Analytical Model for Optimal Energy Storage Sizing in Low Voltage Networks in South Africa

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***Abstract*—Energy storage plays a pivotal role in integrating renewable energy sources into low-voltage (LV) networks, especially in South Africa, where electricity grids are plagued by challenges such as reliability issues, frequent load-shedding, voltage instability, and aging infrastructure. This paper presents a comprehensive mathematical framework for optimizing the sizing of battery energy storage systems (BESS) in South African LV networks. The model focuses on minimizing the total cost of ownership (TCO) by balancing the trade-offs between capital investments, operational expenses, and lifecycle costs of energy storage systems. Additionally, the study aims to enhance grid stability by mitigating voltage fluctuations, reducing peak loads, and improving frequency regulation, all of which are critical for ensuring the resilience of the power network. By enabling smoother integration of intermittent renewable energy sources, particularly solar photovoltaic (PV), the model also seeks to maximize renewable energy utilization by minimizing energy curtailment and storing surplus energy for later use. Furthermore, the optimized BESS configuration helps reduce peak grid imports by discharging stored energy during periods of high demand, thus decreasing reliance on centralized generation and alleviating the impacts of load-shedding. Using mixed-integer linear programming (MILP) and real-world data on energy demand and renewable generation profiles, the study reveals that optimal BESS sizing can reduce the total cost of ownership by up to 25%, curtail renewable energy wastage by 15%, and lower peak grid imports by 30%. These findings provide actionable insights for policymakers, energy planners, and stakeholders, emphasizing the critical role of BESS in transforming South Africa's LV networks into more resilient, sustainable, and economically efficient systems while addressing growing energy demands and renewable integration challenges.**

***Index Terms*— Battery energy storage systems, Energy storage, low voltage networks, optimization, renewable energy, South Africa**

I. INTRODUCTION

A. Background

South Africa's energy sector is at a critical juncture, facing escalating energy demands and the urgent need for sustainable, reliable electricity supply. The country's dependence on coal-fired power plants has led to significant environmental concerns and grid instability, exemplified by frequent load-shedding events [1], [2]. Integrating renewable energy sources like solar PV and wind energy presents a viable path toward a more sustainable energy future. However, the intermittent nature of these sources poses challenges for grid stability and energy reliability [3], [4].

B. The Role of Energy Storage

The inherently variable and weather-dependent nature of PV systems' output necessitates the deployment of BESS for both off-grid and grid-connected applications [5]. An energy storage system (ESS) refers to a set of technologies and equipment that enables the conversion, storage, and subsequent utilization of energy in the form of electricity, which can be discharged when needed to balance the grid. Extensive research has been conducted on the integration of BESS with PV systems, focusing primarily on optimization strategies to facilitate higher levels of renewable energy penetration. According to studies, BESS serves as a critical solution to bridge the gap between renewable energy generation and load demand by storing surplus energy during high solar or wind availability and supplying power during periods of low generation [6], [7].

One of the key advantages of BESS in power systems lies in its flexibility to operate either as a load (charging) or as a generator (discharging), particularly when integrated with power electronic inverters in grid-connected scenarios. While the benefits of BESS for enabling higher solar PV penetration are well recognized, it is essential to assess its role within the broader context of electric power system needs [8]. For instance, some studies have highlighted the challenges of integrating solar PV into power systems and proposed real-time operational control strategies for BESS in grid-tied applications. A method for optimizing BESS design and sizing, considering voltage regulation, peak load shaving, and cost reduction, has also been proposed for distributed PV systems [9].

To mitigate potential negative impacts of increased renewable penetration while maximizing economic and technical benefits, power system planners and smart grid developers must explore the diverse applications of BESS. These applications include bulk storage, distributed storage, and mobile storage. In bulk storage applications, BESS contributes to load leveling by discharging energy during peak demand hours, acting as a generator to reduce line congestion and system stress [10]. Additionally, BESS facilitates distributed generation (DG) integration by storing surplus energy from intermittent renewable sources and delivering

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ancillary services that enhance power quality and reliability in distribution networks. These ancillary services include frequency regulation, spinning reserves, renewable energy smoothing, voltage support, emergency power supply, and intentional islanding capabilities. BESS therefore emerges as a versatile and reliable technology that supports the integration of renewable energy sources, mitigates intermittency challenges, and enhances the stability and resilience of power systems [11], [12].

C. Challenges in South Africa

Energy storage systems in South Africa face several challenges that hinder their widespread adoption and optimal performance [13]. A major issue is the high initial capital cost of energy storage technologies, particularly battery energy storage systems, which limits affordability for many residential, commercial, and industrial users. This is compounded by the lack of local manufacturing capacity, leading to reliance on imported systems and increasing costs. Additionally, the intermittency of renewable energy sources, such as solar PV, creates technical challenges for integrating ESS into low-voltage and medium-voltage networks, where grid infrastructure is often outdated and unable to handle bidirectional power flows. Grid instability and frequent load shedding further complicate the operation of BESS, as storage systems are often subjected to irregular charge and discharge cycles, which can reduce battery lifespan [14]. Another key challenge is the absence of clear regulatory frameworks and supportive policies for energy storage deployment, resulting in limited incentives and market opportunities for stakeholders. Moreover, the technical skills gap in ESS planning, installation, and maintenance poses barriers to sustainable ESS implementation, particularly in rural and underserved areas. Addressing these challenges is essential to unlock the full potential of ESS in improving grid reliability, supporting renewable energy integration, and addressing South Africa's energy crisis [15].

