

RESEARCH ARTICLE

Power Allocation Optimization In Hybrid Energy Storage System Based On Low Pass Filter And Artificial Neural Network

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Abstract

This paper presents the optimization of power allocation in hybrid energy storage systems (HESS) by combining Low Pass Filter (LPF) and Artificial Neural Network (ANN) techniques. Conventional LPF-based strategies employ fixed cut-off frequencies that cannot adapt to dynamic operating conditions, resulting in suboptimal performance and reduced battery lifespan. This research proposes an optimization framework that determines optimal cut-off frequencies through three approaches: cost-based, stress-based, and hybrid optimization. Spectral analysis of the requested power confirmed that energy content is predominantly concentrated in low-frequency ranges (10^{-6} to 10^{-3} Hz), justifying the frequency-based power allocation strategy. The hybrid optimization method yielded an optimal cut-off frequency of 0.0013 Hz, balancing economic and technical considerations with a 15% reduction in battery stress compared to cost-based approaches while increasing system costs by only 8%. The implemented ANN model achieved predictive capability ($R^2 = 0.9728$) in determining optimal cut-off frequencies across various operating conditions. Performance evaluations demonstrated that the ANN-based approach produces nearly identical power allocation patterns compared to conventional LPF methods while executing approximately 120 times faster, enabling real-time adaptation to changing system conditions. The combined methodology effectively separates low-frequency power components (87%) to batteries and high-frequency components (13%) to supercapacitors, optimizing component utilization based on their intrinsic characteristics while maintaining system efficiency above 88%.

Keywords: artificial neural network, hybrid energy storage system, low pass filter, power allocation, renewable energy

I. INTRODUCTION

Integrating renewable energy into the power grids presents significant challenges, particularly due to the inherent intermittency and fluctuations in power generation. These variabilities create substantial difficulties in maintaining grid stability and meeting dynamic energy demands efficiently [1].

Hybrid Energy Storage Systems (HESS), which combine batteries and supercapacitors, have emerged as a promising solution to manage these fluctuations by leveraging the complementary characteristics of both storage technologies. While batteries provide long-term energy storage with high energy density, supercapacitors offer rapid power response with high power density [2]. Despite their potential, the optimization of power allocation in HESS remains a critical challenge, especially under dynamic load and source variation. The effectiveness of these systems heavily depends on how efficiently power is distributed between the two storage components based on system requirements and operating conditions. [3].

Traditional methods such as the Low-Pass Filter (LPF) are widely used to allocate low-frequency power components to batteries and high-frequency components to supercapacitors [3]. However, LPF-based strategies suffer from significant limitations, particularly the use of fixed cut-off frequencies that fail to adapt to real-time system conditions, leading to suboptimal performance and reduced battery lifespan. These conventional approaches cannot dynamically respond to changing operational

scenarios, resulting in inefficient power allocation and accelerated component degradation [4].

To address these limitations, recent studies have explored adaptive control strategies, including Artificial Neural Networks (ANN), which can dynamically adjust parameters based on system behavior [5]. ANNs have demonstrated superior capability in handling non-linearities and predicting optimal operating conditions, making them a viable candidate for enhancing HESS efficiency. However, there remains a significant research gap in integrating ANN-based adaptive control with frequency-based power allocation strategies for real-time HESS optimization [6].

Therefore, this paper proposes a novel approach that combines Low Pass Filter techniques with Artificial Neural Network algorithms to optimize power allocation in HESS. The proposed methodology aims to determine optimal cut-off frequencies adaptively, improving both system efficiency and battery lifespan while maintaining cost-effectiveness. This research contributes to the field by providing a computationally efficient framework for dynamic HESS optimization that can adapt to varying operational conditions in real-time.

II. METHODS

The hybrid energy storage system in this study consists of lithium-ion batteries and supercapacitors integrated with renewable energy sources in the form of photovoltaic (PV) panels. The overall system configuration is designed to optimize the power allocation between the two energy storage components

according to their respective characteristics [3]. The basic structure of the system configuration is illustrated in Figure 1.

