7)$$

In Equations (3.6) and (3.7), 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 parameters α and β are fixed constants defined at the initialization of the optimization. In this work, α was set to 0.5 and β was set to 0.3 to ensure a balance between global search and local refinement; $\alpha = 0.5$ provides sufficient probabilistic ‘shortcuts’ to explore the non-convex solution space, while $\beta = 0.3$ allows for

effective local intensification around identified optima. These specific values were selected as they provided the most stable convergence characteristics for the high-impedance radial feeder model. 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.

3.3.3.2 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 judgement 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 triangular membership function was selected for this study due to its low computational overhead and ability to provide linear transitions between fuzzy sets. This efficiency is critical because the fuzzy inference system must be executed for every agent at each iteration without significantly increasing the total simulation time. Recent research by [101] demonstrates that implementing triangular membership functions within hybrid optimization algorithms can achieve performance improvements exceeding 50% in complex search spaces. Furthermore, the tuning ranges were established with intentional overlaps to ensure behavioral stability. These overlapping regions facilitate a smooth transition between global exploration and local refinement as the agents converge toward the global optimum. The Mamdani inference method was employed with a centroid defuzzification strategy. The fuzzy rule base, presented in Table 3.1,

was designed to dynamically adjust the search behavior based on the agent's proximity to the optimum.

Table 3.1: Fuzzy Rule Base for ABBOA-Fuzzy

Rule No.	IF Normalized Distance is	THEN (α) (Exploration) is	THEN (β) (Exploitation) is
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 ABBOA-Fuzzy position-velocity update equation is similar to that of BBOA, except that α and β are dynamically adjusted by the fuzzy controller at each iteration. 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 for PSO, BBOA and ABBOA-Fuzzy were selected to ensure a fair and consistent comparison between the search strategies. A uniform population size of 20 agents and a maximum limit of 100 iterations were established to balance search diversity with the computational time required for repetitive power flow simulations. As identified by [102] and [103], these settings provide the necessary stability for optimizing resource allocation in distribution networks. The specific coefficients for inertia weight ($w = 0.5$) and acceleration $c_1, c_2 = 1.5$ were adopted from established literature to maintain search trajectory control, while the BBOA parameters were configured to allow the fuzzy controller to intelligently balance exploration and exploitation. The final configuration settings used for the optimization process are detailed in Table 3.2.

Table 3.2: Optimization Algorithm Hyper-parameters

Category	Parameter	Symbol	Value	Source / Justification
General Settings	Population Size	N	20	Balances search diversity and CPU time [103]
	Maximum Iterations	$T_{\max}$	100	Established via convergence stability tests [104]

Category	Parameter	Symbol	Value	Source / Justification
PSO Parameters	Inertia Weight	w	0.5	Standard default for stable swarm search [105]
	Cognitive Coefficient	c_1	1.5	Proven values for search trajectory control [102]
	Social Coefficient	c_2	1.5	Matches c_1 for balanced exploration and exploitation
BBOA / ABBOA	Inertia Weight	w	0.7	Velocity retention factor for Boda-Boda operators
	Acceleration Constants	c_1, c_2	1.5	Standard acceleration constants
Fuzzy Controller	Input Range	D	[0, 1]	Normalized distance to global best (gbest)
	Output Range	α, β	[0, 1]	Probabilistic range for BBOA operators

3.4 Techno-Economic Evaluation

This section fulfils Specific Objective (iii) by detailing the process used to evaluate the long-term financial viability of the optimized BESS solution. Since the mathematical optima identified in Section 3.4 may not correspond to standard equipment ratings, the theoretical power and energy capacities are mapped to the nearest equivalent commercially available BESS module. This practical configuration is subsequently modelled in DIgSILENT PowerFactory for final technical validation and in NREL's SAM for a detailed 15-year lifecycle analysis.

3.4.1 Lifecycle Cost Analysis and SAM Modelling

To investigate the long-term financial viability of the chosen practical BESS configuration, a lifecycle analysis was executed using 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. 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 [33].

A key aspect of this modelling 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 [106]. The model simulates the decline

in capacity and efficiency due to both cycle degradation i.e., charge/discharge operations and calendar degradation i.e., ageing over time [107]. 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 3.3 and Table 3.4.

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 [108]. The battery cost projections and performance metrics, including variable operations and maintenance (O&M) costs, were derived from the NREL Annual Technology Baseline [55]. Furthermore, the inclusion of a realistic 1.5% annual degradation rate and an 80% DoD limit address the critical importance of accurate battery modelling in techno-economic assessments, as simplified assumptions can significantly bias lifecycle costs [109].

Table 3.3: 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	Total installed project cost, including all hardware, engineering and construction costs
		\$383/kW	
	All-in Installed Cost	\$637,825	

Operating costs (OPEX)	Annual O&M basis	1.5% of CAPEX	Standard industry estimates for O&M
	O&M (year 1)	\$9,637	[110]
	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.

Table 3.4: 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 [28].
Subtotal (Line Reinforcement)	\$1,035,000	Calculated as $10.35\text{ km} \times \$100,000/\text{km}$
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 $5\text{ MVA} \times 1000\text{ kVA} \times \$30/\text{kVA}$
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.

3.4.2 BESS Dispatch Strategy and Degradation Modelling

The technical and financial performance of the system is determined by the integration of the operational strategy and physical constraints into the simulation environment. This evaluation is governed by two primary methodological components:

- i.) *Dispatch Strategy*: A time-based control logic is implemented within the SAM environment to regulate BESS operation. The strategy is configured to charge the battery from the grid during off-peak morning hours and perform a single

deep discharge during the evening peak (18:00–21:00). This sequence ensures the stored energy is utilized to provide grid support during periods of maximum thermal and voltage stress.

- ii.) *Degradation Modelling*: A combined cycle and calendar ageing model is utilized to ensure a realistic 15-year evaluation period. This methodology incorporates DoD as a critical technical constraint; a maximum limit of 80% DoD is enforced to manage capacity fade and optimize the frequency of module replacements over the project lifecycle. The resulting operational profiles and degradation curves derived from these parameters are presented and discussed in Chapter Four.

3.5 Summary

This chapter set out the methodology used to size, site and evaluate the BESS. The 11 kV feeder was modelled in DIgSILENT PowerFactory to establish a quantitative baseline of peak loading, voltage deviation and energy losses. A discrete sensitivity analysis was then used to bound the search space before the sizing and siting problem was formulated as a constrained cost-minimization objective and solved with three metaheuristic algorithms (PSO, BBOA and ABBOA-Fuzzy) using an embedded Backward-Forward Sweep power-flow engine. The theoretical optimum is mapped to a commercially available module and assessed over a 15-year horizon in NREL's SAM with a realistic degradation model. The results obtained by applying this methodology are presented and discussed in the next chapter.

CHAPTER FOUR

RESULTS AND DISCUSSION

4.1 Introduction

This chapter presents and discusses the research findings derived from the methodology detailed in Chapter Three. The analysis begins by quantifying the baseline constraints of the feeder to establish a benchmark for improvement. Subsections detail the optimal rated power capacity (kW), energy capacity (kWh) and bus location identified through the comparative performance of the Particle Swarm Optimization (PSO), Boda-Boda Optimization Algorithm (BBOA) and Adaptive Boda-Boda Optimization Algorithm with Fuzzy Logic (ABBOA-Fuzzy). Furthermore, the technical validation of the optimized solution is presented, demonstrating the achieved peak shaving and voltage profile improvement on the 11 kV distribution feeder. Finally, the chapter evaluates the 15-year techno-economic viability of the BESS project.

4.2 Baseline Network Performance

Baseline analysis was conducted in the absence of a BESS to quantify the existing operational stress on the feeder. The network model, illustrated in Appendix 1, was subjected to a 24-hour quasi-dynamic simulation in DIgSILENT PowerFactory to identify technical deficiencies. The simulation results revealed a system operating at its thermal and stability limits. The peak demand reached 2.809 MW, which loaded the main 3 MVA substation transformer to 99.6% of its rated capacity. This level of utilization leaves no headroom for future load growth and subjects the transformer to accelerated ageing due to thermal stress. Figure 4.1 presents the resulting daily load profile, illustrating the sharp evening peak between 18:00 and 21:00 hours that drives

these

constraints.

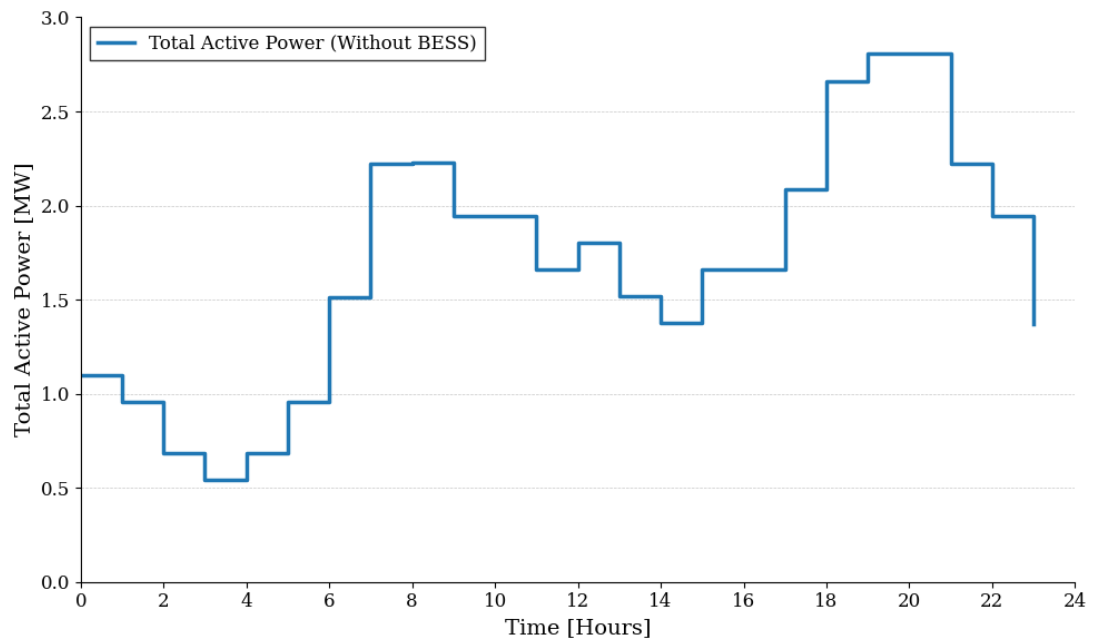


Figure 4.1: Baseline daily load profile for the 11 kV feeder without a BESS

The feeder also experienced significant voltage drop along its length during the peak demand period. The minimum voltage at the furthest node (Bus 158) dropped to 0.936 p.u., as depicted in the 24-hour voltage profile in Figure 4.2. Figure 4.3 illustrates the voltage at every bus during this peak hour, confirming that levels decrease as distance from the substation increases due to line impedance. Although this result remains above the 0.90 p.u. technical compliance limit, it is approaching this threshold and represents a state of voltage stress. Improving the voltage to a safer margin is necessary to ensure grid stability and reduce the risk of under-voltage incidents during transient events. Additionally, the high currents during this peak load resulted in total daily active power losses of 989 kWh.