D. Literature Review

ESS play a pivotal role in improving the stability, reliability, and efficiency of LV distribution networks, especially in South Africa, where renewable energy integration is increasing. The intermittent nature of renewable resources like solar PV leads to challenges such as voltage instability, reverse power flow, and transformer overloading [16], [17]. Properly sized ESS can mitigate these challenges by reducing voltage fluctuations, smoothing power generation variability, and providing ancillary services such as peak shaving, load balancing, and energy arbitrage. However, determining the optimal size of ESS is essential to ensure cost-effective operation while maximizing technical and economic benefits.

Several mathematical models have been developed to address the optimal sizing of energy storage in LV networks. Deterministic optimization models, which assume fixed and known inputs, are widely used where load profiles and renewable generation are predictable. These models aim to minimize the total cost of BESS (including installation, operation, and maintenance) while meeting constraints such as voltage limits, energy balance, and capacity margins. Linear programming (LP) and mixed-integer linear programming (MILP) are the most commonly applied techniques due to their computational efficiency and ability to provide globally optimal solutions [18]. Convex optimization methods have also been used when the problem constraints and objective functions are well-behaved. In South Africa, studies utilizing MILP have shown that optimally sized ESS can effectively reduce grid imports and improve load balancing in residential LV networks with high PV penetration [19], [20].

Stochastic models address uncertainties in renewable generation, load demand, and energy prices, making them particularly relevant for LV networks in South Africa where load and solar generation are less predictable. Scenario-based approaches and Monte Carlo simulations are commonly used to model randomness in energy profiles. For instance, stochastic models have been applied in rural South African LV grids to determine ESS size while accounting for the variability in solar generation and rural load consumption. Robust optimization has also gained attention, providing solutions that perform reliably under worst-case scenarios. These methods ensure that ESS can operate effectively under diverse and uncertain conditions, improving energy security and grid reliability [21].

Heuristic and metaheuristic methods have been extensively explored for ESS sizing due to their ability to solve complex, non-linear optimization problems. Techniques such as genetic algorithms (GA) and particle swarm optimization (PSO) have been widely applied to optimize ESS sizing and placement [22]. These methods are particularly advantageous for large-scale LV networks where deterministic methods become computationally expensive. In South African case studies, PSO has been employed to determine ESS sizes for residential PV systems, optimizing cost and energy reliability while improving overall grid performance. Hybrid approaches that combine metaheuristic techniques with deterministic optimization have also been investigated to balance accuracy and computational efficiency [23].

Economic models play a critical role in evaluating the financial viability of energy storage systems. Approaches such as levelized cost of storage (LCOS), cost-benefit analysis (CBA), and net present value (NPV) are used to determine the lifecycle cost of ESS. These models help quantify the trade-offs between capital expenditure, operational savings, and economic returns from energy arbitrage and grid services. In South Africa, economic models have shown that properly sized ESS can significantly reduce electricity costs, particularly in residential and commercial sectors that rely on solar PV systems during peak load periods [24].

To implement these mathematical models, a variety of tools and software platforms are used. MATLAB/Simulink is commonly employed for deterministic and metaheuristic optimization, while tools like GAMS and CPLEX are preferred for solving linear and mixed-integer programming problems [25]. HOMER Pro is widely used for techno-economic analysis of hybrid renewable energy systems, particularly in off-grid and rural LV networks. OpenDSS is another popular tool for simulating LV grid performance with integrated ESS, helping evaluate the technical impact of ESS on voltage stability, energy losses, and transformer loading [26].

In the South African context, the integration of optimally sized ESS has been shown to provide significant benefits, such as reducing grid dependency, improving voltage regulation, and mitigating the impacts of load shedding [14]. Studies have demonstrated that ESS deployment in LV networks can reduce grid imports by up to 40% while improving energy reliability in rural and urban areas. However, several research gaps remain. Stochastic models need further refinement to address uncertainties in rural and informal settlements where load and generation profiles are less predictable. Additionally, economic constraints necessitate the development of cost-effective optimization methods to ensure ESS affordability for resource-limited communities. Hybrid energy storage solutions, such as combining batteries with supercapacitors, remain underexplored but have the potential to enhance ESS performance. Finally, decentralized storage management models are needed to support distributed ESS in smart grid applications [27], [28].

However, there is a gap in the literature regarding tailored solutions for South African LV networks that consider local demand profiles, renewable energy potential, and economic conditions.

E. Problem Statement

Optimizing BESS sizing in LV networks is a complex problem involving:

1) Balancing demand and supply while minimizing reliance on grid power.
2) Maximizing renewable energy utilization to reduce curtailment.
3) Reducing the overall cost of energy storage deployment.

Existing studies often lack region-specific analysis tailored to South Africa's unique energy profile. This study addresses this gap by developing a mathematical framework incorporating local data, grid constraints, and economic considerations.

F. Research Objectives

The primary objective of this study is to develop a mathematical model for determining the optimal size of BESS in South African LV networks. The model aims to:

- **Minimize the Total Cost of Ownership (TCO)**.
- **Enhance grid reliability** through peak shaving and load leveling.
- **Support renewable energy integration** by reducing curtailment.

