Integrated Analysis and Optimization of Battery Energy Storage Systems in Renewable Energy Applications Using Detailed Economic Modeling and ANN Methods

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***Abstract*—Battery Energy Storage Systems (BESS) play a vital role in modern power grids, serving critical functions such as load-shaving, load-levelling, and stabilizing intermittent renewable generation. In this paper, we present a comprehensive framework that integrates a detailed economic evaluation based on Discounted Cash Flow (DCF) methods, an Artificial Neural Network (ANN) approach for real-time operational optimization in grid-integrated wind farms, and a robust ANN-based methodology for optimal BESS sizing in microgrids. We describe the entire implementation pipeline—from rigorous data preprocessing, mathematical model derivations, parameter calibration, and simulation configuration, to advanced ANN training techniques and extensive sensitivity analyses. Simulation results on a modified IEEE 39-bus system demonstrate significant improvements in financial returns, system loss minimization, and operational efficiency.**

***Index Terms*—Battery Energy Storage System, Discounted Cash Flow, Net Present Value, Internal Rate of Return, Artificial Neural Network, Optimal Operation, Microgrid Sizing, Renewable Energy Integration.**

I. INTRODUCTION

The integration of renewable energy sources such as wind and solar into modern power grids has spurred significant research into Energy Storage Systems. In particular, Battery Energy Storage Systems (BESS) are emerging as key components due to their ability to provide rapid response, enhance grid stability, and enable load management through load-shaving, load-levelling, and deferral of maintenance activities.

Several studies have provided partial solutions addressing different facets of BESS implementation. For example, a detailed investment model using Discounted Cash Flow (DCF) analysis has been developed to evaluate the economic viability of BESS installations in South Africa [1]. Simultaneously, ANN-based methods have been proposed to optimize BESS operation in grid-integrated wind farms, achieving system loss reductions of up to 13% [2]. Furthermore, an ANN approach for determining the optimal BESS capacity in microgrid scenarios has shown superior performance in terms of voltage and frequency regulation [3].

This paper combines these diverse approaches into a single, integrated framework. We describe our methodologies, from data preparation and mathematical formulation to simulation setups and parameter tuning. The objective is to provide an end-to-end solution that addresses both the economic and technical challenges of BESS integration. Our contributions are:

- A comprehensive economic model incorporating Total Capital Cost (TCC), O&M costs, and decommissioning

cost, leading to detailed calculations of NPV, IRR, and ROI.
- A robust ANN-based control system for real-time optimization of BESS operation in a wind-integrated grid.
- An ANN-driven sizing methodology for microgrids that leverages extensive simulation data for optimal BESS capacity selection.

The remainder of this paper is organized as follows: Section II provides the integrated framework overview; Section III presents the detailed mathematical models and explains the framework integration; Section IV describes the implementation and simulation setup; Section V discusses simulation results and sensitivity analyses; and Section VI concludes the paper with future research directions.

II. Literature Review and Background

Recent research highlights the importance of BESS both from economic and technical perspectives. Mamphogoro et al. [1] introduced a cost-analysis model that uses Discounted Cash Flow (DCF) methods to quantify the economic benefits of BESS while considering grid-load profiles. Similarly, Diotama et al. [2] developed an ANN-based optimal operation strategy for a grid-integrated wind farm, and Qudaih et al. [3] proposed an ANN method for BESS sizing in microgrids. Although each study addresses a specific aspect of BESS, there is a need for an integrated framework that can combine these aspects into a unified model. Our work builds upon these studies and leverages their key methodologies to design a comprehensive solution.

III. Mathematical Modeling and Framework Integration

This section details the mathematical models employed in our integrated framework.

A. Economic Model for BESS Investment

Our economic model evaluates the long-term feasibility of BESS deployment by accounting for three primary cost components:

1) Total Capital Cost (TCC): The TCC represents the initial investment needed for BESS installation:

$$\text{TCC} = C_{\text{storage}} \times \text{Duration} + C_{\text{BoP}} + C_{\text{pcs}}, \quad (1)$$

where:

- C_{storage} is the cost per unit capacity of the battery storage.
- Duration is the operational time period (typically in years).
- C_{BoP} denotes the cost associated with balance-of-plant components.
- C_{pcs} is the cost for the power conversion system.