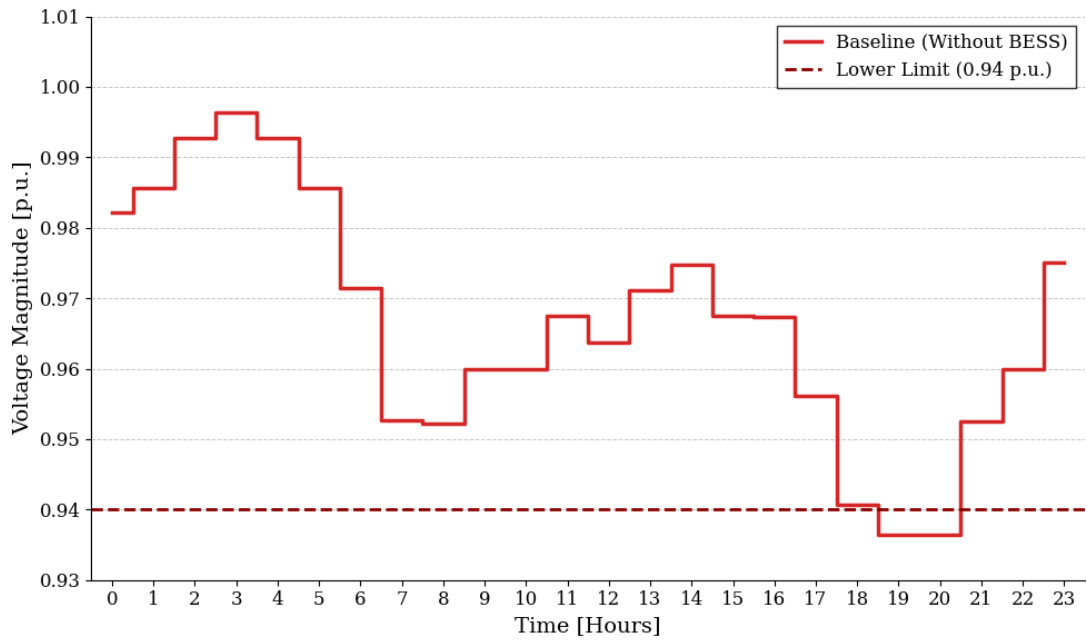


Figure 4.2: Baseline 24-hour voltage profile at the electrically weakest node (Bus 158)

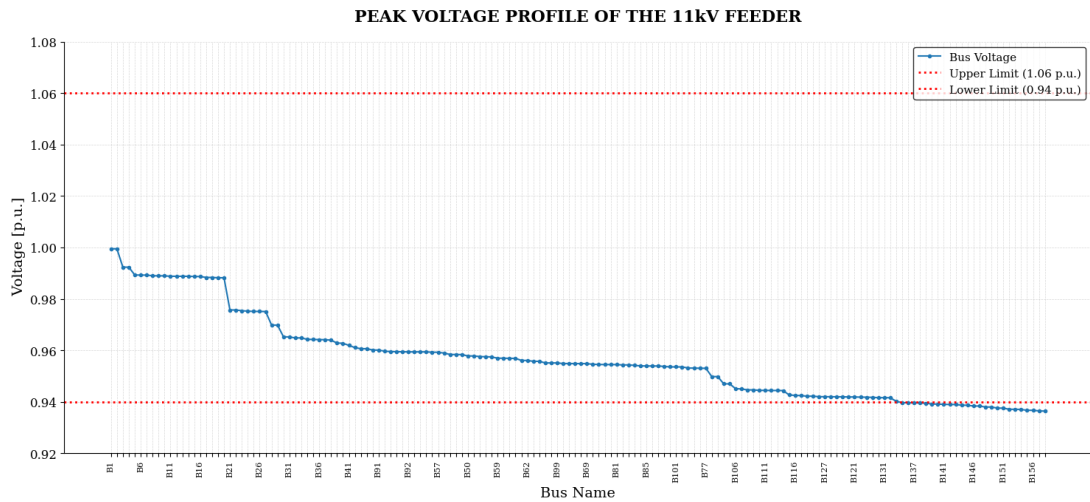


Figure 4.3: Voltage profile across all feeder buses during the peak demand period

4.3 BESS Optimization and Algorithmic Results

4.3.1 Preliminary Sizing via Discrete Sensitivity Analysis

The technical impact of BESS integration was initially assessed through a discrete sensitivity analysis involving standard commercial sizes, all located at Bus 158. This specific location was selected because it represents the point of maximum technical stress identified during the baseline analysis. While a dispersed configuration of multiple smaller BESS units could potentially offer voltage support, a single-asset approach was adopted for this study to minimize installation complexity and reduce CAPEX.

Three BESS configurations were simulated: 200 kW / 600 kWh, 400 kW / 1200 kWh and 600 kW / 1800 kWh. The resulting impact on the substation load profile is shown in Figure 4.4 and the corresponding 24-hour voltage profiles at Bus 158 are illustrated in Figure 4.5. The comparative performance metrics for these scenarios are summarized in Table 4.1.

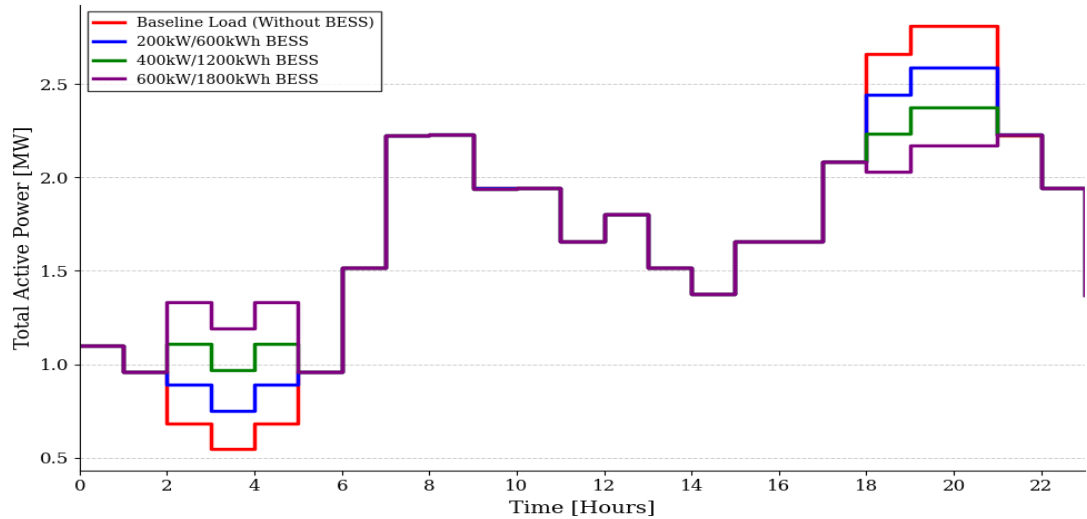


Figure 4.4: Daily substation load profiles for baseline and discrete BESS sizes

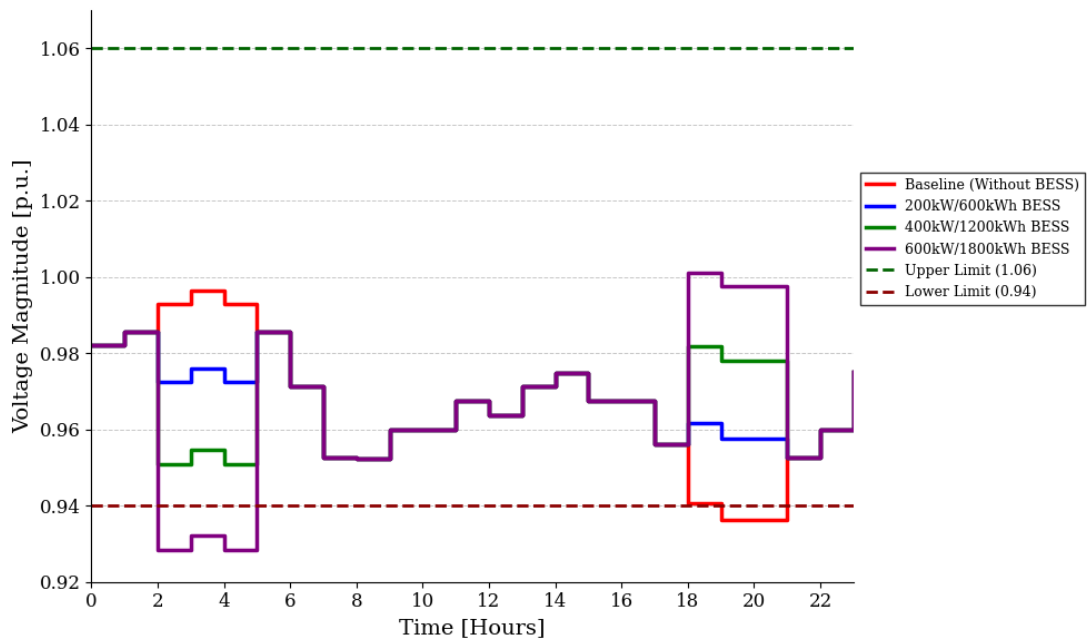


Figure 4.5: Impact of different BESS sizes on the voltage at the weakest point (Bus 158)

Table 4.1: Comparison of Performance Metrics for Preliminary Discrete Sizes

Performance Metric	Baseline	200 kW BESS	400 kW BESS	600 kW BESS
Peak Load (MW)	2.809	2.589	2.376	2.373

Peak Load Reduction (MW)	–	0.220	0.433	0.436
Transformer Loading (%)	99.6	91.6	84.1	83.8
Total Energy Losses (kWh)	989	967	969	1021
Minimum Voltage at Bus 158(p.u)	0.936	0.948	0.948	0.928

Table 4.1 and Figure 4.4 demonstrate a non-linear relationship between BESS capacity and grid improvement. The 200 kW/600 kWh system reduced transformer loading from 99.6% to 91.6%, while the 400 kW/1200 kWh system provided a more significant reduction to 84.1%, effectively shaving 0.433 MW from the peak demand. The 600 kW/1800 kWh system, however, produced a marginal additional peak reduction of only 0.003 MW compared to the 400 kW/1200 kWh scenario. The technical active power losses followed a similar trend; these losses decreased in the 200 kW/600 kWh and 400 kW/1200 kWh cases but rose to 1021 kWh in the 600 kW/1800 kWh deployment, exceeding the baseline level of 989 kWh.

The voltage analysis in Figure 4.5 further supports the identification of diminishing technical returns. While the 400 kW/1200 kWh BESS maintained the minimum voltage at 0.948 p.u., the 600 kW/1800 kWh system caused a voltage sag to 0.928 p.u. during the morning hours. This sag resulted from the high-power draw required to charge the larger battery capacity from the grid. Because 0.928 p.u. violates the technical target of 0.94 p.u., the 600 kW/1800 kWh configuration is classified as oversized for this specific feeder. These results serve to narrow the search region for the algorithmic optimization detailed in the following section.

4.3.2 Algorithmic Convergence and Performance Comparison

This phase utilized a Python-based environment to execute and benchmark three metaheuristic algorithms (PSO, BBOA and ABBOA-Fuzzy). Appendix 4 shows the Python code for the optimization process. The comparative evaluation focused on convergence speed, solution stability and the final fitness score achieved by each method. Figure 4.6 shows the first 30 iterations to provide a clear visualization of the search behaviour, while Figure 4.7 shows the results of extending the simulation to 100 iterations.