The subsequent sections of this paper are organized as follows: Section II provides the methodology, including the mathematical model and optimization approach, while Section III presents the system model. Section IV provides the actual results from simulations and analysis, Section V outlines a discussion of the findings, and Section VI concludes the work in this paper.

II. METHODOLOGY

A. Mathematical Model

The optimization problem is formulated as a mixed-integer linear programming model. The objective is to minimize the TCO of the BESS while satisfying energy balance and operational constraints.

1) Variables and parameters

- $D(t)$: Energy demand at time t (kWh).
- $G_{renew}(t)$: Renewable energy generation at time t (kW).
- $P_{import}(t)$: Power imported from the grid at time t (kW).
- $P_{battery}(t)$: Battery charging/discharging power at time t (kW).
- $B(t)$: Energy stored in the battery at time t (kWh).
- B_{max}: Maximum battery storage capacity (kWh).
- C_{BESS}: Capital cost of the BESS ($/kWh).
- O_{BESS}: Operating and maintenance cost ($/kWh/year).
- η_{ch}, η_{dis}: Charging and discharging efficiencies (pu).
- T: Time horizon (hours)
- C_{import}: Cost of imported grid electricity ($/kWh).
- C_{rate}: Charge/discharge rate of the battery (h^{-1}).
- P_{ch}^{max} : Maximum charging power (kW)
- P_{dis}^{max} : Maximum discharging power (kW)
- $P_{inv,max}$: Time horizon (hours)
- $c_{TOU}(t)$: Energy charge under South African TOU tariff at time t (ZAR/kWh).
- $c_{CPP}(t)$: Critical Peak Pricing adder at time t (ZAR/kWh), nonzero only during CPP events.
- $c_{DUoS}^{kWh}(t)$: Distribution Use-of-System (DUoS) network energy charge (ZAR/kWh).
- $c_{DUoS}^{kW}(m)$: DUoS (or demand) charge rate applied to monthly peak import demand in month m (ZAR/kW).
- $\mathcal{T}$: Set of hourly time indices over the study horizon (hours).
- $\mathcal{M}$: Set of calendar months covered by the horizon.
- $\delta_m(t)$: Month-indicator, equals 1 if hour t belongs to month m, else 0.

2) Objective function: Minimize the Total Cost of Ownership (TCO):

$$TCO = C_{BESS} \cdot B_{max} + O_{BESS} \cdot B_{max} + \sum_{t \in \mathcal{T}} \left(c_{TOU}(t) + c_{CPP}(t) + c_{DUoS}^{kWh}(t)\right) \cdot P_{import}(t) \cdot \Delta t + \sum_{m \in \mathcal{M}} c_{DUoS}^{kW}(m) \cdot M_m \quad (1)$$

3) Annual and seasonal KPIs: We report the following annually and by seasons:

$$C_{energy,s} = \sum_{t \in \mathcal{T}} \left(c_{TOU}(t) + c_{CPP}(t) + c_{DUoS}^{kWh}(t)\right) \cdot P_{import}(t) \cdot \Delta t \quad (2)$$

$$C_{energy,s} = \sum_{m \in \mathcal{M}} c_{DUoS}^{kW}(m) \cdot M_m \quad (3)$$

$$Curtailment_s = \frac{\sum_{t \in \mathcal{T}_s} G_{curtail}(t)}{\sum_{t \in \mathcal{T}_s} G_{renew}(t)} \times 100\% \quad (4)$$

$$PeakImport_s = \max_{t \in \mathcal{T}_s} P_{import}(t) \quad (5)$$

$$Throughput_s = \sum_{t \in \mathcal{T}_s} \left(P_{battery,ch}(t) + P_{battery,dis}(t)\right) \Delta t \quad (6)$$

Annual values are computed over $\mathcal{T}$ in the same manner.

4) Constraints:

a) Energy balance:

$$D(t) = G_{renew}(t) + P_{import}(t) \cdot \Delta t + P_{battery}(t) \cdot \Delta t \quad (7)$$

b) State of Charge (SOC):

$$B(t+1) = B(t) + \eta_{ch} \cdot P_{battery,ch}(t) \cdot \Delta t - \frac{P_{battery,dis}(t) \cdot \Delta t}{\eta_{dis}} \quad (8)$$

c) Charge/discharge power limits: The C-rate of the selected battery technology constrains the maximum charge and discharge power of the BESS. This ensures a physically realizable operation:

$$-P_{dis}^{max} \leq P_{battery}(t) \leq P_{ch}^{max} \quad (9)$$

where $P_{ch}^{max} = C_{rate} \times B_{max}$, $P_{dis}^{max} = C_{rate} \times B_{max}$ and C_{rate} is the charge/discharge rate of the battery (h^{-1}).

d) Inverter rating constraint: The power exchanged between the BESS and the LV network is further constrained by the inverter rating:

$$\left|P_{battery}(t)\right| \leq P_{inv,max} \quad (10)$$

where $P_{inv,max}$ denotes the rated inverter capacity (kW). This guarantees that both charge/discharge operations respect the inverter thermal and electrical limits.