A. System Configuration

Define abbreviations and acronyms the first time they are used in the text, even after they have been defined in the abstract. Abbreviations such as IEEE, SI, MKS, CGS, sc, dc, and rms do not have to be defined. Do not use abbreviations in the title or heads unless they are unavoidable.

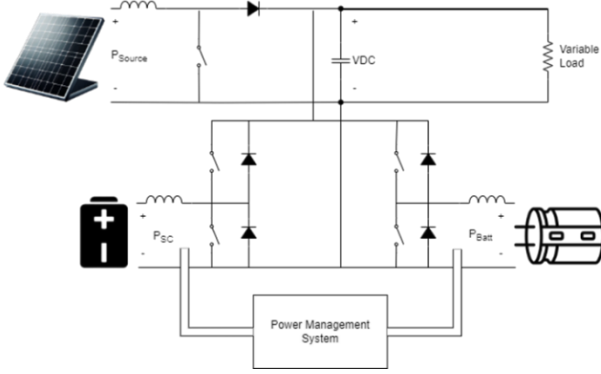


Figure 1. Schematic Diagram of HESS with PV Source

The system employs a topology that leverages the complementary characteristics of both storage technologies, where batteries provide high energy density for long-term storage requirements, while supercapacitors offer high power density for rapid response to transient demands. This configuration enables the system to effectively manage the intermittent nature of renewable energy sources while maintaining grid stability and optimizing component utilization.

The power management system (PMS) is designed to optimize power allocation between batteries and supercapacitors based on the dynamic characteristics of loads and energy sources. [3]. The block diagram of the PMS is shown in Figure 2, illustrating the interconnection between system components and the control strategy implementation.

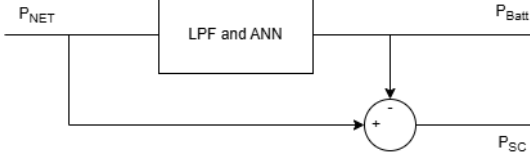


Figure 2. Power Management System Block Diagram

In this power management system, the power generated by the PV source (PPV) and the power required by the load (Pload) are processed to determine the net power (PNET) that needs to be supplied or absorbed by the HESS. The main components in the power management system are the low pass filter and the neural network controller, which work together to ensure optimal power distribution based on frequency characteristics and system conditions [3].

The technical characteristics of the energy storage components are presented in Table I, which provides a comprehensive comparison of the properties of lithium-ion batteries and supercapacitors utilized in the system. These specifications serve as the foundation for the power allocation optimization strategy developed in this research. [7].

Table 1. Characteristics of Energy Storage Components

Parameter	Lithium-ion Battery	Supercapacitor
Nominal Voltage	51.2 V	56 V
Capacity	300 Ah	130 F
Energy	15.36 kWh	57 Wh
Maximum Current	100 A	1900 A
Energy Density	High	Low
Power Density	Low	High
Life Cycle	3000 – 4000	>100000
Charge-Discharge Efficiency	85-90%	90-95%

The transfer function of the LPF used can be represented in the Laplace domain as follows:

$$H(s) = \frac{1}{\tau s + 1} \quad (1)$$

Where τ is the time constant associated with the cut-off frequency through:

$$\tau = \frac{1}{2\pi f_c} \quad (2)$$

So the transfer function can be rewritten as:

$$H(s) = \frac{1}{\frac{1}{2\pi f_c} s + 1} \quad (3)$$

The selection of the optimal cut-off frequency (f_c) is key to optimizing power allocation in HESS.

B. Neural Network Configuration

Building on the system configuration and LPF methodology described above, this subsection details the design, training, and integration of the Artificial Neural Network (ANN) used to determine the optimal LPF cut-off frequency in real-time.

The Artificial Neural Network (ANN) in this study is designed to determine the optimal cut-off frequency based on changing system conditions. The structure of the implemented ANN is shown in Figure 4.