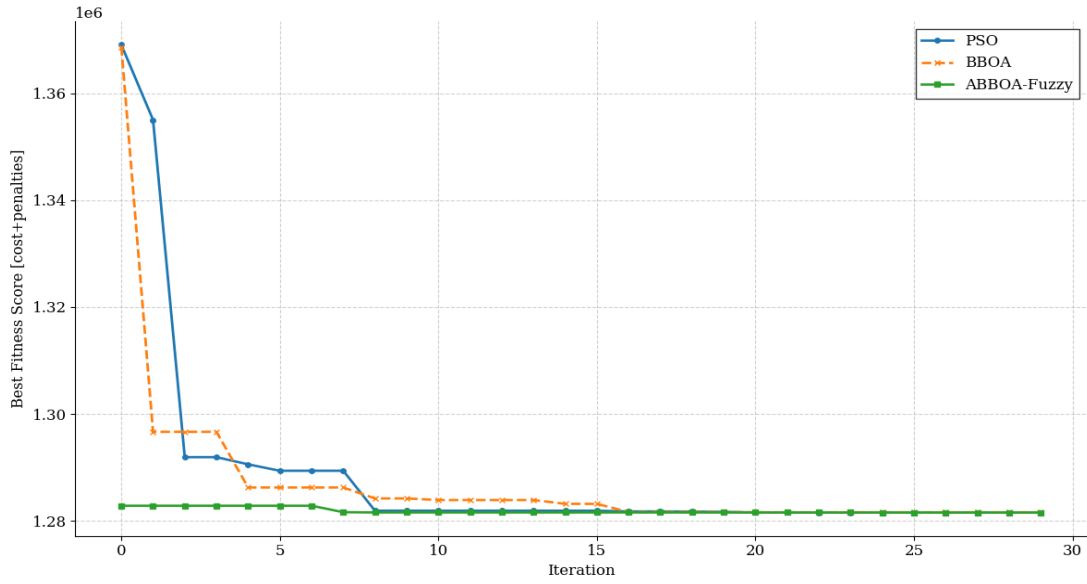


Figure 4.6: Convergence of PSO, BBOA and ABBOA-Fuzzy over 30 iterations

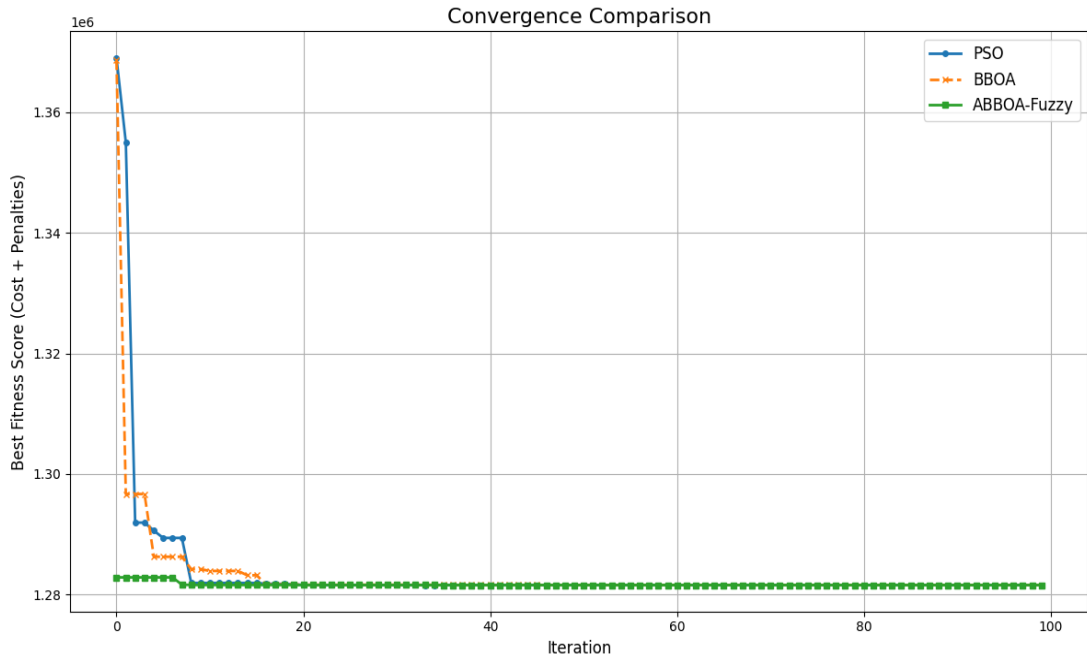


Figure 4.7: Results of the extended 100-iteration simulation

Observations from Figure 4.6 and Figure 4.7 show specific differences in how each solver finds the global minimum. ABBOA-Fuzzy began the search with a fitness score approximately 6.5% lower than the starting points of PSO and BBOA. As seen in the 30-iteration plot, ABBOA-Fuzzy reached the constant floor at iteration 8. PSO also reached the same level at iteration 8, but required two large steps to get there.

BBOA showed the most difficulty in finding the optimal path, as indicated by the horizontal plateaus between iterations 1–3, 4–7 and 8–15. These flat lines provide

technical evidence that the algorithm was temporarily stuck in local optima before identifying a better coordinate. BBOA joined the constant line at iteration 16. The extended plot in Figure 4.7 confirms that all three algorithms maintained these values without any change up to 100 iterations.

Based on these observations, ABBOA-Fuzzy is identified as the superior optimization strategy for the BESS sizing and siting problem. Although both PSO and ABBOA-Fuzzy reached convergence at iteration 8, the adaptive algorithm demonstrated higher initial search quality and a more direct trajectory toward the global minimum. The absence of horizontal plateaus in the ABBOA-Fuzzy curve indicates that the fuzzy logic controller effectively manages the exploration-exploitation balance, preventing the algorithmic stagnation observed in the standard PSO and BBOA baselines.

4.3.3 Determination of the Optimal BESS Solution

The final optimized parameters obtained from each of the three algorithms are summarized in Table 4.2.

Table 4.2: 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	392.64 kW / 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
Number of iterations	8	16	7

Table 4.2 reveals that all three algorithms independently identified Bus 117 as the optimal BESS location, providing cross-validation for the siting result. The final fitness scores and CAPEX values show marginal variations; PSO identified the lowest fitness score, while BBOA produced the highest result. These slight differences in BESS size and cost occur because each algorithm begins with a different random distribution of agents, leading to variations in the final decimal precision of the search.

The superiority of the ABBOA-Fuzzy algorithm is evidenced by its search efficiency and speed. ABBOA-Fuzzy reached the stable global optimum in only 7 iterations (the lowest). This performance is due to the fuzzy logic controller, which allows the algorithm to adapt its search behaviour in real-time. By dynamically tuning the exploration and exploitation parameters, ABBOA-Fuzzy identifies the near-optimal solution almost immediately, bypassing the slower refinement stages required by fixed-parameter algorithms.

4.3.4 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 400 kW/1200 kWh BESS was modelled at its optimal location (Bus 117). Table 4.3 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 4.3: Technical Performance of the Feeder with Optimized BESS

Performance Metric	Baseline (Without 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%
Daily Energy Losses (kWh)	989	842.8	-14.78%

Figure 4.8 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.

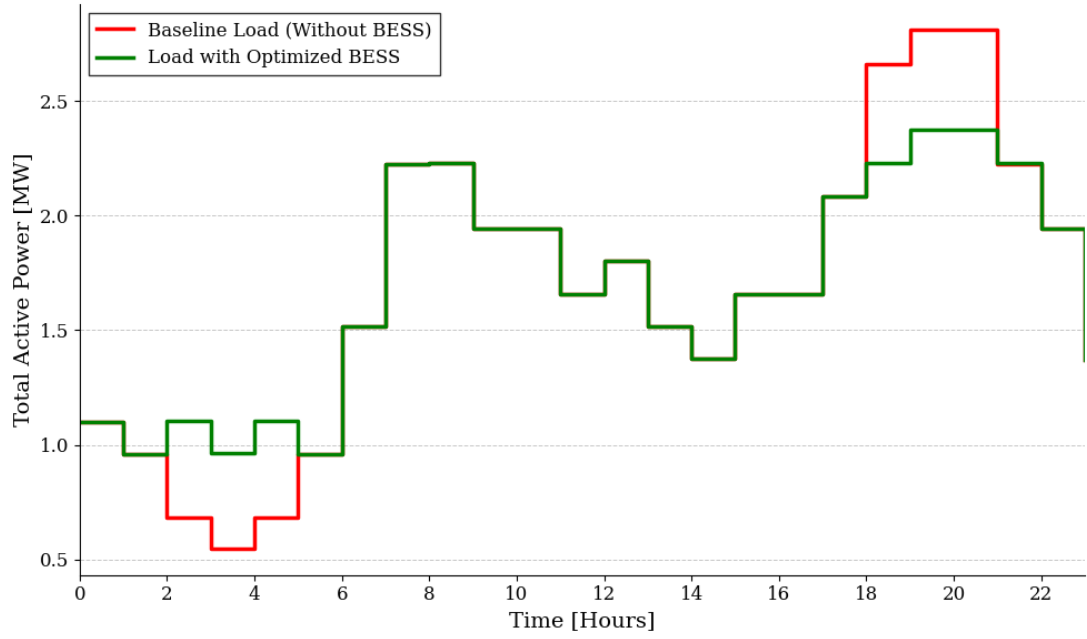


Figure 4.8: Comparison of the 24-hour feeder load profile with and without the optimized BESS

The optimized BESS integration addresses the voltage constraints identified during the baseline analysis. As shown in Table 4.3, the minimum bus voltage increased from 0.936 p.u. to 0.952 p.u., representing a technical improvement of 1.71%. This voltage enhancement at the electrically weakest node (Bus 158) is illustrated for a 24-hour period in Figure 4.9. The results indicate that the voltage sag occurring during peak hours is effectively mitigated, ensuring that the feeder voltage remains above the 0.94 p.u. operational target throughout the simulation period.

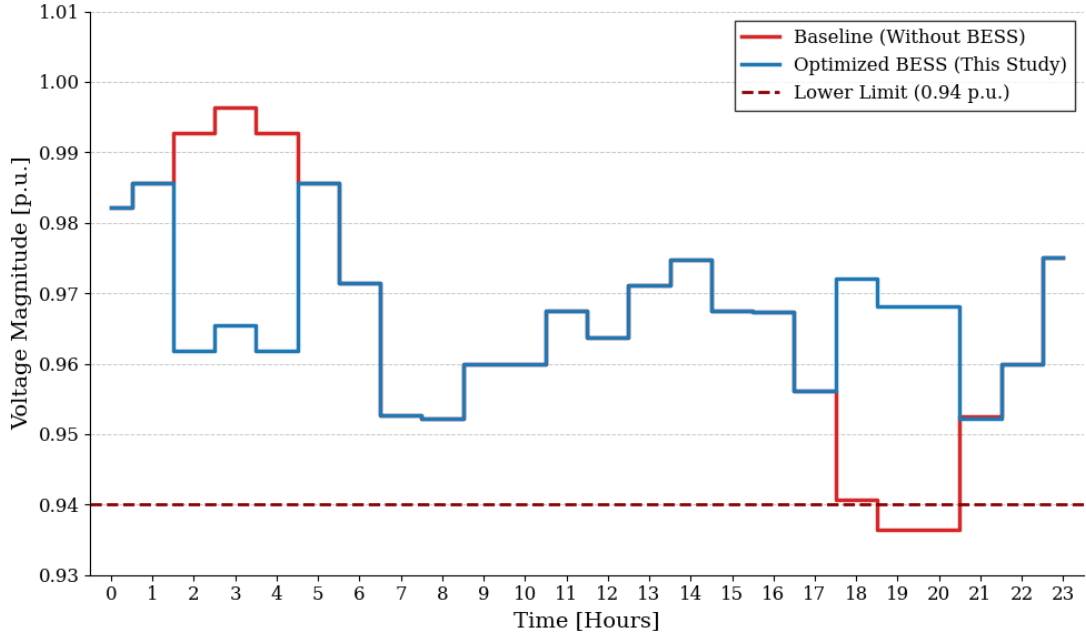


Figure 4.9: 24-Hour Voltage Profile at Weakest Bus (Bus 158)

4.4 Validation of Results Against Existing Literature

The performance of the optimized BESS design was compared with published research to validate the findings. A primary objective was peak demand reduction, where the final configuration achieved a 15.5% reduction. This result aligns with the findings of [13], who achieved a similar peak reduction of 16.7%. A technical similarity between these two studies is the use of a real-world distribution network, which accounts for the close correspondence in the results.

In contrast, [57] reported a slightly higher peak reduction of 18% using a similar PSO methodology. This difference is attributed to the test system; while [57] utilized the standard IEEE 33-bus system this study utilized an actual 11 kV Kenyan feeder. This real-world feeder is a long radial network characterized by high impedance and non-uniform load distribution. These topological differences explain the slight variance in peak-shaving results, as real-world feeders often present more complex voltage drop constraints than standardized test systems.

Additionally, the BESS-to-peak-load power ratio in this study, which is approximately 14% (392.60 kW BESS for a 2.809 MW peak), is consistent with the ratios found in the literature. Specifically, [57] reported a ratio of 20% (0.94 MW BESS for a 4.65 MW peak) and [13] identified a ratio of 25% (0.3 MW BESS for a 1.2 MW peak). The correspondence in technical performance and sizing ratios with these external

works confirms that the optimized results are within the expected range for distribution-level storage applications.

4.4.1 Compliance with Technical Standards

The optimized results were also assessed against recognized technical planning standards. Standard distribution-planning practice recommends that transformer loading should not exceed 85% of the rated capacity to preserve a safety margin and avoid premature ageing [11]; the optimized BESS reduced the substation transformer loading from 99.6% to 83.9%, bringing the feeder into compliance with this benchmark. Voltage-quality standards require the network voltage to remain within the statutory band of 0.90-1.10 p.u. [31]; the minimum bus voltage improved from 0.936 p.u. to 0.952 p.u. and remained above the stricter 0.94 p.u. operational target adopted in this study throughout the 24-hour cycle. The results therefore satisfy both the thermal-loading and voltage-regulation criteria used in utility distribution planning.

4.5 Techno-Economic Viability

The final evaluation phase examines the long-term financial performance of the optimized 400 kW / 1200 kWh BESS. This analysis integrates the operational dispatch strategy and the physical impact of battery degradation to establish a 15-year lifecycle assessment. These results provide the basis for determining the economic feasibility of BESS as a non-wires alternative on the 11 kV rural distribution network.

4.5.1 BESS Operational Dispatch Profile

The daily operation of the BESS was simulated to verify its impact on the feeder load. Figure 4.10 illustrates the 24-hour power dispatch profile.