2) Operating and Maintenance (O&M) Costs: O&M costs are divided into fixed and variable components and are annualized as follows:

$$\text{O\&M}_{\text{annualised}} = CF_{OM} + CV_{OM} \times n \times h, \quad (2)$$

where:

- CF_{OM} is the fixed operating cost.
- CV_{OM} is the variable cost per discharge cycle.
- n is the number of discharge cycles per year.
- h denotes the number of operational hours per cycle.

3) Decommissioning Cost: The decommissioning cost is given by:

$$\text{Dcost} = d \times P_{\text{BESS}}, \quad (3)$$

where:

- d is the specific disposal cost (per kW).
- P_{BESS} is the total battery energy storage capacity.

4) Life-Cycle Cost (LCC) and Financial Metrics: The aggregate Life-Cycle Cost (LCC) over an investment period N (e.g., 20 years) is:

$$\text{LCC}_{BESS} = \text{TCC} + \sum_{n=1}^{N} \frac{\text{O\&M}_{\text{annualised}} + \text{Dcost}}{(1+i)^n}, \quad (4)$$

where i is the discount rate.

Financial metrics computed include:

1) **Net Present Value (NPV):**

$$\text{NPV} = \sum_{n=1}^{N} \frac{CF_n}{(1+i)^n} - \text{LCC}_{BESS}, \quad (5)$$

where CF_n is the net cash flow in year n.

2) **Internal Rate of Return (IRR):** The rate at which the NPV equals zero.
3) **Return on Investment (ROI):**

$$\text{ROI} = \frac{\sum_{n=1}^{N} CF_n - \text{LCC}_{BESS}}{\text{LCC}_{BESS}} \times 100\%. \quad (6)$$

B. ANN-based Operational Optimization Model

Dynamic operation of BESS in grid-integrated wind farms requires adaptation to fluctuating generation. Our ANN model is based on a multilayer perceptron and is structured as follows:

1) Model Architecture:

- **Input Variables:** $X(t) = [L(t), P_{\text{wf}}(t), S(t)]$ where:
  - $L(t)$ is the grid load at time t.
  - $P_{\text{wf}}(t)$ is the wind power generation.
  - $S(t)$ is the current state-of-charge (SOC).
- **Hidden Layers:** Three hidden layers, each containing five neurons, with a Tanh activation function to capture nonlinearities.
- **Output Variable:** $P_{\text{BESS}}(t)$, representing the optimal charging/discharging power.

2) Objective Function and Training: The ANN is trained to minimize the objective function:

$$OF = \sum_{t=1}^{T} \left(L(t) + P_{\text{BESS}}^{d}(t) - P_{\text{wf}}(t) - P_{\text{BESS}}^{c}(t)\right)^2, \quad (7)$$

where $P_{\text{BESS}}^{d}(t)$ and $P_{\text{BESS}}^{c}(t)$ denote the discharging and charging powers at time t, respectively, and T represents the total number of time steps (typically 24 for hourly data). The back-propagation algorithm, enhanced with a tuned learning rate and momentum term, is used to update the weights.

C. ANN-based Sizing Model for Microgrids

For microgrid applications, accurately sizing the BESS is critical. Our sizing model is developed as follows:

1) Dataset Generation:

- A nonlinear microgrid simulation is run for a 24-hour period.
- SOC values vary from 10% to 90% in 1% increments, resulting in approximately 5760 data samples.
- The dataset includes parameters such as load profiles, generation data, voltage, frequency, and renewable penetration.

2) Model Architecture and Training: The ANN used for sizing shares a similar architecture with the operational model:

- **Input Layer:** Receives features such as load, voltage, frequency, wind power, and SOC.
- **Hidden Layers:** Multiple hidden layers capture the nonlinear relationships between the inputs and the optimal BESS size.
- **Output Layer:** Predicts the optimal BESS capacity S_{opt}.

The network is trained by minimizing the mean squared error between the ANN predictions and the simulation-based optimal sizing.

IV. IMPLEMENTATION AND SIMULATION SETUP

This section explains the practical steps for implementing and testing our integrated framework.

A. Data Preprocessing and Calibration

Data quality directly influences model performance. We undertake the following preprocessing steps:

1) **Cleaning:** Interpolate missing values in wind and load datasets using linear regression methods. Apply filters to remove outlier values.
2) **Normalization:** Scale all variables (e.g., load, wind power, SOC) to the [0,1] interval. This uniform range speeds up the ANN training process.
3) **Economic Parameter Calibration:** Set the discount rate to 8.53%, annual price escalation to 6%, and corporate tax to 28% based on current financial reports.