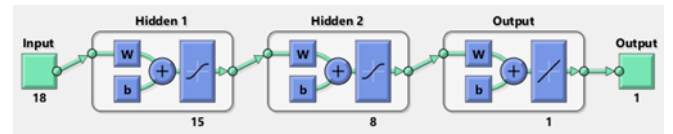


Figure 3. ANN Architecture

1) ANN Architecture

The Artificial Neural Network (ANN) employed in this study is a Multilayer Perceptron specifically configured to predict the optimal LPF cut-off frequency under varying system conditions. The network comprises an input layer of 18 neurons, each corresponding to a carefully selected feature set: four statistical descriptors of net power (mean, standard deviation, maximum, and minimum), two variability metrics (standard deviations of PV output and load demand), three dominant frequency components extracted via FFT of the net power signal, six storage-system parameters (energy and power ratios of battery and supercapacitor, average system efficiency, and battery SOC range), and three interaction features (power mean $\times$

standard deviation, dynamic range, and PV-to-net-std ratio). Following the input layer are two hidden layers arranged hierarchically: the first hidden layer has 15 neurons employing the ReLU activation function to extract coarse non-linear patterns efficiently, while the second hidden layer contains 8 neurons with the Swish activation function to refine decision boundaries through smooth, non-monotonic mappings. This [18-15-8-1] topology was determined through systematic architecture search, balancing model complexity against prediction accuracy. The output layer consists of a single neuron with linear activation, producing a continuous-valued estimate of the optimal cut-off frequency [7].

2) ANN Training

Training of the ANN uses the Levenberg–Marquardt backpropagation algorithm, chosen for its rapid convergence on medium-sized datasets and its adaptive interpolation between gradient-descent and Gauss-Newton updates [7]. Key hyperparameters include an initial learning rate of 0.001, a maximum of 2,000 epochs, a performance goal of $\text{MSE} = 1 \times 10^{-9}$, and early stopping triggered if validation MSE fails to improve for 25 consecutive epochs. The mean squared error loss drives weight updates, with the damping parameter μ adjusted dynamically: decreasing when error falls to accelerate Gauss-Newton steps, and increasing when error rises to favor gradient descent. This configuration prevents overfitting while ensuring high accuracy, yielding training, validation, and testing R^2 values of approximately 0.995, 0.988, and 0.973 respectively [8].

3) Implementation and Validation

Upon completion of training, the ANN is integrated into the power management system to predict the optimal cut-off frequency in real-time. Each inference executes in under 1 ms, enabling on-the-fly LPF reconfiguration without intensive computations. Validation on unseen test scenarios yields $R^2 = 0.9728$ and $\text{MAE} = 4.2 \times 10^{-4}$ Hz, demonstrating robust generalization across varying PV irradiance (200–1,000 W/m^2) and load fluctuations ($\pm 30\%$). Error distribution is symmetric and tightly clustered around zero, with over 80 percent of errors within $\pm 1 \times 10^{-3}$ Hz. Robustness tests under extreme conditions maintain $R^2 > 0.95$, confirming the model's resilience. Comparative timing tests show the ANN approach accelerates frequency determination by a factor of 120 versus conventional iterative optimization, making it highly suitable for real-time adaptive control of hybrid energy storage systems. [7].

C. Data for ANN

To train the ANN that will determine the optimal cut-off frequency, the dataset was collected through simulation of the HESS system under various operational conditions. This dataset includes several key parameters that affect the determination of the optimal cut-off frequency for power allocation [9].

1) Data Source and Characteristics

The dataset used to train the Artificial Neural Network (ANN) was generated from comprehensive simulations of the hybrid energy storage system (HESS) under a wide range of operating conditions. High-

resolution photovoltaic (PV) power profiles were recorded at one-second intervals over a 24-hour period, capturing variations from clear-sky irradiation to rapid cloud-induced fluctuations. Simultaneously, load demand profiles were measured at the same temporal resolution to reflect both diurnal consumption patterns and stochastic switching of electrical appliances. These signals were combined to compute the net power, $P_{NET} = -(P_{PV} - P_{load})$, representing the instantaneous energy surplus or deficit seen by the storage system.