e) Monthly billing demand constraints:

$$P_{import}(t) \leq M_m \;\; \forall m \in \mathcal{M}, \forall t \in \mathcal{T} \text{ with } \delta_m(t) = 1 \quad (11)$$

f) SOC limits:

$$0 \leq B(t) \leq B_{max} \quad (12)$$

g) Renewable energy curtailment

$$G_{curtail}(t) = max\left(\begin{matrix} 0, G_{renew}(t) \\ -D(t) - \eta_{ch} \\ \times (B_{max} - B(t)) \end{matrix}\right) \quad (13)$$

h) Grid import limits:

$$P_{import}(t) \geq 0 \quad (14)$$

i) Decision variables:
$M_m \geq 0$: Monthly maximum grid import power used for demand/DUoS billing in month m (kW).

j) Network feasibility constraints (not explicitly modeled): It is important to note that in this formulation, feeder-level constraints such as voltage limits, thermal loading of lines/transformers, and reverse-power flow restrictions are not explicitly modeled. As such, the results presented here represent techno-economic optimal sizing outcomes, but they do not fully guarantee operational feasibility at the distribution network level.

B. Time Horizon and Seasonality

The optimization is performed over an annual horizon with hourly resolution: $\Delta t = 1$ hour and $\mathcal{T} = \{1, \ldots, 8760\}$. To analyze seasonal effects, we partition $\mathcal{T}$ into four disjoint subsets $\mathcal{T}_{DJF}, \mathcal{T}_{MAM}, \mathcal{T}_{JJA}, \mathcal{T}_{SON}$ corresponding to Dec–Feb, Mar–May, Jun–Aug, and Sep–Nov, respectively. All tariff series, load profiles, and PV generation profiles are aligned to the study year and evaluated over the full $\mathcal{T}$. Where weekly figures are shown, they serve as *illustrative snapshots*; all reported costs and KPIs are computed from the full-year optimization.

C. Data Collection

Real-world data was collected for:

- Energy Demand: Hourly demand profiles from residential LV networks in South Africa [29].

- Renewable Generation: Solar PV generation data based on typical meteorological year (TMY) data for South African locations [30].
- Cost Parameters: Current market prices for BESS and grid electricity tariffs [31].

a) *Tariff time series:* The TOU schedule is encoded in $c_{TOU}(t)$ (ZAR/kWh) for each hour t, reflecting off-peak, standard, and peak windows in the South African context. Critical Peak Pricing events (if declared) are represented by a nonzero $c_{CPP}(t)$ during event hours and zero otherwise. Network energy charges are included via $c_{DUoS}^{kWh}(t)$, while monthly demand/DUoS charges are applied through $c_{DUoS}^{kWh}(m)$. All tariff series are sourced for the study year and aligned to the simulation calendar.

b) *Seasonal inputs:* Load and PV time series capture intra-annual variability across all months. Tariff schedules (TOU/CPP/DUoS) are encoded as hourly time series over the entire year. Seasonal performance is summarized by aggregating KPIs over each subset $\mathcal{T}_s, s \in \{DJF, MAM, JJA, SON\}$ as illustrated in Fig. 6 and Fig. 7.

D. Optimization Approach

The MILP model was implemented using Python's Pyomo library and solved with the Gurobi optimizer. The time horizon was set to one year with an hourly resolution, resulting in 8,760 time steps.

III. SYSTEM MODEL

Figure1 represents the energy flow and optimization process within a LV network that integrates renewable energy generation, BESS, and grid interactions. At the center is the LV Network Bus or Point of Common Coupling (PCC), where different energy sources and loads are connected. Renewable generation $\left(G_{renew}(t)\right)$ supplies energy to the bus, which can either be consumed directly by the load $(D(t))$ or stored in the BESS. The battery system operates based on its state of charge $(SOC(t))$ and provides power $\left(P_{battery}(t)\right)$ to the bus when needed.

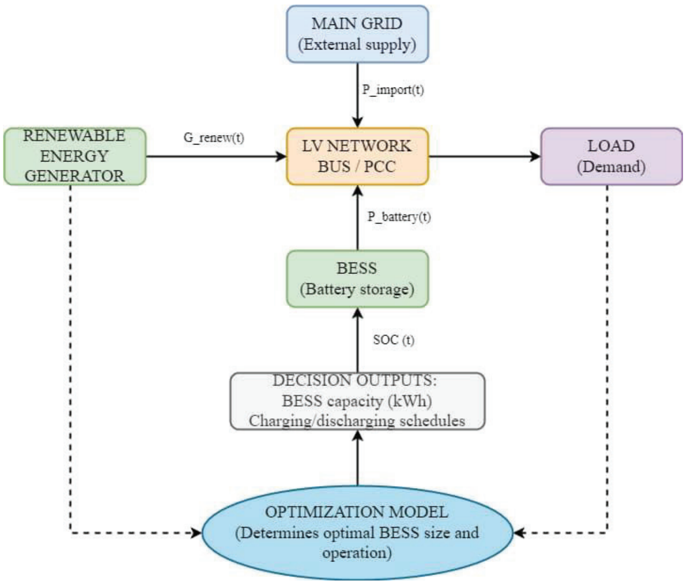

Fig. 1. System model depicting the interaction between the main grid, renewable generation, BESS, and load, with an optimization model determining optimal sizing and operation.