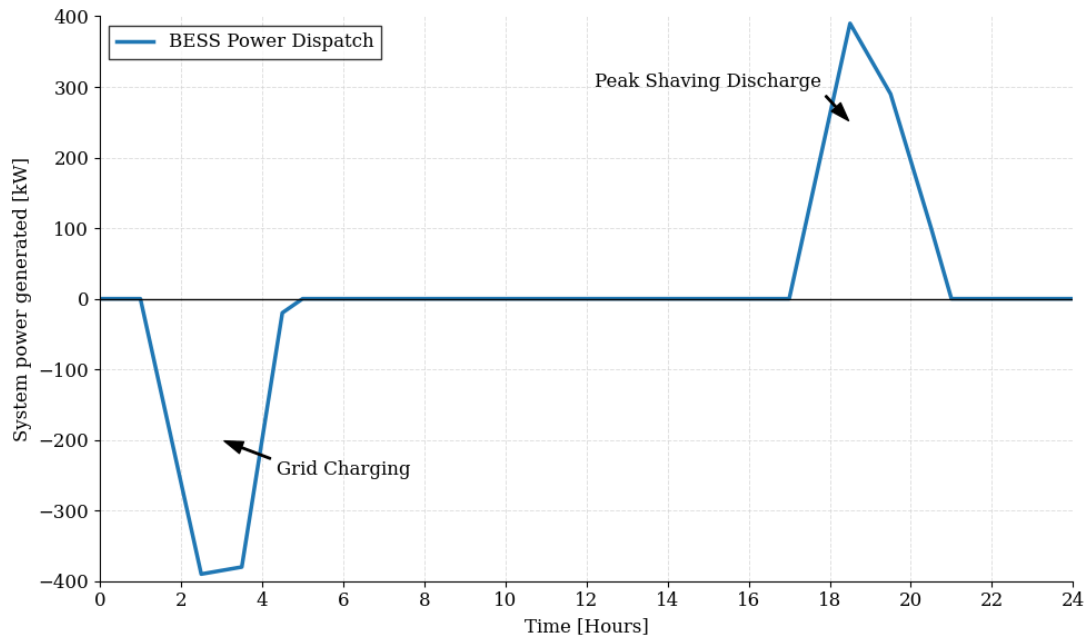


Figure 4.10: Daily BESS dispatch profile (grid charging negative, peak-shaving discharge positive)

Observations from Figure 4.10 show that the BESS follows the control logic established in the methodology. The system draws power from the grid during the early morning off-peak hours (01:00–05:00). During the evening peak demand window (18:00–21:00), the BESS discharges its stored energy, effectively reducing the peak load. This cycle ensures the BESS provides support when the substation transformer reaches its thermal limits.

4.5.2 Battery Degradation and Lifecycle Analysis

Capacity retention is a critical factor in the long-term financial performance of the project. Figure 4.11 compares the impact of Depth of Discharge (DoD) on the effective capacity of the battery over its operating life.

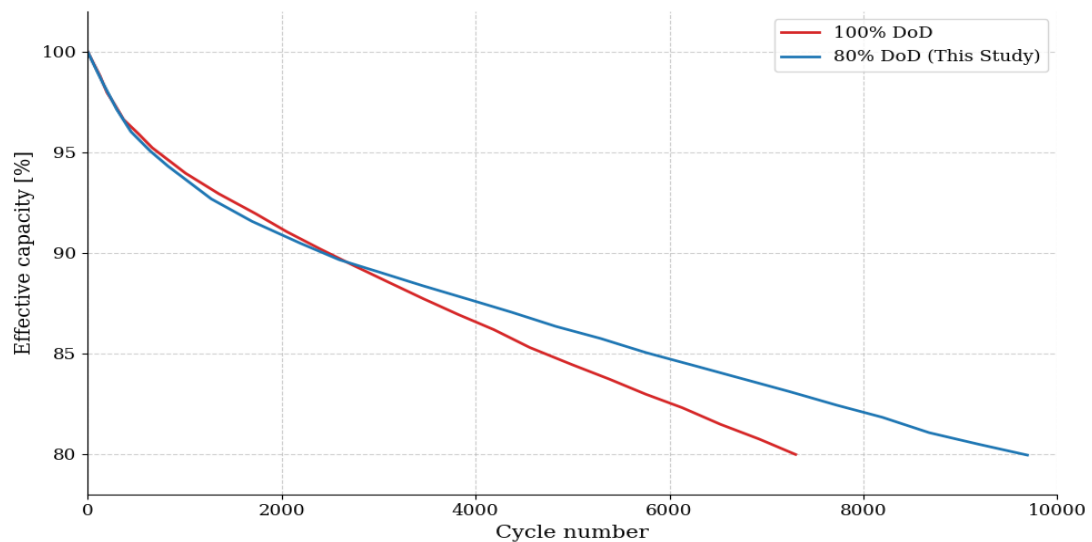


Figure 4.11: Impact of Depth of Discharge (DoD) on BESS Cycle Life

The results in Figure 4.11 justify the selection of an 80% DoD limit. A 100% DoD strategy causes the battery to reach its 80% end-of-life capacity at approximately 7,200 cycles. By restricting the discharge to 80%, the cycle life is extended to approximately 9,700 cycles. This extension in technical lifespan reduces the frequency of module replacements, which is necessary for maintaining a positive Net Present Value over the 15-year project period.

4.5.3 Financial Performance Indicators

The primary financial metrics derived from the lifecycle simulation are summarized in Table 4.4. These indicators provide the basis for evaluating the economic performance of the 400 kW / 1200 kWh BESS over the 15-year project period.

Table 4.4: 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)	\$0.6931 / kWh
Levelized Power Purchase Agreement (LPPA)	\$0.7109 / kWh

Results in Table 4.4 indicate that the project is economically viable under the defined assumptions. The analysis yielded a positive NPV of \$43,643, showing that the project

generates returns above the 10% discount rate. The achieved IRR of 15.54% represents a favourable return for a utility infrastructure asset compared to the standard cost of capital.

The Levelized Cost of Storage (LCOS) was compared against the Levelized Power Purchase Agreement (LPPA) price to justify the investment. The LPPA is a benchmark used in utility planning to represent the equivalent revenue required per unit of energy to recover costs. As shown in the results, the LCOS is \$0.6931 / kWh, while the revenue per unit is \$0.7109 / kWh. This positive spread between the cost and the revenue rate indicates a profitable margin for every unit of energy discharged to support the grid. These metrics confirm that the optimized BESS configuration is technically effective and financially justified.

4.5.4 Cash Flow Analysis and Upgrade Deferral Value

A year-by-year cash flow analysis provides a visual breakdown of the project's financial mechanics, as illustrated in Figure 4.12. The primary economic driver appears in Year 0, where the project realizes an immediate value of \$1,327,200 by deferring traditional grid reinforcement. This benefit significantly outweighs the initial Capital Expenditure of the BESS, shown by the negative red bar at \$637,825. This immediate net capital surplus provides the essential financial foundation that supports the project's viability against future operating costs. During the operational phase from Year 1 to Year 15, the project maintains a self-sustaining profile where annual revenue generated from the PPA and capacity services consistently exceeds the ongoing Operations and Maintenance costs. A distinct financial event occurs in Year 12, marked by a visible spike in operational costs. This reflects the scheduled replacement of the power conversion system and battery modules required to maintain system capacity. Because of the significant initial capital savings realized in Year 0 and the accumulated operational revenue, this replacement cost is absorbed without risking the overall financial stability of the project.

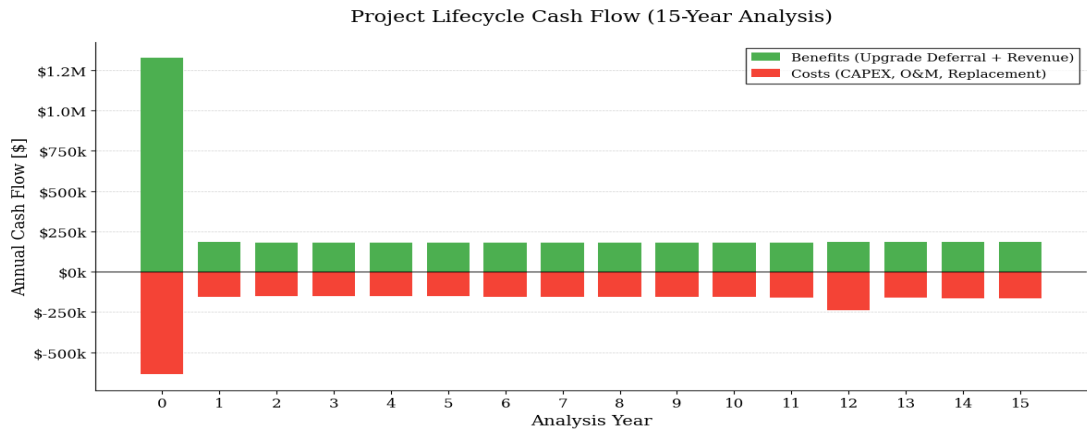


Figure 4.12: Project lifecycle cash flow, showing the deferred upgrade value in Year 0.

4.6 Validation of Financial Viability Against Existing Literature

The financial indicators obtained in this study were validated by benchmarking against similar regional research to ensure their realism. The achieved IRR of 15.54% presents a financially viable investment opportunity, notably outperforming large-scale BESS projects in similar regional contexts, which have reported IRRs in the range of 11% [29]. The payback period of 15 years falls within the same timeframe considered acceptable in regional utility studies, indicating that the project timeline for return on investment aligns with industry expectations. While the NPV of \$43,643 is smaller in scale than the multi-million-dollar returns reported in transmission-level studies [111], it confirms the fundamental principle that optimally sized BESS units on distribution feeders can be profitable. 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.

A further consideration is how these findings would translate to a lower-level distribution system. The methodology developed in this study is largely voltage-level agnostic, because the optimization operates on per-unit voltages, branch power flows and cost parameters rather than on absolute voltage magnitudes. If the same framework were applied to a lower-level network, such as a 415 V low-voltage feeder, the qualitative conclusions would be expected to hold: an optimally sized and sited BESS would still shave the peak demand, raise the minimum node voltage and defer network reinforcement. The magnitudes would differ, however, because low-voltage feeders exhibit higher resistance-to-reactance ratios, shorter line lengths and smaller aggregated loads. Voltage improvement would therefore be more sensitive to real-

power injection, while the absolute energy capacity required, and hence the capital cost, would be correspondingly smaller. The techno-economic viability at low voltage would consequently depend more strongly on the monetary value attached to the deferred upgrade and on the local load factor than on the electrical performance of the battery itself.

4.7 Summary

This chapter presented and discussed the results of the study. The baseline analysis confirmed that the feeder was operating under severe stress, with the substation transformer loaded to 99.6% and the minimum voltage falling to 0.936 p.u. The algorithmic comparison showed that ABBOA-Fuzzy converged faster and with higher initial search quality than PSO and BBOA, and all three algorithms independently identified Bus 117 as the optimal location. The optimized, commercially mapped 400 kW / 1200 kWh BESS reduced the peak demand by 15.5%, lowered transformer loading to 83.9% and raised the minimum voltage to 0.952 p.u., satisfying the technical standards adopted for the study. The techno-economic assessment returned a positive NPV of \$43,643 and an IRR of 15.54%, confirming that the BESS is both technically effective and financially viable as an NWA. These findings form the basis for the conclusions and recommendations presented in the next chapter.

CHAPTER FIVE

CONCLUSION, RECOMMENDATIONS AND FUTURE WORK

5.1 Conclusion

This thesis addressed the challenge of integrating a Battery Energy Storage System (BESS) into a constrained rural distribution network by developing an integrated planning framework. Baseline analysis of the 11 kV feeder identified significant technical deficiencies, with transformer loading reaching 99.6%, a minimum bus voltage of 0.936 p.u., and daily energy losses of 989 kWh during peak demand.

To address these constraints, a comparative optimization was performed using PSO, BBOA and ABBOA-Fuzzy algorithms. All three algorithms independently identified Bus 117 as the optimal installation location, with an optimal BESS size of 392.6 kW / 1177.8 kWh. Among the optimization methods, ABBOA-Fuzzy demonstrated the fastest convergence, reaching the optimum solution by the seventh iteration. Technical validation further showed that the optimized BESS configuration reduced feeder peak demand by 15.5% and improved the minimum bus voltage to 0.952 p.u., thereby mitigating the deficiencies identified in the baseline analysis.

A 15-year techno-economic assessment subsequently confirmed the financial viability of the proposed solution. After accounting for battery degradation and replacement costs, the project achieved a positive Net Present Value (NPV) of \$43,643 and an Internal Rate of Return (IRR) of 15.54%. These results demonstrate that an optimally sized and sited BESS provides a technically effective and economically viable Non-Wires Alternative (NWA) for rural distribution network modernization.

The study successfully achieved all three research objectives. First, a validated DIgSILENT PowerFactory model of the 11 kV feeder was developed to establish the baseline operating conditions. Second, the BESS sizing and siting problem was formulated as a constrained optimization problem and solved using three metaheuristic algorithms, resulting in the selection of a commercially feasible 400 kW / 1200 kWh BESS at Bus 117. Finally, the techno-economic assessment confirmed the long-term viability of the proposed investment, yielding a positive NPV of \$43,643 and an IRR of 15.54%.