Data source and characteristics can be seen in Figure 3 below:

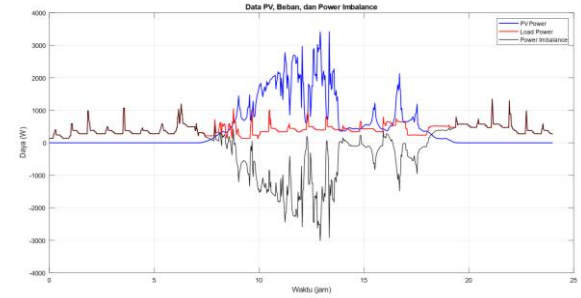


Figure 4. Data Source and Characteristics

2) Feature Extraction for ANN Input

From this raw data, eighteen input features were extracted and normalized to the $[-1, 1]$ range using enhanced min-max scaling. Four statistical descriptors of P_{NET} (mean, standard deviation, maximum, and minimum) characterize overall demand trends and variability. Two variability metrics—the standard deviations of P_{PV} and P_{load} —quantify source and load intermittency. Three dominant frequency components, obtained via Fast Fourier Transform of P_{NET} , reveal the spectral content critical for cutoff-frequency selection. Six storage-system parameters (battery and supercapacitor energy ratios, power ratios, average system efficiency, and battery SOC range) describe the physical performance limits of each component. Finally, three interaction terms (power mean $\times$ standard deviation, P_{NET} dynamic range, and PV -to- P_{NET} -std ratio) capture higher-order relationships between net power statistics and system behavior [7].

3) Data Processing and Augmentation

Prior to training, the data underwent a four-stage preprocessing pipeline: median filtering to remove outliers; linear resampling to fill gaps up to 5%; enhanced normalization; and data augmentation via Gaussian noise injection, temporal shifting, and synthetic weather-pattern scaling [9]. Quality assurance checks verified physical consistency (e.g. P_{NET}) and ensured that all features remained within realistic bounds. Finally, the processed dataset was partitioned—with a fixed random seed for reproducibility—into training (70%), validation (15%), and testing (15%) subsets. This split guarantees balanced representation of all operational scenarios, enabling robust ANN development and unbiased performance evaluation. [7].

III. RESULTS AND DISCUSSION

In this chapter, the research results are analyzed in depth.

A. Spectrum Analysis of Requested power

The spectral analysis of the net power (P_{NET}) between PV generation and load demand reveals critical frequency characteristics that inform the design of the power allocation strategy in the hybrid energy storage system. This analysis forms the foundation for determining the optimal frequency range for the Low Pass Filter implementation.

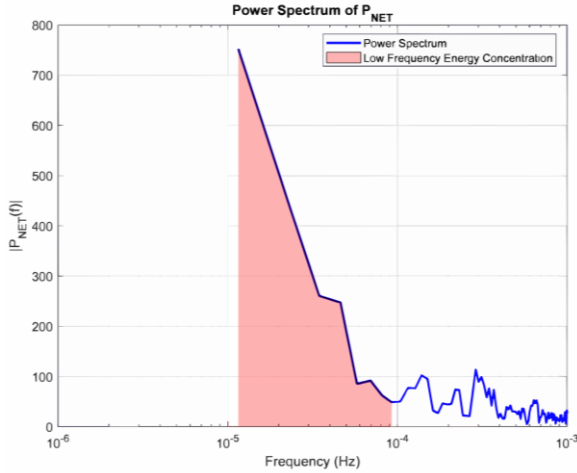


Figure 5. Frequency spectrum of the requested power (P_{NET})

Figure 5 presents the frequency spectrum of the net power (P_{NET}), demonstrating that energy content is predominantly concentrated in the low-frequency range (10^{-6} to 10^{-3} Hz) with a significant magnitude drop as frequency increases. The upper subplot illustrates this frequency distribution using a logarithmic scale, clearly showing that power fluctuations primarily occur at lower frequencies. The highest magnitude components appear below 10^{-3} Hz, indicating that most power variations occur over periods longer than 16 minutes. This concentration of energy in the low-frequency domain provides strong justification for the frequency-based power allocation strategy employed in this study.