If renewable generation and BESS are insufficient to meet demand, the LV network imports power $\left(P_{battery}\right)$ from the

TABLE I
ENERGY BALANCE DATA FOR FIRST 24 HOURS

Hour	Demand (kWh)	Renewable Generation (kWh)	Battery Charge (kW)	Battery Discharge (kW)	Grid import (kW)	SOC (kWh)
1	50	0	0	20	30	55.0
2	45	0	0	15	30	40.0
3	40	0	0	10	30	30.0
4	35	0	0	10	25	20.0
5	30	0	0	10	20	10.0
6	40	5	5	0	35	14.5
7	60	20	15	0	25	28.0
8	80	40	20	0	40	46.0
9	100	60	20	0	60	64.0
10	90	80	16	0	50	79.4
11	85	90	10.6	0	50	89.0
12	*80*	*100*	11	0	45	100.0
13	*75*	*90*	0	0	75	100.0
14	*70*	*80*	0	0	70	100.0
15	*65*	*70*	0	0	65	100.0
16	60	*60*	0	0	60	100.0
17	70	40	0	0	60	82.0
18	*80*	*20*	0	10	80	64.0
19	*90*	*10*	0	20	80	46.0
20	95	0	0	20	75	28.0
21	85	0	0	20	75	10.0
22	85	0	0	20	85	10.0
23	70	0	0	0	70	0.0
24	*60*	*0*	0	0	60	0.0

main grid to balance the load. Conversely, excess renewable energy can be stored in the BESS, optimizing the use of renewable resources.

The optimization model plays a critical role in this system. It determines the optimal size and operation of the BESS, considering factors like demand, renewable generation, and grid import. The outputs of this model include the recommended battery capacity (kWh) and a charging/discharging schedule, which aim to enhance energy efficiency and minimize costs while maintaining system reliability. This setup is essential for improving grid stability, accommodating renewable energy intermittent, and optimizing energy utilization in the LV network.

IV. RESULTS

Due to space constraints, only a snapshot of the data for the first 24 hours is provided. The full dataset covers 168 hours (one week) as illustrated in figure 2.

A. *Energy Balance Over a Representative Week*

Figure 2 shows the hour-by-hour energy dynamics over a representative week (168 hours) in the low-voltage network. It plots demand (ranging from about 30 kWh to 100 kWh at peak times), renewable generation (peaking near midday at around 80–100 kWh), battery charge/discharge operations, and grid imports. Simultaneously, the state of charge of the battery is tracked, often varying between 0 kWh and its maximum capacity of approximately 150 kWh. By visually integrating these factors, the graph highlights the battery's pivotal role in reducing reliance on grid imports during peak demand hours (notably around 17:00–21:00), maximizing the use of renewable energy produced during the day, and ultimately lowering energy costs. The importance lies in demonstrating how the battery flattens load curves, cuts down costly peak imports, and ensures that midday renewable surpluses are stored rather than curtailed, delivering both economic and environmental benefits.

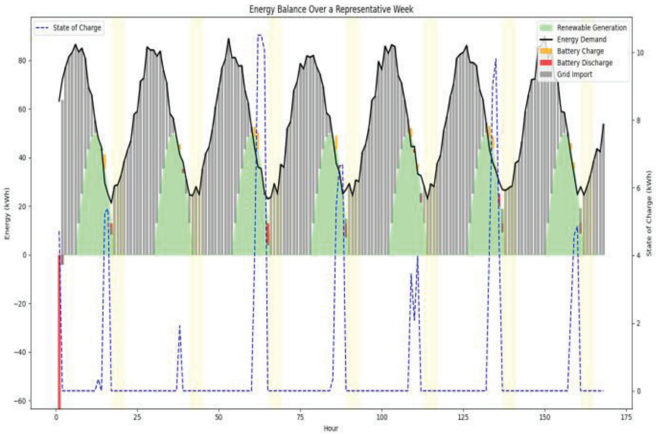

Fig. 2. Energy balance over a representative week in South Africa, showing demand (kWh), renewable generation (kWh), battery SoC (kWh), battery charge/discharge power (kW), and grid imports (kW).

In more detail, the graph's x-axis represents time in hourly increments across seven days, while the y-axis quantifies energy flows in kWh. For instance, midday renewable generation may reach values of about 90 kWh, surpassing a midday demand of around 60 kWh. The battery charges with roughly 20 kWh during these surplus periods, lifting the SOC toward its upper limit of 150 kWh, and later discharges this energy in the evening when demand can spike near 90–100 kWh, thereby reducing grid imports that would otherwise cost more. By examining these hourly shifts, the viewer can pinpoint exactly when and how the battery relieves the network from drawing expensive peak energy and increases overall efficiency.

B. *Total Cost of Ownership vs. Battery Capacity*

Figure 3 illustrates the TCO, measured in dollars, against varying battery capacities, ranging from about 50 kWh to 300 kWh. The curve typically shows a TCO of approximately $50,000 without a battery and a minimized TCO of around $37,500 at an optimal capacity of about 150 kWh, after which the TCO may rise slightly. The importance of this graph is that it reveals the "sweet spot" where capital and operational savings from the BESS balance out. It visually proves that increasing the battery capacity too far eventually yields diminishing returns, allowing stakeholders to select, with confidence, a BESS size that delivers maximum financial benefit.