4) **Learning Parameter Tuning:** Adjust the ANN learning rate and include a momentum factor to smooth out the convergence of the network.

B. Test System Configuration

The simulation is conducted on a modified IEEE 39-bus system. Key modifications include:

- **Voltage Regulation:** Enforce bus voltage limits to within ±5% of nominal values. For buses exceeding 1.05 P.U., voltage adjustments are applied using injection control methods.
- **Load Profiles:** Adopt realistic load profiles, such as those from the German BDEW, on critical buses to mimic real operating conditions.
- **Wind Farm Integration:** Install a wind farm at a bus with low load demand, setting its maximum capacity $P_{\text{wf\_max}}$ according to field data.
- **Generator Adjustments:** Deactivate selected coal-fired generators to simulate grid stress conditions and highlight the role of BESS intervention.

C. Simulation Scenarios and Model Integration

Two simulation scenarios are implemented for validation:

1) **Baseline Scenario:** The grid operates with only wind generation (no BESS). This scenario establishes baseline metrics for system losses and stability.
2) **Enhanced BESS Scenario:** Integrate a 4000 MW BESS into the system. Both the DCF-based economic model and the ANN-based operational and sizing models are applied. Hourly simulations over a 24-hour period capture dynamic system responses.

The entire simulation is controlled using Python scripts interfaced with DIgSILENT PowerFactory. Convergence in load-flow calculations is verified to achieve an error threshold below 0.001 P.U.

V. Results and Analysis

Detailed simulation results are presented in this section.

A. Economic Analysis Results

For the enhanced scenario, the DCF model delivers:

- **NPV:** Approximately 6892 ZAR'Mil.
- **IRR:** Estimated at 11%, which exceeds the required threshold.
- **Payback Period:** Approximately 15 years.

Sensitivity analysis (Figure 1) shows the impact of varying the discount rate and electricity price escalation on NPV and IRR, reinforcing the robustness of the economic model.

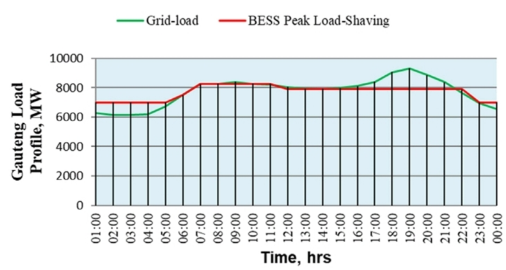


Fig. 2. Load-shaving.

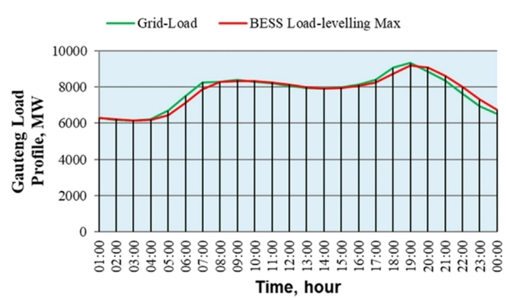


Fig. 3. Load-levelling.

Fig. 1. Load shaving and Load-levelling analysis showing the better results with the BESS integrated system

B. ANN Operational Optimization Results

The ANN control system for BESS operation demonstrates:

- A reduction of overall system power losses by roughly 13% compared to the baseline scenario.

- Effective maintenance of optimal SOC levels during periods of fluctuating load and wind generation.

Figures 2 and 3 illustrate these improvements.

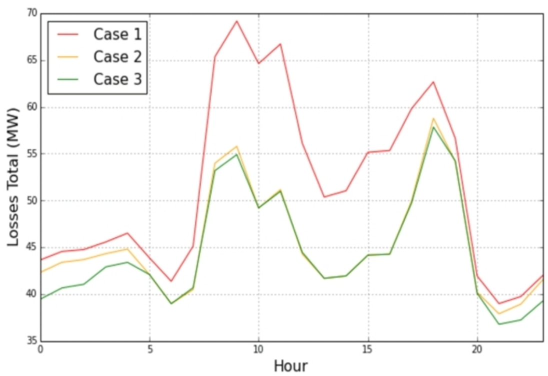


Fig. 2. Comparison of system power losses: conventional control vs. ANN-based optimization.