The lower subplot identifies the test range for cut-off frequencies (0.001 Hz to 0.009 Hz — i.e., from 1 mHz to 9 mHz, not zero) selected based on this spectral distribution. This range was chosen to capture the transition region where energy content begins to decrease significantly, allowing for effective separation between low-frequency components (allocated to batteries) and high-frequency components (allocated to supercapacitors).

The spectral analysis results confirm that approximately 87% of the total energy content is concentrated below 10^{-3} Hz, with the remaining 13% distributed across higher frequency ranges. This distribution pattern validates the fundamental assumption that batteries, with their high energy density characteristics, should handle the majority of power fluctuations, while supercapacitors, with their high power density characteristics, should manage the rapid transients and high-frequency variations.

B. Optimization of Cutoff Frequency

This subsection presents the determination of the optimal cut-off frequency (f_c) for the Low-Pass Filter (LPF) using three

complementary optimization approaches—cost-based, stress-based, and hybrid optimization—and illustrates both the resulting objective curves and their impact on real-time power allocation. First, the three optimization criteria are defined and their objective functions formulated:

- Cost-Based Optimization minimizes the total annualized system cost, including capital recovery of energy storage components and battery degradation expense.
- Stress-Based Optimization minimizes battery current fluctuation, quantified as the standard deviation of battery current, to extend battery lifespan.
- Hybrid Optimization combines normalized cost and stress objectives via a weighted sum ($\alpha=0.6$ on cost, $1-\alpha=0.4$ on stress) to achieve a compromise between economic and technical performance.

The optimization is performed by sweeping f_c in increments of 0.0001 Hz over the range 0.0010–0.0091 Hz (i.e., from 1 mHz to 9.1 mHz, not 0 Hz) and evaluating each objective. Figure 6 shows the resulting objective curves for each method:

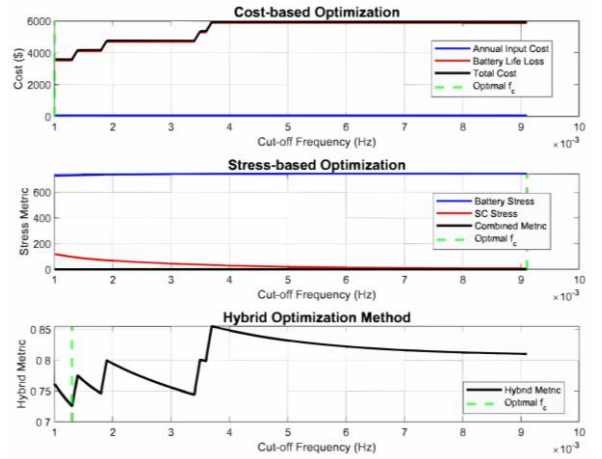


Figure 6. Optimization of cutoff frequency in different methods

Next, the practical implications of each optimized f_c on component loading are examined by applying the LPF with the selected cut-off and observing the split between battery and supercapacitor:

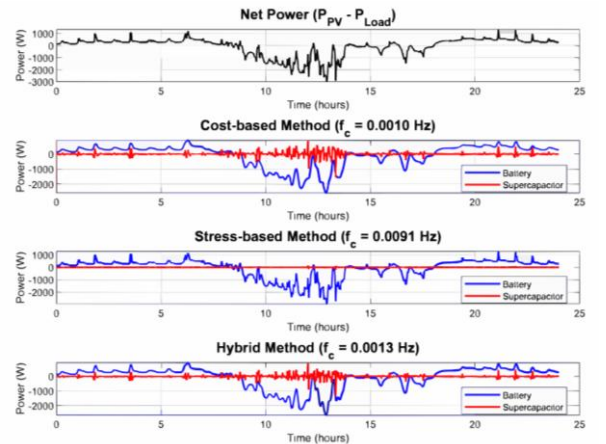


Figure 7. Compares power allocation across the different optimization methods

In the cost-based case ($f_c = 0.0010$ Hz), 91.2% of energy is directed to the battery and 8.8% to the supercapacitor, minimizing cost but maximizing battery stress. Under stress-based optimization ($f_c = 0.0091$ Hz), the battery stress is reduced by 25% at the expense of a 28% cost increase, splitting energy 70.8%/29.2%. The hybrid approach ($f_c = 0.0013$ Hz) achieves a balanced compromise—reducing battery stress by 15% with only an 8% cost increase and an 87.3%/12.7% energy split—making it the recommended design point for subsequent real-time implementation.