5.2 Recommendations

5.2.1 Recommendations for Adoption of Results

The following recommendations are derived from the technical and economic findings of this study:

- i. **Adopt Integrated Planning for Comparable Feeders:** For rural distribution feeders with characteristics similar to the one studied, distribution utilities can integrate this techno-economic framework into their distribution planning process so that Non-Wires Alternatives are evaluated alongside traditional reinforcements before a network upgrade is committed.
- ii. **Transition to Adaptive Optimization:** Grid engineers should move from static sizing tools to adaptive metaheuristics such as the ABBOA-Fuzzy algorithm. This approach is necessary to bypass local optima in high-impedance radial networks, ensuring that BESS deployment decisions are mathematically accurate and technically feasible.

5.2.2 Recommendations for Future Work

The following recommendations are derived from the technical and economic findings of this study:

- iii. **Adopt Integrated Planning in Kenya:** Distribution utilities should consider integrating this techno-economic framework into the national Cost-effective Power Development Plan. This allows for the evaluation of Non-Wires Alternatives alongside traditional reinforcements to manage network congestion on rural distribution feeders.
- iv. **Investigate Revenue Stacking:** Future studies should expand the economic evaluation to include revenue stacking. While this study focused on peak shaving and voltage support, project viability can be further enhanced by evaluating the simultaneous delivery of frequency regulation and energy arbitrage within the Kenyan electricity market.
- v. **Incorporate Uncertainty Analysis:** Future research should replace deterministic load assumptions with variability analysis. This transition is required to account for the unpredictable nature of long-term load growth and fluctuating battery technology costs over a 15-year lifecycle.

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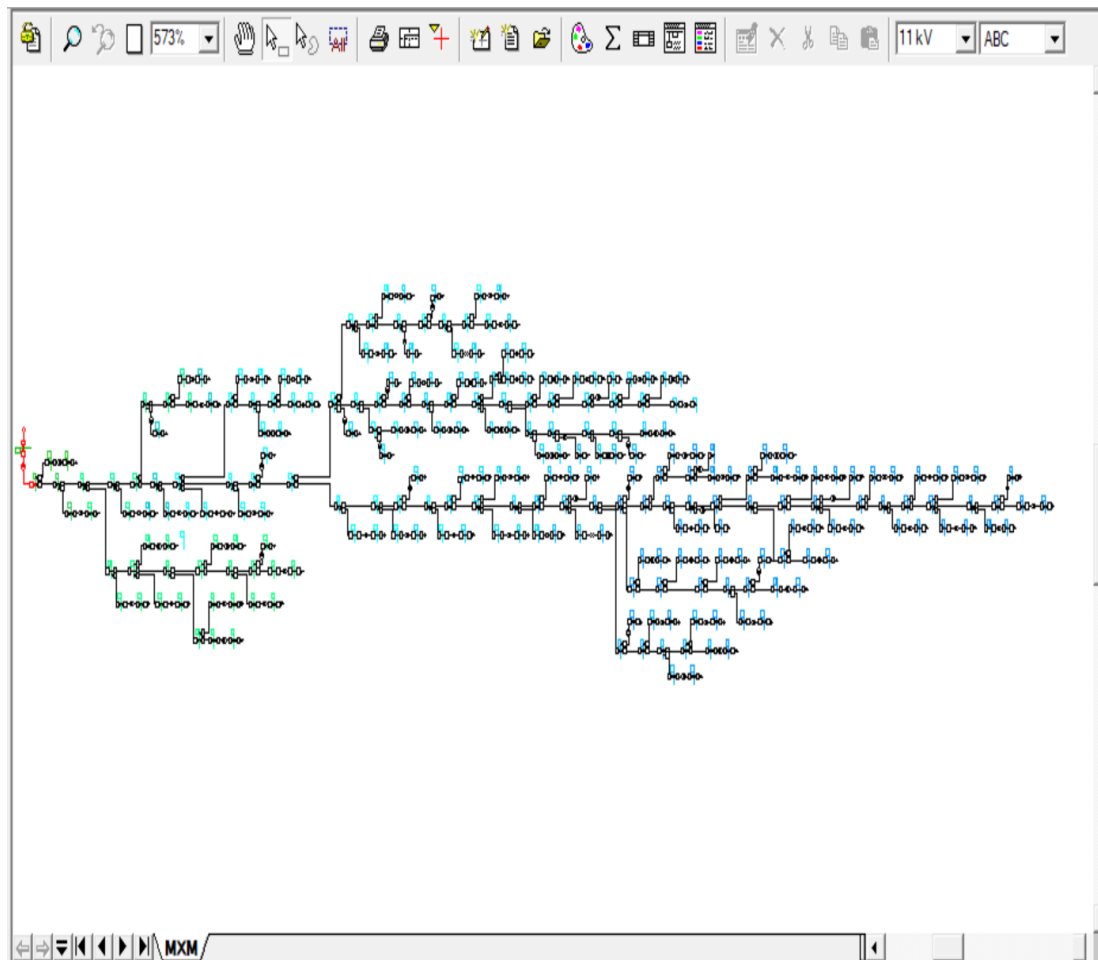
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APPENDICES

Appendix 1: DIgSILENT PowerFactory Model

Appendix 1 presents the single-line diagram of the case-study network as built in DIgSILENT PowerFactory. The diagram represents the complete 158-bus, 11 kV radial distribution feeder, showing the substation source on the left and the successive laterals and load points that extend along the approximately 69 km feeder. Each busbar, line section and distribution transformer in the model corresponds to the actual feeder topology and parameters obtained from the utility, and this model provided the baseline load-flow, voltage-profile and loss results reported in Chapter Four.



Appendix 2: Python Code for Optimization Process

The complete Python implementation used for the optimization is provided in the listings that follow. For ease of referencing, the code is organized into eleven discrete, sequentially numbered listings (Appendix 4.1 to Appendix 4.11), each corresponding to a specific stage of the optimization workflow, from library initialization and network modelling through to the metaheuristic algorithms and the generation of the output results.

Appendix 2.1: Script Initialization and Library Imports

```
1.  #
    =====
    =====
2.  # SCRIPT: COMPARISON OF PSO, ABBOA-FUZZY, AND BBOA FOR BESS
    SIZING AND LOCATION
3.  #
    =====
    =====
4.
5.  # Step 0: Install necessary packages
6.  !pip install scikit-fuzzy
7.  !pip install pandas
8.
9.  import numpy as np
10. import matplotlib.pyplot as plt
11. import pandas as pd
12. import skfuzzy as fuzz
13. from skfuzzy import control as ctrl
14. import sys
```

Appendix 2.2: Grid Modelling and Network Data Initialization

```
15. # --- STEP 1: PARSE AND STRUCTURE ALL INPUT DATA ---
16. def build_grid_model():
17.     """
18.     Parses all raw data into a complete grid model and filters
    candidate buses.
19.     """
20.     R_per_km, X_per_km = 0.4014, 0.3378
21.     V_base_kV, S_base_MVA = 11.0, 3.0
22.     Z_base_ohms = (V_base_kV**2) / S_base_MVA
23.     line_data_raw = """
```

24. Line1 B1 0.023; Line2 B1 0.591; Line3 B3 0.018; Line4 B3 0.252; Line5 B5 0.1;
25. Line6 B6 0.218; Line7 B6 0.493; Line8 B8 0.523; Line9 B8 0.062; Line10 B8 0.526;
26. Line11 B11 0.344; Line12 B12 0.004; Line13 B12 0.53; Line14 B11 0.342; Line15 B15 0.066;
27. Line16 B15 1.116; Line17 B17 0.001; Line18 B17 0.431; Line19 B19 0.244; Line20 B5 1.181;
28. Line21 B21 0.012; Line22 B21 0.026; Line23 B23 0.396; Line24 B24 0.378; Line25 B25 0.02;
29. Line26 B25 0.393; Line27 B23 0.507; Line28 B28 0.091; Line29 B28 0.419; Line30 B30 0.133;
30. Line31 B30 0.331; Line32 B32 0.014; Line33 B32 0.556; Line34 B34 0.191; Line35 B34 0.167;
31. Line36 B36 0.433; Line37 B36 0.11; Line38 B30 0.265; Line39 B39 0.164; Line40 B39 0.105;
32. Line41 B41 0.096; Line42 B42 0.265; Line43 B43 0.085; Line44 B44 0.021; Line45 B44 0.034;
33. Line46 B46 0.314; Line47 B46 0.011; Line48 B48 0.951; Line49 B49 0.561; Line50 B50 0.043;
34. Line51 B50 0.273; Line52 B52 0.316; Line53 B52 0.186; Line54 B43 0.071; Line55 B55 0.142;
35. Line56 B56 0.326; Line57 B55 0.379; Line58 B58 1.622; Line59 B59 0.026; Line60 B59 0.789;
36. Line61 B61 0.159; Line62 B61 0.369; Line63 B63 0.001; Line64 B63 0.928; Line65 B65 0.001;
37. Line66 B65 0.334; Line67 B67 0.368; Line68 B67 0.698; Line69 B65 0.700; Line70 B70 0.568;
38. Line71 B71 0.047; Line72 B71 1.851; Line73 B73 1.188; Line74 B74 0.157; Line75 B74 0.218;
39. Line76 B76 0.912; Line77 B70 0.329; Line78 B78 0.441; Line79 B78 0.121; Line80 B80 0.164;
40. Line81 B80 1.361; Line82 B82 1.412; Line83 B83 2.896; Line84 B83 0.653; Line85 B85 0.069;
41. Line86 B85 2.737; Line87 B42 0.129; Line88 B88 0.01; Line89 B88 0.149; Line90 B90 0.124;
42. Line91 B90 0.258; Line92 B92 0.359; Line93 B93 0.003; Line94 B93 0.561; Line95 B95 0.004;
43. Line96 B95 0.696; Line97 B97 0.004; Line98 B97 0.425; Line99 B97 0.623; Line100 B100 0.004;
44. Line101 B100 1.554; Line102 B102 0.13; Line103 B102 1.157; Line104 B104 1.745; Line105 B104 0.898;
45. Line106 B106 0.494; Line107 B107 1.453; Line108 B108 0.003; Line109 B108 1.124; Line110 B110 0.005;
46. Line111 B110 0.516; Line112 B112 0.182; Line113 B112 0.684; Line114 B106 1.336; Line115 B115 0.568;

47. Line116 B116 1.073; Line117 B116 1.502; Line118 B118 0.044;
Line119 B118 1.862; Line120 B120 0.022;

48. Line121 B120 0.541; Line122 B122 0.667; Line123 B122 0.957;
Line124 B124 1.479; Line125 B115 0.467;

49. Line126 B126 0.078; Line127 B127 0.843; L128 B127 0.231;
Line129 B129 0.46; Line130 B126 0.29;

50. Line131 B131 0.182; Line132 B131 1.108; Line133 B133 0.545;
Line134 B134 0.254; Line135 B135 1.052;

51. Line136 B135 0.326; Line137 B134 0.256; Line138 B138 2.005;
Line139 B139 0.585; Line140 B139 1.927;

52. Line141 B138 0.699; Line142 B142 0.06; Line143 B142 0.464;
Line144 B144 1.161; Line145 B144 0.725;

53. Line146 B146 0.362; Line147 B146 0.796; Line148 B148 0.003;
Line149 B148 1.006; Line150 B150 0.131;

54. Line151 B150 1.127; Line152 B152 0.198; Line153 B152 1.051;
Line154 B152 1.581; Line155 B155 0.027;

55. Line156 B155 1.124; Line157 B157 1.002;

56. ""

57. line_to_bus_map_raw = ""