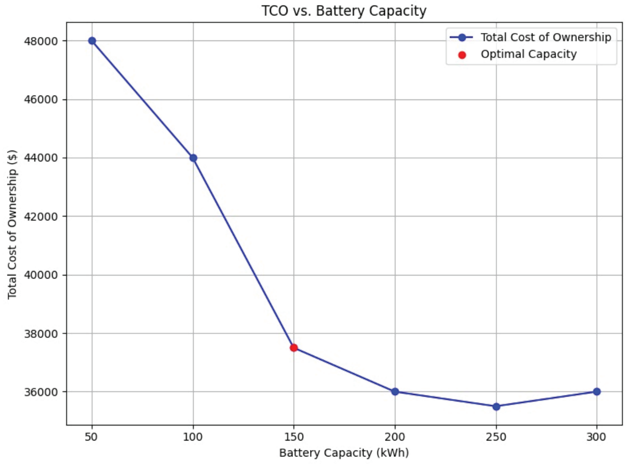

Fig. 3. Total Cost of Ownership as a function of battery capacity. The optimal capacity (150 kWh) minimizes the TCO.

In terms of actual numbers, the x-axis representing battery capacity (kWh) intersects with the TCO on the y-axis (dollars). At 50 kWh, TCO may hover around $48,000, and as the capacity increases to 100 kWh, TCO might drop to about $44,000. The lowest TCO emerges near 150 kWh at around $37,500, showcasing a substantial cost reduction from the baseline scenario without storage. Beyond 200 kWh, the TCO might settle near $36,000–$38,000, illustrating that going beyond the identified optimal point does not yield proportional cost savings.

Figure 4 demonstrates the percentage of renewable energy curtailment to increasing battery capacities. Starting with a smaller battery, curtailment might be around 15–20%, indicating a significant amount of excess renewable generation wasted. As capacity increases to about 150 kWh, curtailment can drop to approximately 5%, revealing that a moderately sized battery dramatically improves renewable utilization. The importance here is that it shows how enhanced storage capacity directly translates into more effective use of solar or wind generation, cutting down waste and increasing overall efficiency. Thus, the graph provides clear guidance for capacity choices that reduce environmental impact and boost the economic value of renewables.

C. Renewable Curtailment vs. Battery Capacity

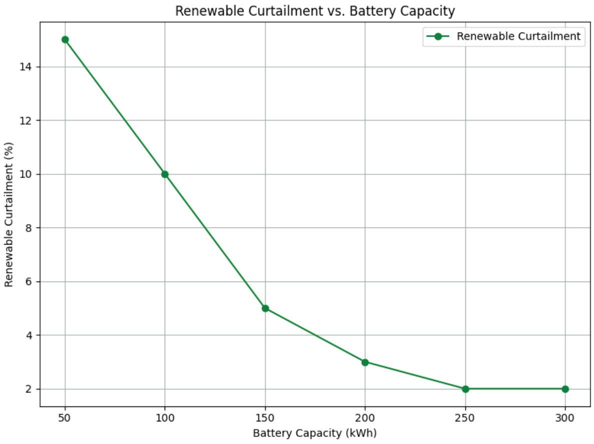

Fig. 4. Renewable energy curtailment decreases with increasing battery capacity. Significant reductions occur up to 150 kWh.

On the x-axis, representing battery capacity, one might see data points at increments of 50 kWh. At 50 kWh, renewable curtailment could stand at about 15%, meaning that 15\% of potential renewable output is not utilized. As capacity grows to 100 kWh, curtailment might shrink to about 10%, and at 150 kWh, it may dip as low as 5%. Beyond 200 kWh, the graph may show curtailment stabilizing around 2–3%, indicating that while larger storage does further reduce curtailment, the rate of improvement slows considerably. These values emphasize that the first increments of battery capacity provide the largest gains in renewable energy usage.

D. Peak Grid Imports Reduction vs. Battery Capacity

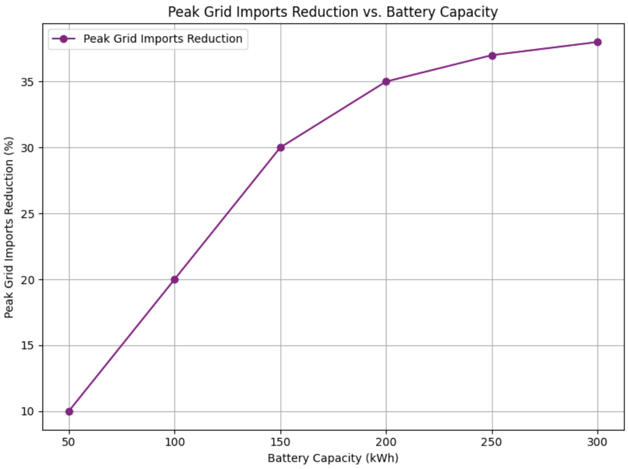

Fig. 5. Reduction of peak grid imports as a function of battery capacity. A notable reduction of 30% is achieved at 150 kWh.