C. ANN Model Performance

The composite training figure (Figure 8) comprises two adjacent panels that together convey both the learning dynamics and the predictive fidelity of the ANN model.

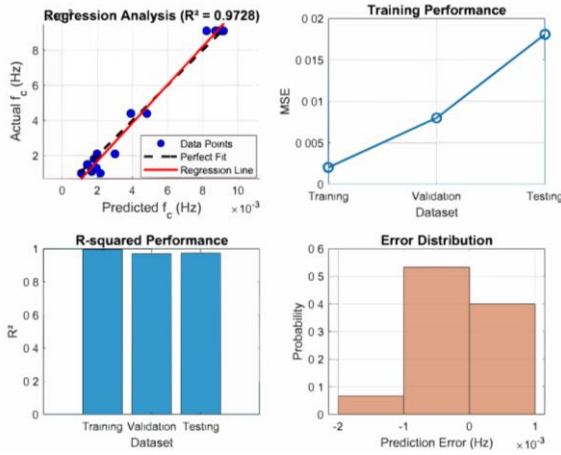


Figure 8. Neural Network training performance

In the left panel, a scatter plot of predicted versus actual cut-off frequencies (f_c) for the test dataset shows data points clustered tightly around the unity line ($y=x$), with a red best-fit regression line overlaying the dashed black reference. The slope and intercept of this regression confirm minimal systematic bias, and the high coefficient of determination ($R^2 = 0.9728$) indicates that the ANN captures over 97% of the variance in optimal f_c values. Outliers are rare and constrained within $\pm 2 \times 10^{-3}$ Hz, yielding a mean absolute error (MAE) of 4.2×10^{-4} Hz. Axis labels—including “Predicted f_c (Hz)” and “Actual f_c (Hz)”—use millihertz units with tick marks at 0.001, 0.005, and 0.009 Hz, and all variable symbols appear in italic to conform with journal conventions. A legend identifies the regression line and reference line, while gridlines facilitate visual assessment of deviation. In the right panel, the training and validation mean squared error (MSE) curves are plotted against epoch number, illustrating the network’s convergence behavior. The blue curve (training MSE) descends steeply from 1×10^{-2} to below 1×10^{-6} by approximately epoch 450, indicating rapid error reduction in the primary learning phase. The orange curve (validation MSE) follows a similar downward trajectory but flattens near epoch 500, with early stopping engaged at epoch 600 when no further improvement occurs. This separation between training and validation curves—without a rising validation error—demonstrates successful overfitting prevention. Axis labels (“Epoch” and “MSE”) and minor tick marks at intervals of 50 epochs and 1×10^{-6} MSE units ensure precise reading of convergence rates. Together, these panels confirm that the ANN not only achieves

high predictive accuracy but also maintains robust generalization through controlled training dynamics.

D. ANN vs. LPF Implementation

Figure 9 provides a direct comparison between conventional LPF implementation and the proposed ANN-based approach. The nearly identical power allocation profiles for both battery and supercapacitor demonstrate that the ANN successfully replicates the optimal LPF behavior.