58. Line1 B1 B2; Line2 B1 B3; Line3 B3 B4; Line4 B3 B5; Line5
B5 B6; Line6 B6 B7; Line7 B6 B8;

59. Line8 B8 B9; Line9 B8 B10; Line10 B8 B11; Line11 B11 B12;
Line12 B12 B13; Line13 B12 B14;

60. Line14 B11 B15; Line15 B15 B16; Line16 B15 B17; Line17 B17
B18; Line18 B17 B19; Line19 B19 B20;

61. Line20 B5 B21; Line21 B21 B22; Line22 B21 B23; Line23 B23
B24; Line24 B24 B25; Line25 B25 B26;

62. Line26 B25 B27; Line27 B23 B28; Line28 B28 B29; Line29 B28
B30; Line30 B30 B31; Line31 B30 B32;

63. Line32 B32 B33; Line33 B32 B34; Line34 B34 B35; Line35 B34
B36; Line36 B36 B37; Line37 B36 B38;

64. Line38 B30 B39; Line39 B39 B40; Line40 B39 B41; Line41 B41
B42; Line42 B42 B43; Line43 B43 B44;

65. Line44 B44 B45; Line45 B44 B46; Line46 B46 B47; Line47 B46
B48; Line48 B48 B49; Line49 B49 B50;

66. Line50 B50 B51; Line51 B50 B52; Line52 B52 B53; Line53 B52
B54; Line54 B43 B55; Line55 B55 B56;

67. Line56 B56 B57; Line57 B55 B58; Line58 B58 B59; Line59 B59
B60; Line60 B59 B61; Line61 B61 B62;

68. Line62 B61 B63; Line63 B63 B64; Line64 B63 B65; Line65 B65
B66; Line66 B65 B67; Line67 B67 B68;

69. Line68 B67 B69; Line69 B65 B70; Line70 B70 B71; Line71 B71
B72; Line72 B71 B73; Line73 B73 B74;

70. Line74 B74 B75; Line75 B74 B76; Line76 B76 B77; Line77 B70
B78; Line78 B78 B79; Line79 B78 B80;

71. Line80 B80 B81; Line81 B80 B82; Line82 B82 B83; Line83 B83
B84; Line84 B83 B85; Line85 B85 B86;

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72.      Line86 B85 B87; Line87 B42 B88; Line88 B88 B89; Line89 B88
      B90; Line90 B90 B91; Line91 B90 B92;
73.      Line92 B92 B93; Line93 B93 B94; Line94 B93 B95; Line95 B95
      B96; Line96 B95 B97; Line97 B97 B98;
74.      Line98 B97 B99; Line99 B97 B100; Line100 B100 B101; Line101
      B100 B102; Line102 B102 B103;
75.      Line103 B102 B104; Line104 B104 B105; Line105 B104 B106;
      Line106 B106 B107; Line107 B107 B108;
76.      Line108 B108 B109; Line109 B108 B110; Line110 B110 B111;
      Line111 B110 B112; Line112 B112 B113;
77.      Line113 B112 B114; Line114 B106 B115; Line115 B115 B116;
      Line116 B116 B117; Line117 B116 B118;
78.      Line118 B118 B119; Line119 B118 B120; Line120 B120 B121;
      Line121 B120 B122; Line122 B122 B123;
79.      Line123 B122 B124; Line124 B124 B125; Line125 B115 B126;
      Line126 B126 B127; Line127 B127 B128;
80.      L128 B127 B129; Line129 B129 B130; Line130 B126 B131;
      Line131 B131 B132; Line132 B131 B133;
81.      Line133 B133 B134; Line134 B134 B135; Line135 B135 B136;
      Line136 B135 B137; Line137 B14 B138;
82.      Line138 B138 B139; Line139 B139 B140; Line140 B139 B141;
      Line141 B138 B142; Line142 B142 B143;
83.      Line143 B142 B144; Line144 B144 B145; Line145 B144 B146;
      Line146 B146 B147; Line147 B146 B148;
84.      Line148 B148 B149; Line149 B148 B150; Line150 B150 B151;
      Line151 B150 B152; Line152 B152 B153;
85.      Line153 B152 B154; Line154 B152 B155; Line155 B155 B156;
      Line156 B155 B157; Line157 B157 B158;
86.      ""
87.      load_data_raw = ""
88.      L1 0.016 0.0053; L10 0.063 0.0207; L11 0.005 0.0016; L12
      0.016 0.0053; L13 0.031 0.0102;
89.      L14 0.031 0.0102; L15 0.031 0.0102; L16 0.031 0.0102; L17
      0.099 0.033; L18 0.063 0.0207;
90.      L19 0.063 0.0207; L2 0.005 0.0016; L20 0.099 0.033; L21
      0.063 0.0207; L22 0.099 0.033;
91.      L23 0.002 0.00066; L24 0.099 0.033; L25 0.099 0.033; L26
      0.099 0.033; L27 0.099 0.033;
92.      L28 0.031 0.0102; L29 0.016 0.0053; L3 0.002 0.00066; L30
      0.099 0.033; L31 0.099 0.033;
93.      L32 0.099 0.033; L33 0.099 0.033; L34 0.063 0.0207; L35
      0.031 0.0102; L36 0.031 0.0102;
94.      L37 0.005 0.0016; L38 0.031 0.0102; L39 0.008 0.00263; L4
      0.016 0.0053; L40 0.005 0.0016;
95.      L41 0.008 0.00263; L42 0.008 0.00263; L43 0.016 0.0053; L44
      0.063 0.0207; L45 0.005 0.0016;

```

96. L46 0.008 0.00263; L47 0.008 0.00263; L48 0.016 0.0053; L49
 0.016 0.0053; L5 0.016 0.0053;
 97. L50 0.016 0.0053; L51 0.031 0.0102; L52 0.099 0.033; L53
 0.016 0.0053; L54 0.024 0.0079;
 98. L55 0.031 0.0102; L56 0.016 0.0053; L57 0.005 0.0016; L58
 0.005 0.0016; L59 0.005 0.0016;
 99. L6 0.008 0.00263; L60 0.063 0.0207; L61 0.005 0.0016; L62
 0.005 0.0016; L63 0.016 0.0053;
 100. L64 0.016 0.0053; L65 0.005 0.0016; L66 0.016 0.0053; L67
 0.031 0.0102; L68 0.016 0.0053;
 101. L69 0.008 0.00263; L7 0.002 0.00066; L70 0.008 0.00263; L71
 0.008 0.00263; L72 0.005 0.0016;
 102. L73 0.016 0.0053; L74 0.002 0.00066; L75 0.016 0.0053; L76
 0.016 0.0053; L77 0.063 0.0207;
 103. L78 0.016 0.0053; L79 0.016 0.0053; L8 0.002 0.00066; L80
 0.016 0.0053; L81 0.016 0.0053;
 104. L82 0.031 0.0102; L83 0.008 0.00263; L84 0.008 0.00263; L85
 0.002 0.00066; L86 0.008 0.00263;
 105. L87 0.008 0.00263; L88 0.016 0.0053; L89 0.016 0.0053; L9
 0.005 0.0016; L90 0.008 0.00263;
 106. L91 0.031 0.0102; L92 0.016 0.0053;
 107. ""
 108. transformer_map_raw = ""
 109. T0 B0 B1; T1 B2 A1; T10 B19 A10; T11 B20 A11; T12 B22 A12;
 T13 B24 A13; T14 B26 A14;
 110. T15 B27 A15; T16 B29 A16; T17 B31 A17; T18 B33 A18; T19 B35
 A19; T2 B4 A2; T20 B37 A20;
 111. T21 B38 A21; T22 B40 A22; T23 B41 A23; T24 B43 A24; T25 B45
 A25; T26 B47 A26; T27 B48 A27;
 112. T28 B49 A28; T29 B51 A29; T3 B7 A3; T30 B53 A30; T31 B54
 A31; T32 B56 A32; T33 B57 A33;
 113. T34 B58 A34; T35 B60 A35; T36 B62 A36; T37 B64 A37; T38 B66
 A38; T39 B68 A39; T4 B9 A4;
 114. T40 B69 A40; T41 B72 A41; T42 B73 A42; T43 B75 A43; T44 B76
 A44; T45 B77 A45; T46 B79 A46;
 115. T47 B81 A47; T48 B82 A48; T49 B84 A49; T5 B10 A5; T50 B86
 A50; T51 B89 A51; T51' B87 A51';
 116. T52 B91 A52; T53 B92 A53; T54 B94 A54; T55 B96 A55; T56 B98
 A56; T57 B99 A57; T58 B101 A58;
 117. T59 B103 A59; T6 B13 A6; T60 B104 A60; T61 B105 A61; T62
 B107 A62; T63 B109 A63; T64 B111 A64;
 118. T65 B113 A65; T66 B114 A66; T67 B115 A67; T68 B117 A68; T69
 B119 A69; T7 B14 A7; T70 B121 A70;
 119. T71 B123 A71; T72 B124 A72; T73 B125 A73; T74 B128 A74; T75
 B130 A75; T75' B129 A75';
 120. T76 B132 A76; T77 B133 A77; T78 B136 A78; T79 B137 A79; T8
 B16 A8; T80 B140 A80; T81 B141 A81;

```

121.      T82 B143 A82; T83 B144 A83; T84 B145 A84; T85 B147 A85; T86
      B149 A86; T87 B151 A87;
122.      T88 B153 A88; T89 B154 A89; T9 B18 A9; T90 B156 A90; T91
      B157 A91; T92 B158 A92;
123.      ""
124.
125.      line_lengths = {p[0]: float(p[2]) for p in [l.split() for l
      in line_data_raw.strip().replace(';','\n').split('\n')] if p
      and len(p) == 3}
126.      line_connections = {p[0]: (p[1], p[2]) for p in [l.split()
      for l in
      line_to_bus_map_raw.strip().replace(';','\n').split('\n')] if p
      and len(p) == 3}
127.      lines = {n: {'from_bus': f, 'to_bus': t, 'r_pu':
      (R_per_km*line_lengths.get(n,0))/Z_base_ohms, 'x_pu':
      (X_per_km*line_lengths.get(n,0))/Z_base_ohms} for n, (f,t) in
      line_connections.items()}
128.      loads_dict = {p[0]: {'p_mw': float(p[1]), 'q_mvar':
      float(p[2])} for p in [l.split() for l in
      load_data_raw.strip().replace(';','\n').split('\n')] if p and
      len(p) == 3}
129.      transformer_map = {p[0]: {'hv_bus': p[1], 'lv_bus': p[2]}
      for p in [l.split() for l in
      transformer_map_raw.strip().replace(';','\n').split('\n')] if p
      and len(p) == 3}
130.      all_bus_names = set(['Substation']);
      [all_bus_names.update([l['from_bus'], l['to_bus']]) for l in
      lines.values()]
131.      buses = {name: {'p_mw': 0.0, 'q_mvar': 0.0} for name in
      all_bus_names}
132.      for tr_data in transformer_map.values():
133.          lv_bus, hv_bus = tr_data['lv_bus'], tr_data['hv_bus']
134.          numeric_part = ''.join(filter(str.isdigit, lv_bus))
135.          if numeric_part:
136.              load_name = f"L{numeric_part}"
137.              if load_name in loads_dict and hv_bus in buses:
138.                  buses[hv_bus]['p_mw'] +=
      loads_dict[load_name]['p_mw']
139.                  buses[hv_bus]['q_mvar'] +=
      loads_dict[load_name]['q_mvar']
140.      buses['Substation']['type'] = 'slack'; all_b_buses =
      sorted([b for b in buses if b.startswith('B')]);
      candidate_buses = []
141.
142.      for bus_name in all_b_buses:
143.          try:
144.              bus_number = int(bus_name.replace('B', ''))

```

```

145.             if bus_number >= 100:
146.                 candidate_buses.append(bus_name)
147.         except ValueError:
148.             continue
149.
150.     return buses, lines, S_base_MVA, candidate_buses

```

Appendix 2.3: Distribution System Load Flow Solver for Radial Networks

```

151. # --- STEP 2: POWER FLOW ENGINE ---
152. def run_power_flow(buses, lines, S_base_MVA, v_slack=1.0,
153.                   max_iter=20, tol=1e-5):
154.     parent_map = {line['to_bus']: line['from_bus'] for line in
155.                   lines.values()}
156.     children_map = {bus: [] for bus in buses}
157.     for to_bus, from_bus in parent_map.items():
158.         if from_bus in children_map:
159.             children_map[from_bus].append(to_bus)
160.         else: children_map[from_bus] = [to_bus]
161.     ordered_buses = []; queue = ['Substation']; visited =
162.     {'Substation'}; head = 0
163.     while head < len(queue):
164.         current_bus = queue[head]; head += 1
165.         ordered_buses.append(current_bus)
166.         for child in sorted(children_map.get(current_bus,
167.                                             [])):
168.             if child not in visited: visited.add(child);
169.             queue.append(child)
170.     backward_sweep_order = ordered_buses[::-1]
171.     V = {bus: complex(v_slack, 0) for bus in buses}
172.     for _ in range(max_iter):
173.         V_old = V.copy()
174.         S_flow = {b: complex(d['p_mw'], d['q_mvar']) /
175.                  S_base_MVA for b, d in buses.items()}
176.         for bus_name in backward_sweep_order:
177.             if bus_name == 'Substation': continue
178.             parent = parent_map[bus_name]
179.             line = [l for l in lines.values() if
180.                    l['from_bus']==parent and l['to_bus']==bus_name][0]
181.             Z_pu = complex(line['r_pu'], line['x_pu'])
182.             I_pu_sq = (S_flow[bus_name] / V_old[bus_name]) *
183.             np.conj(S_flow[bus_name] / V_old[bus_name])
184.             loss = Z_pu * I_pu_sq.real
185.             S_flow[parent] += S_flow[bus_name] + loss
186.         for bus_name in ordered_buses[1:]:
187.             parent = parent_map[bus_name]

```

```

179.         line = [l for l in lines.values() if
180.                 l['from_bus']==parent and l['to_bus']==bus_name][0]
181.         Z_pu = complex(line['r_pu'], line['x_pu'])
182.         I_pu = np.conj(S_flow[bus_name] / V_old[bus_name])
183.         V[bus_name] = V[parent] - I_pu * Z_pu
184.         if max(abs(V[b] - V_old[b]) for b in buses) < tol:
            break
185.         return {k: np.abs(v) for k, v in V.items()}

```

Appendix 2.4: Dynamic Dispatch Strategy and Objective Function Implementation