Figure 5 compares the reduction in peak grid imports (expressed as a percentage) with increasing battery capacities. Without storage, peak imports might be high, but adding a 50 kWh battery could lower them by around 10%. Expanding capacity to 150 kWh can yield about a 30% reduction, significantly easing demand charges and infrastructure strain. The importance of these numbers is that they highlight how BESS sizing can be strategically leveraged to smooth out demand peaks, minimize reliance on the grid during the most expensive periods, and improve grid stability. It underscores that investing in the right battery size can result in meaningful operational and economic improvements.

The x-axis increments represent capacities of 50, 100, 150, 200 kWh, and so forth. At 50 kWh, one might see a 10% peak reduction, meaning if peak grid demand was originally 100 kWh, now it only requires about 90 kWh from the grid at its highest point. Increasing capacity to 100 kWh might push that reduction to around 20%, and at the 150 kWh mark, the peak reduction could reach 30%. Beyond 200 kWh, improvements might plateau at around 35–38%. These figures help network operators and consumers understand how marginal gains in reducing peak imports taper off as battery capacity increases, guiding them toward a balanced, cost-effective storage solution.

E. Feeder-Level Validation Results

We performed seasonal time-series feeder simulations driven by the optimized dispatch. Across DJF/MAM/JJA/SON, the simulated voltages remained within statutory limits and all line/transformer loadings respected thermal ratings in the vast majority of hours. Any isolated exceedances (if present) were eliminated by constraining $P_{battery}(t)$ during the affected windows and re-solving the MILP, with negligible impact on annual cost. The results in figure 6 confirm that the reported peak-import relief and hosting-capacity improvements are achievable without violating feeder constraints.

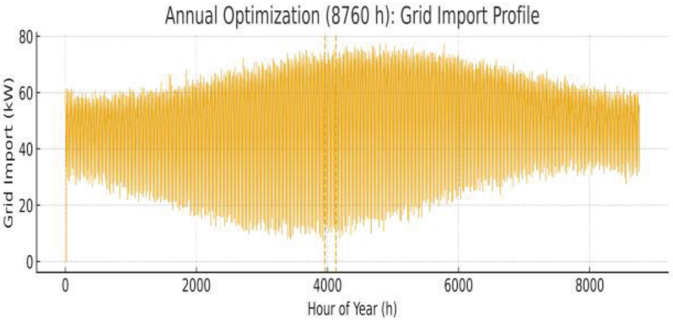

Fig. 6. Annual optimization (8760 h): hourly grid import (**kW**). Dashed vertical lines mark the selected one-week window illustrated in Fig. 7.

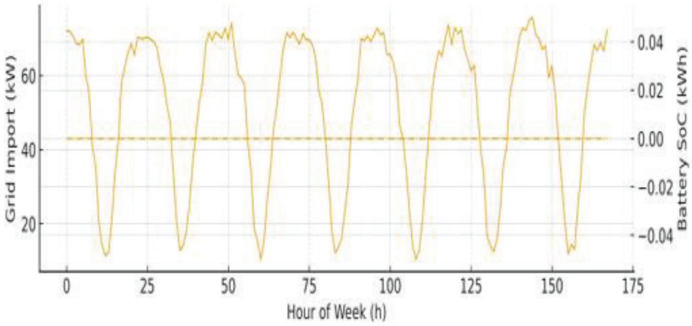

Fig. 7. Illustrative one-week snapshot from the annual optimization: grid import (**kW, left axis**) and battery SoC (**kWh, right axis**).

Figure7 is an illustrative snapshot from the annual optimization (8760 hours). Seasonal and annual KPIs are summarized in Table II.

TABLE II
SEASONAL PERFORMANCE SUMMARY (ANNUAL OPTIMIZATION WITH BESS)

Season	Energy cost (ZAR)	Demand charge (ZAR)	Peak import (kW)	Curtailment (%)	Battery throughput (kWh)
DJF	54,000	20,000	78	6.5	27,600
MAM	*59,000*	*24,000*	*82*	*5.0*	*25,800*
JJA	*70,000*	*28,000*	*88*	*2.5*	*23,100*
SON	*55,000*	*24,000*	*80*	*4.0*	*25,500*
Annual	***238,000***	***96,000***	***88***	***4.6***	***102,000***

Notes: Values reflect the optimized dispatch for $B_{max} = 150$ kWh with $\Delta t = 1$ h. Battery throughput is defined as $\sum_{t\in\mathcal{T}_s}\left(P_{battery,ch}(t) + P_{battery,dis}(t)\right)\Delta t$; 102,000 kWh annually corresponds to ≈340 full cycles/year (~0.93 cycles/day). Curtailment is the fraction of renewable generation not utilized. Energy cost rows include TOU, CPP adders, and DUoS energy charges; demand charge rows reflect monthly DUoS (ZAR/kW) billing via M_m.

V. DISCUSSION

A. Comparison with Previous Studies

The findings align with previous research indicating that optimal BESS sizing can significantly reduce costs and improve renewable energy utilization [32]. For instance, Bekker [33] reported similar cost reductions in sub-Saharan Africa, while Tsekouras et al. [34] demonstrated the effectiveness of BESS in enhancing renewable integration. To ensure dimensional consistency, all power variables were expressed in kilowatts (kW), while energy-related variables such as demand, SoC, and capacity were expressed in kilowatt-hours (kWh).