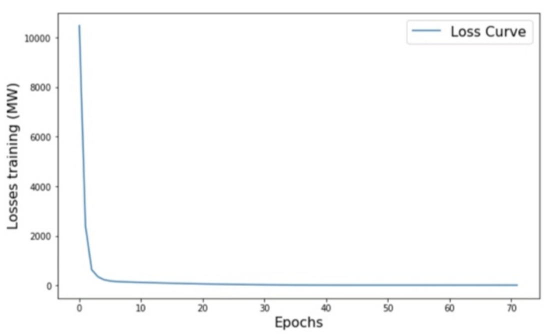


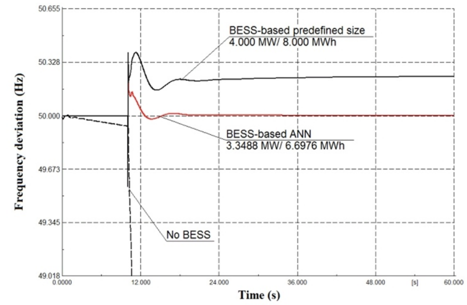
Fig. 3. SOC BESS performance optimization using convergent ANN method on iteration 72th.

C. ANN-based Sizing Results

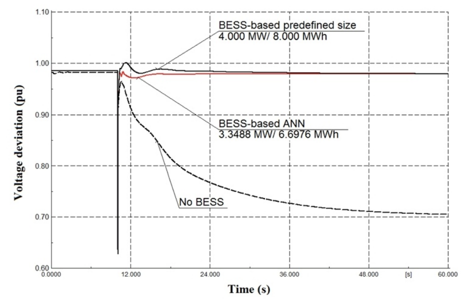
The ANN sizing model, trained on a dataset of 5760 samples, provides highly accurate predictions for the optimal BESS capacity:

- The model minimizes voltage and frequency deviations by providing a tailored BESS size.
- Capital expenditure is optimized by avoiding oversizing while ensuring grid stability.

Figure 4 compares ANN-predicted BESS capacity against simulation outcomes.



Frequency deviation of the microgrid after islanding.



Voltage deviation of the microgrid after islanding.

Fig. 4. Comparison between the BESS system based on predefined size and the optimal BESS capacity from ANN-based sizing.

VI. Discussion

The integrated framework delivers a holistic solution for BESS deployment:

- **Economic Viability:** The DCF model confirms the financial benefits of large-scale BESS installation under the enhanced scenario.
- **Operational Efficiency:** ANN-based control significantly reduces energy losses and maintains grid stability during variable operating conditions.
- **Accurate Sizing:** The ANN-sizing model outperforms traditional methods, ensuring proper resource allocation and improved microgrid performance.

Key implementation challenges—such as data normalization issues, ANN convergence behavior, and load-flow solution stability—were addressed by refining preprocessing techniques and tuning learning parameters. Future work will incorporate real-time data and explore hybrid optimization methods to further enhance performance under diverse operating scenarios.

VII. Conclusion

This paper presents an extensively detailed integrated framework for analyzing and optimizing Battery Energy Storage Systems in renewable energy applications. By merging a DCF-based economic model with ANN-driven operational optimization and sizing techniques, our approach addresses both the economic and technical challenges inherent to modern power grids. Simulation results on a modified IEEE 39-bus system validate the framework, showing significant improvements in economic returns, loss reduction, and grid stability. Future research will refine these methods by integrating real-time feedback and investigating advanced hybrid control strategies.

VIII. Future Direction

As a future extension of this work, we will be working on developing a unified full-stack platform that integrates the DCF-based economic analysis, ANN-based sizing methodology, and ANN-driven real-time operational control into a single deployable system for BESS applications. This platform would feature a backend computational engine executing financial models and neural network inference, a middleware API layer for data handling, and a user-friendly frontend interface allowing users to input parameters, view economic metrics (e.g., NPV, IRR), analyze optimal BESS sizing, and monitor SOC and grid losses in real time. Such an integrated solution would serve as a powerful decision-support tool for grid planners and renewable energy stakeholders, enabling scenario testing, adaptive control, and scalable deployment across different grid environments. Future enhancements could include hybrid AI models, cloud-based deployment for broader access, and GIS integration for location-specific planning.

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