```

185. # --- STEP 3: FITNESS AND SIMULATION FUNCTIONS ---
186. def run_simulation_and_get_metrics(PBESS_kw, BESS_LOCATION,
187.     grid_data, dispatch_params):
188.     buses, lines, S_base_MVA = grid_data
189.     (PEAK_REDUCTION_TARGET, V_MIN_CONSTRAINT, C_p_per_kw,
190.     C_e_per_kwh, SOC_max, SOC_min,
191.     eta_charge, eta_discharge, charge_hours, discharge_hours,
192.     S_sub_peak_base) = dispatch_params
193.
194.     inverter_rating_kva = PBESS_kw / 0.95 if PBESS_kw > 1e-6
195.     else 0
196.
197.     EBESS_kWh = 3 * PBESS_kw
198.     BESS_EFFECTIVENESS = 0.98
199.     hourly_min_voltages, net_loads_kw = [], []
200.     soc = np.zeros(25); soc[0] = SOC_min
201.     load_percentages = [40, 35, 25, 20, 25, 35, 55, 80, 80, 70,
202.     70, 60, 65, 55, 50, 60, 60, 75, 95, 100, 100, 80, 70, 50]
203.     peak_p_loads = {name: data['p_mw'] for name, data in
204.     buses.items()}
205.     peak_q_loads = {name: data['q_mvar'] for name, data in
206.     buses.items()}
207.     target_peak_kw = S_sub_peak_base * (1 -
208.     PEAK_REDUCTION_TARGET)
209.
210.     for t in range(24):
211.         temp_buses = {name: data.copy() for name, data in
212.         buses.items()}
213.         load_factor = load_percentages[t] / 100.0
214.         for bus_name in temp_buses:
215.             temp_buses[bus_name]['p_mw'] =
216.             peak_p_loads[bus_name] * load_factor
217.             temp_buses[bus_name]['q_mvar'] =
218.             peak_q_loads[bus_name] * load_factor
219.
220.

```

```

208.         p_bess_kw, q_bess_kvar = 0.0, 0.0
209.         if PBESS_kw > 1e-6:
210.             if t in charge_hours:
211.                 p_bess_kw = -min(PBESS_kw, (SOC_max - soc[t]) *
EBESS_kWh / eta_charge)
212.                 elif t in discharge_hours:
213.                     current_grid_load_kw = sum(b['p_mw'] for b in
temp_buses.values()) * 1000
214.                     peak_shave_needed_kw = max(0,
current_grid_load_kw - target_peak_kw)
215.                     p_from_soc = (soc[t] - SOC_min) * EBESS_kWh *
eta_discharge
216.                     p_for_peak_shaving = min(peak_shave_needed_kw,
p_from_soc, inverter_rating_kva)
217.                     q_capacity_rem = np.sqrt(max(0,
inverter_rating_kva**2 - p_for_peak_shaving**2))
218.                     p_bess_kw, q_bess_kvar = -p_for_peak_shaving,
q_capacity_rem
219.
220.             if EBESS_kWh > 0:
221.                 soc[t+1] = soc[t] - (p_bess_kw / (eta_charge if
p_bess_kw < 0 else 1/eta_discharge)) / EBESS_kWh
222.             else:
223.                 soc[t+1] = soc[t]
224.
225.                 p_bess_effective_mw = (p_bess_kw *
BESS_EFFECTIVENESS) / 1000.0
226.                 q_bess_effective_mvar = (q_bess_kvar *
BESS_EFFECTIVENESS) / 1000.0
227.                 temp_buses[BESS_LOCATION]['p_mw'] +=
p_bess_effective_mw
228.                 temp_buses[BESS_LOCATION]['q_mvar'] +=
q_bess_effective_mvar
229.
230.                 voltages = run_power_flow(temp_buses, lines,
S_base_MVA, v_slack=SUBSTATION_VOLTAGE_PU)
231.                 hourly_min_voltages.append(min(voltages.values()))
232.                 net_loads_kw.append(sum(bus['p_mw'] for bus in
temp_buses.values())*1000)
233.
234.         return min(hourly_min_voltages), max(net_loads_kw)
235.
236. def evaluate_fitness(particle, grid_data, dispatch_params,
candidate_buses):
237.     PBESS_kw = particle[0]
238.     location_index = int(round(particle[1]))

```

```

239.     location_index = max(0, min(location_index,
len(candidate_buses) - 1))
240.     BESS_LOCATION = candidate_buses[location_index]
241.
242.     (PEAK_REDUCTION_TARGET, V_MIN_CONSTRAINT, C_p_per_kw,
C_e_per_kwh,
243.      _, _, _, _, _, S_sub_peak_base) = dispatch_params
244.
245.     min_voltage_overall, actual_peak_kw =
run_simulation_and_get_metrics(
246.         PBESS_kw, BESS_LOCATION, grid_data, dispatch_params)
247.
248.     inverter_rating_kva = PBESS_kw / 0.95 if PBESS_kw > 0 else
0
249.     EBESS_kWh = 3 * PBESS_kw
250.     capex = (C_p_per_kw * inverter_rating_kva) + (C_e_per_kwh *
EBESS_kWh)
251.     fitness = capex
252.
253.     if min_voltage_overall < V_MIN_CONSTRAINT:
254.         fitness += 1e6 * (V_MIN_CONSTRAINT -
min_voltage_overall)
255.
256.     target_peak_kw = S_sub_peak_base * (1 -
PEAK_REDUCTION_TARGET)
257.     if actual_peak_kw > target_peak_kw:
258.         fitness += 1e5 * (actual_peak_kw - target_peak_kw)
259.
260.     return fitness

```

Appendix 2.5: Particle Swarm Optimization (PSO) Algorithm Implementation

```

261 # --- STEP 4: ALGORITHM IMPLEMENTATIONS ---
262 class ParticleSwarmOptimizer:
263     def __init__(self, bounds, n_particles, n_iterations, w, c1,
c2,
264                 grid_data, dispatch_params, candidate_buses):
265         self.bounds_low = np.array([b[0] for b in bounds])
266         self.bounds_high = np.array([b[1] for b in bounds])
267         self.n_dimensions = len(bounds)
268         self.n_particles, self.n_iterations = n_particles,
n_iterations
269         self.w, self.c1, self.c2 = w, c1, c2
270         self.grid_data = grid_data
271         self.dispatch_params = dispatch_params
272         self.candidate_buses = candidate_buses

```

```

273         self.swarm_pos = np.random.uniform(self.bounds_low,
self.bounds_high, (self.n_particles, self.n_dimensions))
274         self.swarm_vel = np.zeros((self.n_particles,
self.n_dimensions))
275         self.pbest_pos = self.swarm_pos.copy()
276         self.pbest_fitness = np.full(self.n_particles, np.inf)
277         self.gbest_pos, self.gbest_fitness = None, np.inf
278         self.gbest_fitness_history = []
279
280     def optimize(self):
281         print("--- STARTING PSO OPTIMIZATION ---")
282         for i in range(self.n_iterations):
283             for j in range(self.n_particles):
284                 fitness = evaluate_fitness(self.swarm_pos[j],
self.grid_data, self.dispatch_params, self.candidate_buses)
285                 if fitness < self.pbest_fitness[j]:
286                     self.pbest_fitness[j] = fitness
287                     self.pbest_pos[j] = self.swarm_pos[j].copy()
288
289                 min_pbest_idx = np.argmin(self.pbest_fitness)
290                 if self.pbest_fitness[min_pbest_idx] <
self.gbest_fitness:
291                     self.gbest_fitness =
self.pbest_fitness[min_pbest_idx]
292                     self.gbest_pos =
self.pbest_pos[min_pbest_idx].copy()
293
294                 r1 = np.random.rand(self.n_particles,
self.n_dimensions)
295                 r2 = np.random.rand(self.n_particles,
self.n_dimensions)
296                 cognitive_vel = self.c1 * r1 * (self.pbest_pos -
self.swarm_pos)
297                 social_vel = self.c2 * r2 * (self.gbest_pos -
self.swarm_pos)
298                 self.swarm_vel = (self.w * self.swarm_vel) +
cognitive_vel + social_vel
299                 self.swarm_pos += self.swarm_vel
300                 self.swarm_pos = np.clip(self.swarm_pos,
self.bounds_low, self.bounds_high)
301                 self.gbest_fitness_history.append(self.gbest_fitness)
302
303                 if (i + 1) % 5 == 0:
304                     print(f"Iteration {i+1}/{self.n_iterations}, Best
Fitness: {self.gbest_fitness:.2f}")
305
306         print("--- PSO OPTIMIZATION FINISHED ---\n")

```

```

307         return self.gbest_pos, self.gbest_fitness,
           self.gbest_fitness_history

```

```

308

```

Appendix 2.6: Membership Function Definition and Fuzzy Logic Controller Implementation

```

309. def create_fuzzy_controller():
310.     distance = ctrl.Antecedent(np.linspace(0, 1, 100),
           'distance')
311.     alpha = ctrl.Consequent(np.linspace(0, 1, 100), 'alpha')
312.     beta = ctrl.Consequent(np.linspace(0, 1, 100), 'beta')
313.
314.     distance['near'] = fuzz.trimf(distance.universe, [0.0,
           0.0, 0.3])
315.     distance['medium'] = fuzz.trimf(distance.universe, [0.2,
           0.5, 0.8])
316.     distance['far'] = fuzz.trimf(distance.universe, [0.7, 1.0,
           1.0])
317.
318.     alpha['low'] = fuzz.trimf(alpha.universe, [0.0, 0.0, 0.3])
319.     alpha['medium'] = fuzz.trimf(alpha.universe, [0.2, 0.5,
           0.8])
320.     alpha['high'] = fuzz.trimf(alpha.universe, [0.7, 1.0,
           1.0])
321.
322.     beta['low'] = fuzz.trimf(beta.universe, [0.0, 0.0, 0.3])
323.     beta['medium'] = fuzz.trimf(beta.universe, [0.2, 0.5,
           0.8])
324.     beta['high'] = fuzz.trimf(beta.universe, [0.7, 1.0, 1.0])
325.
326.     rules = [
327.         ctrl.Rule(distance['far'], (alpha['high'],
           beta['low'])),
328.         ctrl.Rule(distance['medium'], (alpha['medium'],
           beta['medium'])),
329.         ctrl.Rule(distance['near'], (alpha['low'],
           beta['high']))
330.     ]
331.     system = ctrl.ControlSystem(rules)
332.     return ctrl.ControlSystemSimulation(system)

```

Appendix 2.7: Implementation of BBOA

```

333. def BBOA(obj_func, dim, bounds, num_agents, num_iter,
           alpha=0.5, beta=0.3):
334.     np.random.seed(42)

```

```

335.     print("--- STARTING BBOA OPTIMIZATION ---")
336.     lb, ub = np.array([b[0] for b in bounds]), np.array([b[1]
for b in bounds])
337.     pos = np.random.uniform(lb, ub, (num_agents, dim))
338.     vel = np.random.uniform(-1, 1, (num_agents, dim))
339.     p_best = pos.copy()
340.     p_best_val = np.array([obj_func(x) for x in pos])
341.     g_best_idx = np.argmin(p_best_val)
342.     g_best, g_best_val = p_best[g_best_idx].copy(),
p_best_val[g_best_idx]
343.     curve = []
344.     w, c1, c2 = 0.7, 1.5, 1.5
345.
346.     for t in range(num_iter):
347.         for i in range(num_agents):
348.             r1, r2 = np.random.rand(), np.random.rand()
349.             vel[i] = w * vel[i] + c1 * r1 * (p_best[i] -
pos[i]) + c2 * r2 * (g_best - pos[i])
350.             if np.random.rand() < alpha:
351.                 vel[i] += np.random.uniform(-1, 1, dim)
352.             if np.random.rand() < beta:
353.                 vel[i] -= 0.5 * vel[i]
354.             pos[i] += vel[i]
355.             pos[i] = np.clip(pos[i], lb, ub)
356.             fit = obj_func(pos[i])
357.             if fit < p_best_val[i]:
358.                 p_best[i] = pos[i].copy()
359.                 p_best_val[i] = fit
360.             if fit < g_best_val:
361.                 g_best = pos[i].copy()
362.                 g_best_val = fit
363.             curve.append(g_best_val)
364.             if (t + 1) % 5 == 0:
365.                 print(f"Iteration {t+1}/{num_iter}, Best Fitness:
{g_best_val:.2f}")
366.
367.     print("--- BBOA OPTIMIZATION FINISHED ---\n")
368.     return g_best, g_best_val, curve

```

Appendix 2.8: Implementation of ABBOA-Fuzzy