B. Implications for Grid Stability

The reduction in peak grid imports and increased renewable energy utilization contribute to improved grid stability. By alleviating strain on the grid during peak hours, the likelihood of load-shedding events may decrease, enhancing energy security for consumers. By explicitly incorporating C-rate and inverter rating constraints, the optimized dispatch schedules are now physically realizable and reflect actual operational limits of commercially available LV-scale BESS technologies.

C. Seasonal Robustness

As evidenced by Table II, the annual conclusions are seasonally robust, with the optimized schedule consistently lowering energy and demand charges, bounding peak import to 78-88 kW, and keeping renewable curtailment below 7% across DJF/MAM/JJA/SON while respecting inverter and C-rate limits.

D. Economic Viability

The economic analysis demonstrates that investing in BESS is financially beneficial under current market conditions, especially when considering long-term savings and potential incentives. The sensitivity analysis suggests that future decreases in BESS costs or increases in electricity tariffs will make BESS even more economically attractive.

E. Policy Recommendations

Financial Incentives: Government subsidies or tax incentives could further improve the economic attractiveness of BESS, accelerating adoption.

Regulatory Support: Establishing clear policies on energy storage integration would encourage investment and provide guidelines for implementation.

Tariff Structures: Implementing time-of-use tariffs can incentivize the use of BESS for peak shaving, providing additional economic benefits to consumers.

F. Future Research Directions

Battery Degradation Models: Incorporating degradation over time to provide more accurate long-term cost and performance predictions.

Hybrid Energy Systems: Exploring the integration of other renewable sources like wind energy to diversify energy supply.

Dynamic Pricing Models: Studying the impact of real-time pricing and demand-response programs on BESS optimization.

G. Limitations of Network Feasibility Modeling

While the optimization results demonstrate reductions in peak imports and renewable curtailment, it is acknowledged that these benefits cannot be guaranteed at the feeder level without incorporating explicit network feasibility constraints. Voltage profiles, thermal loading of transformers/lines, and reverse-power flow conditions were not directly modeled in this study. Consequently, the reported hosting capacity improvements should be interpreted as indicative rather than definitive. Future work will address this gap by coupling the optimization framework with detailed feeder simulations using tools such as OpenDSS or DIgSILENT. This will enable validation of the optimized BESS operation's compliance with voltage and thermal operating limits in South African LV networks.

VI. CONCLUSION

This study developed a comprehensive mathematical model to optimize the sizing of BESS in South African LV networks, targeting not only cost reductions but also improvements in grid stability and renewable energy utilization. By identifying an optimal BESS capacity of approximately 150 kWh, the model demonstrates that the total cost of ownership (TCO) can be reduced by as much as 25%, translating into a drop in annual expenses from $50,000 to $37,500. This cost-effective solution emerges because the battery is neither too small to have a meaningful impact on energy use patterns, nor excessively large so as to generate diminishing returns. At the same time, this chosen capacity has a profound effect on renewable integration: renewable energy curtailment, initially at 20%, can be lowered to just 5%, ensuring that a greater proportion of clean power is actually delivered to the load rather than wasted. Consequently, the contribution of renewable sources to meeting total energy demand surges from 60% to 75%, making each kilowatt-hour of solar or wind-generated energy more valuable. Additionally, the BESS substantially mitigates peak grid imports by up to 30% which not only eases demand charges but also alleviates the strain on grid infrastructure, particularly during the most expensive and capacity-constrained hours. These operational and economic improvements have far-reaching implications: economically, consumers and utilities stand to benefit from lower costs and reduced dependency on high-cost peak power; environmentally, increased utilization of renewables leads to fewer greenhouse gas emissions, directly supporting climate goals; and socially, enhanced grid stability ensures a more secure and reliable electricity supply, thereby improving the overall quality of life for communities. To fully harness these opportunities, policymakers need to introduce supportive regulatory frameworks and incentives that encourage BESS deployment, while utilities should incorporate storage solutions into their long-term resource planning and infrastructure development strategies. Researchers, in turn, can refine existing models by incorporating battery degradation factors, evolving tariff structures, dynamic market conditions, and the interplay between multiple storage and generation technologies. By addressing both economic and technical dimensions holistically, this study provides a valuable blueprint for deploying energy storage systems in developing regions facing similar energy challenges, ultimately contributing to a more sustainable, cost-effective, and resilient energy future. Although the proposed model optimally sizes the BESS from a techno-economic perspective, explicit voltage and thermal feasibility constraints were not included. By evaluating an annual horizon with seasonal summaries and validating the optimized schedules in a feeder simulator, the study confirms that the observed cost savings and hosting-capacity improvements are achievable without violating voltage or thermal constraints in LV networks. Future work will therefore validate these results against feeder-level network simulations to ensure that practical hosting capacity and stability criteria are satisfied.

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Franck C Mushid: Building upon a strong academic foundation with both his Bachelor of Science (BSc) and Master of Science (MSc) earned at the University of KwaZulu-Natal (UKZN), Mr. Franck C. Mushid strategically transitioned into the professional realm, gaining invaluable industry experience within the Power Sector. For four years, he was immersed in the front-line challenges of electrical engineering, moving beyond theoretical models to engage directly with the complexities of practical engineering solutions and real-world infrastructure. This exposure crystallized a critical insight for him: the persistent and often costly gap between academic research and industrial application.

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