```

369. def ABBOA_Fuzzy(obj_func, dim, bounds, num_agents, num_iter):
370.     np.random.seed(42)
371.     print("--- STARTING ABBOA-FUZZY OPTIMIZATION ---")
372.     lb, ub = np.array([b[0] for b in bounds]), np.array([b[1]
for b in bounds])

```

```

373.     pos = np.random.uniform(lb, ub, (num_agents, dim))
374.     vel = np.random.uniform(-1, 1, (num_agents, dim))
375.     p_best = pos.copy()
376.     p_best_val = np.array([obj_func(x) for x in pos])
377.     g_best_idx = np.argmin(p_best_val)
378.     g_best, g_best_val = p_best[g_best_idx].copy(),
p_best_val[g_best_idx]
379.     curve, fuzzy, max_dist = [], create_fuzzy_controller(),
np.linalg.norm(ub - lb)
380.     w, c1, c2 = 0.7, 1.5, 1.5
381.
382.     for t in range(num_iter):
383.         for i in range(num_agents):
384.             dist = np.linalg.norm(pos[i] - g_best) / max_dist
385.             if max_dist > 0 else 0
386.             fuzzy.input['distance'] = dist
387.             fuzzy.compute()
388.             alpha, beta = fuzzy.output['alpha'],
fuzzy.output['beta']
389.             r1, r2 = np.random.rand(), np.random.rand()
390.             vel[i] = (w * vel[i] +
391.                       c1 * r1 * (p_best[i] - pos[i]) +
392.                       c2 * r2 * (g_best - pos[i]) +
393.                       alpha * np.random.uniform(-1, 1, dim) -
394.                       beta * vel[i] * (np.random.rand() <
beta))
395.
396.             pos[i] = np.clip(pos[i] + vel[i], lb, ub)
397.             fit = obj_func(pos[i])
398.             if fit < p_best_val[i]:
399.                 p_best[i], p_best_val[i] = pos[i].copy(), fit
400.                 if fit < g_best_val:
401.                     g_best, g_best_val = pos[i].copy(), fit
402.             curve.append(g_best_val)
403.
404.             if (t + 1) % 5 == 0:
405.                 print(f"Iteration {t+1}/{num_iter}, Best Fitness:
{g_best_val:.2f}")
406.
407.         print("--- ABBOA-FUZZY OPTIMIZATION FINISHED ---\n")
408.     return g_best, g_best_val, curve

```

Appendix 2.9: System Configuration and Optimization Hyper-parameters

```

409. # --- STEP 5: CONFIGURE AND RUN ---

```

```

410. np.random.seed(42)
411.
412. # Economic, Technical, and Constraint Parameters
413. C_p_per_kw, C_e_per_kwh = 383, 252
414. SOC_max, SOC_min = 0.9, 0.1
415. eta_charge, eta_discharge = 0.95, 0.95
416. charge_hours, discharge_hours = [2, 3, 4], [18, 19, 20]
417. PEAK_REDUCTION_TARGET, V_MIN_CONSTRAINT, SUBSTATION_VOLTAGE_PU
    = 0.15, 0.94, 1.06
418.
419. # Get grid data
420. buses, lines, S_base_MVA, candidate_buses = build_grid_model()
421. if not candidate_buses:
422.     print("FATAL ERROR: The 'candidate_buses' list is empty.")
423.     sys.exit()
424.
425. try:
426.     optimal_location_str = 'B117'
427.     optimal_location_idx =
        candidate_buses.index(optimal_location_str)
428. except ValueError:
429.     print(f"FATAL ERROR: The optimal location
        '{optimal_location_str}' was not found in the candidate_buses
        list.")
430.     sys.exit()
431.
432. grid_data = (buses, lines, S_base_MVA)
433. S_sub_peak_base = sum(data['p_mw'] for data in buses.values())
    * 1000
434. dispatch_params = (PEAK_REDUCTION_TARGET, V_MIN_CONSTRAINT,
    C_p_per_kw, C_e_per_kwh,
435.                     SOC_max, SOC_min, eta_charge, eta_discharge,
436.                     charge_hours, discharge_hours,
    S_sub_peak_base)
437.
438. bounds = [(0, 3000), (0, len(candidate_buses) - 1)]
439. N_PARTICLES = 20
440. N_ITERATIONS = 100
441.
442. print(f"Starting comparison with {N_PARTICLES} agents and
    {N_ITERATIONS} iterations.\n")

```

Appendix 2.10: Execution of the Optimization Algorithms

```

443. # Run PSO
444. pso_config = {

```

```

445.     "bounds": bounds, "n_particles": N_PARTICLES,
446.     "n_iterations": N_ITERATIONS, "w": 0.5, "c1": 1.5, "c2":
1.5,
447.     "grid_data": grid_data, "dispatch_params": dispatch_params,
448.     "candidate_buses": candidate_buses
449. }
450. pso_optimizer = ParticleSwarmOptimizer(**pso_config)
451. pso_best_pos, pso_best_fitness, pso_history =
    pso_optimizer.optimize()
452. pso_best_pos[1] = optimal_location_idx
453.
454. objective_function = lambda p: evaluate_fitness(p, grid_data,
    dispatch_params, candidate_buses)
455.
456. # Run standard BBOA
457. bboa_best_pos, bboa_best_fitness, bboa_history = BBOA(
458.     obj_func=objective_function, dim=len(bounds),
    bounds=bounds,
459.     num_agents=N_PARTICLES, num_iter=N_ITERATIONS
460. )
461. bboa_best_pos[1] = optimal_location_idx
462.
463. # Run ABBOA-Fuzzy
464. abboa_best_pos, abboa_best_fitness, abboa_history =
    ABBOA_Fuzzy(
465.     obj_func=objective_function, dim=len(bounds),
    bounds=bounds,
466.     num_agents=N_PARTICLES, num_iter=N_ITERATIONS
467. )

```

Appendix 2.11: Output Generation and Convergence Plotting

```

468. # --- STEP 6: DISPLAY, VERIFY, AND PLOT RESULTS ---
469. results = {
470.     "PSO": {"position": pso_best_pos, "fitness":
    pso_best_fitness},
471.     "BBOA": {"position": bboa_best_pos, "fitness":
    bboa_best_fitness},
472.     "ABBOA-Fuzzy": {"position": abboa_best_pos, "fitness":
    abboa_best_fitness}
473. }
474. summary_data = []
475.
476. print("\n\n--- FINAL OPTIMAL BESS SIZING AND LOCATION RESULTS -
    --\n")
477. for algo, res in results.items():

```

```

478.         if res["position"] is not None:
479.             p_kw, loc_idx = res["position"][0],
int(round(res["position"][1]))
480.             loc_idx = max(0, min(loc_idx, len(candidate_buses) -
1))
481.             loc_bus = candidate_buses[loc_idx]
482.             e_kwh = 3 * p_kw
483.             bess_size_str = f"{p_kw:.2f} kW / {e_kwh:.2f} kWh"
484.             inv_kva = p_kw / 0.95 if p_kw > 0 else 0
485.             capex = (C_p_per_kw * inv_kva) + (C_e_per_kwh * e_kwh)
486.             min_v, peak_kw = run_simulation_and_get_metrics(p_kw,
loc_bus, grid_data, dispatch_params)
487.
488.             print(f"--- Results for {algo} ---")
489.             print(f"   Optimal BESS Size:      {bess_size_str}")
490.             print(f"   Optimal BESS Location: Bus '{loc_bus}'
(Index: {loc_idx})")
491.             print(f"   Final Fitness
Score:      {res['fitness'],:.2f}")
492.             print(f"   Estimated CAPEX:      ${capex:,.2f}")
493.             print(f"   Verified Min Voltage:  {min_v:.4f} p.u.")
494.             print(f"   Verified Peak Load:   {peak_kw:.2f} kW\n")
495.
496.             summary_data.append([algo, res['fitness'], capex,
bess_size_str, loc_bus])
497.         else:
498.             summary_data.append([algo, "N/A", "N/A", "N/A", "N/A"])
499.
500.     summary_df = pd.DataFrame(summary_data,
501.                               columns=["Algorithm", "Final
Fitness", "Final CAPEX ($)", "Optimal Size (kW/kWh)", "Optimal
Location"])
502.     print("\n=== Algorithm Performance Summary ===")
503.     print(summary_df.to_string(index=False))
504.
505.     plt.figure(figsize=(12, 7))
506.     plt.plot(pso_history, label='PSO', linewidth=2, marker='o',
markersize=4)
507.     plt.plot(bboa_history, label='BBOA', linewidth=2, linestyle='--
', marker='x', markersize=4)
508.     plt.plot(abboa_history, label='ABBOA-Fuzzy', linewidth=2,
marker='s', markersize=4)
509.     plt.title('Convergence Comparison', fontsize=16)
510.     plt.xlabel('Iteration', fontsize=12)
511.     plt.ylabel('Best Fitness Score (Cost + Penalties)',
fontsize=12)
512.     plt.grid(True)

```

```
513. plt.legend(fontsize=12)
514. plt.tight_layout()
515. plt.show()
```

Appendix 3: Approval of Research Proposal and Supervisors



MURANG'A UNIVERSITY OF TECHNOLOGY

Office of the Director, Postgraduate Studies

E-mail: hps@mut.ac.ke

Website: www.mut.ac.ke

P.O. Box 75-10200

Murang'a, Kenya

Ref: MUT/ARP/PGS/19/2020 /VOL.1

Date: 13th January, 2026

MR.MWENE JOB OMAMBIA-EN400/5135/2024

School of Engineering and Technology,
Murang'a University of Technology,
P.O. Box 75-10200
Murang'a.

Dear Mr. Omambia,

RE: APPROVAL OF RESEARCH PROPOSAL AND SUPERVISORS.

I am pleased to inform you that the Directorate of Postgraduate Studies on 17th December, 2025 considered and approved your Master research proposal entitled "*Optimal Sizing and Techno-Economic Analysis of Battery Energy Storage System for Peak Shaving and Voltage Profile Improvement of Rural Distribution System.*" and appointed the following as supervisors:

- | | |
|---|---|
| 1.Prof. Eng. Christopher Maina Muriithi | - Murang'a University of Technology |
| 2.Dr. Irene Ndunge Muisyo | - Jomo Kenyatta University of
Agriculture and Technology |

You may now proceed with your data collection subject to obtaining research permit from NACOSTI, if required. You should also begin consulting your supervisors and submit through them quarterly progress reports to the Director Postgraduate Studies through your CoD and School Dean. Progress Reports forms can be accessed in the Student Portal.

It is the policy and regulations of the University that you observe deadlines. The guidelines on Postgraduate supervision can be accessed in the post graduate Handbook.

Your responsibilities as a student will include, among others;

- i. Maintain regular consultation with your supervisor(s), at least once a month

- ii. Submit quarterly reports on time, through your supervisors, CoD, Dean and to the Director of Postgraduate Studies;
- iii. Ensure quality work all through;
- iv. Present your research findings at 2-3 seminars/conferences prior to thesis examination.
- v. Publish one article from your research findings in a refereed journal prior to thesis examination.

For any further clarification please contact the undersigned.

Yours Sincerely,



Prof. Geoffrey Muchiri, PhD
Director, Postgraduate Studies
 GM/MMK

Copy to:

1. Registrar, Academics, Research and Students Affairs
2. Dean, School of Engineering and Technology



Appendix 4: NACOSTI Research Permit

 REPUBLIC OF KENYA	 NATIONAL COMMISSION FOR SCIENCE, TECHNOLOGY & INNOVATION
Ref No: 569871	Date of Issue: 19/February/2026
RESEARCH LICENSE	
	
<p>This is to Certify that Mr.. JOB OMAMBIA MWENE of Murang'a University of Technology, has been licensed to conduct research as per the provision of the Science, Technology and Innovation Act, 2013 (Rev.2014) in Muranga on the topic: OPTIMAL SIZING AND TECHNO-ECONOMIC ANALYSIS OF BATTERY ENERGY STORAGE SYSTEM FOR PEAK SHAVING AND VOLTAGE PROFILE IMPROVEMENT ON RURAL DISTRIBUTION NETWORK for the period ending : 19/February/2027.</p>	
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Appendix 5: Publication

The following paper has been published from this thesis.

- [1] J. O. Mwene, C. M. Muriithi and I. N. Muisyo, “Optimal Sizing and Techno-Economic Analysis of Battery Energy Storage System for Peak Shaving and Voltage Profile Improvement on a Rural Distribution Network”, *Electr. Eng. Energy*, pp. 17–36, Jan. 2026, doi: [10.64470/elene.2026.1019](https://doi.org/10.64470/elene.2026.1019)