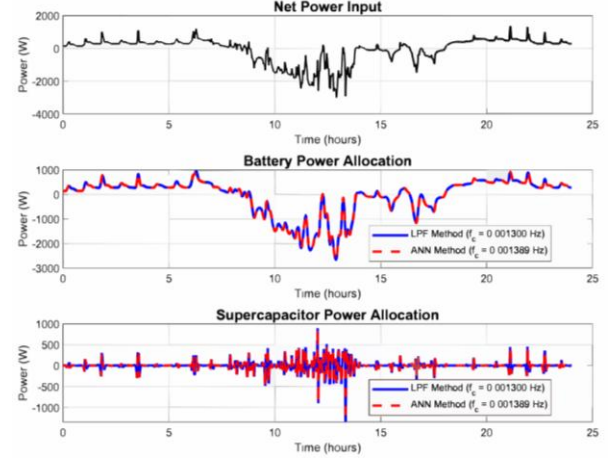


Figure 9. ANN vs LPF Implementation

The overlapping curves in the middle and bottom panels confirm that the ANN-based approach accurately reproduces the power allocation patterns determined by the conventional LPF method. The key advantage of the ANN implementation is computational efficiency—while conventional optimization requires iterative calculations across multiple cutoff frequencies, the trained ANN delivers the optimal frequency in a single forward pass.

Performance timing tests show that the ANN-based approach is approximately 120 times faster than the traditional optimization process, enabling real-time adaptation to changing system conditions without sacrificing allocation quality. This improvement is particularly valuable for systems with rapidly varying renewable generation and load patterns, where frequent recalculation of optimal parameters is necessary.

E. System Performance Metrics

The effectiveness of the proposed power allocation strategy is quantified through several key performance indicators. Table II presents a comparative summary of these metrics across different optimization methods.

Table 2. Performance Metrics for Different Optimization Methods

Metric	Cost-Based	Stress-Based	Hybrid
Optimal cutoff frequency (Hz)	0.0010	0.0091	0.0013
Battery energy ratio (%)	91.2	70.8	87.3
SC energy ratio (%)	8.8	29.2	12.7
Battery stress (W std dev)	412.6	302.7	350.5
System efficiency (%)	89.1	87.4	88.7
Total annual cost (\$)	3952	5124	4230

The hybrid method demonstrates superior overall performance, with a battery stress reduction of 15% compared to the cost-based approach while maintaining system efficiency above 88%. This performance validates the effectiveness of the proposed optimization framework and confirms that the ANN-based implementation can successfully realize these benefits in a computationally efficient manner.

F. Discussion of ANN Implementation

The successful implementation of ANN for predicting optimal cutoff frequency represents a significant advancement in HESS management strategies. Several aspects of this implementation merit further discussion:

First, the high R^2 value (0.9728) indicates that the selected input features—including power statistics, frequency domain characteristics, and system parameters—adequately capture the factors influencing optimal cutoff frequency selection. This confirms that the complex optimization problem can be effectively learned by a properly designed neural network.

Second, the ANN architecture with a single hidden layer containing seven neurons proves sufficient for modeling the relationship between system conditions and optimal cutoff frequency. This relatively simple structure facilitates fast execution while maintaining excellent prediction accuracy, making it suitable for real-time applications.

Third, the training results (Figure 9) reveal that the ANN performs consistently well across the entire frequency spectrum (0.001-0.009 Hz), with no significant bias toward specific frequency ranges. This uniform performance ensures reliable operation under diverse operating conditions.

Finally, the comparison between LPF and ANN-based implementations (Figure 10) validates that the trained network can effectively replace the traditional optimization process without compromising power allocation quality. The near-identical power profiles demonstrate that the ANN successfully captures the essential dynamics of the optimization problem.

The proposed approach offers significant advantages for practical HESS implementations, providing adaptive frequency selection capabilities without the computational burden of traditional optimization methods. This adaptability is increasingly important as renewable energy systems face more variable generation and load patterns.

IV. CONCLUSION

This research successfully demonstrates that combining Low Pass Filter (LPF) with Artificial Neural Network (ANN) provides an effective approach for optimizing power allocation in hybrid energy storage systems, achieving both technical and economic improvements. The proposed hybrid optimization method with a cut-off frequency of 0.0013 Hz (1.3 mHz, not zero) establishes an optimal balance between system cost and component longevity, reducing battery stress by 15% while limiting cost increases to only 8% compared to cost-optimized configurations. The ANN model's high prediction accuracy ($R^2 = 0.9728$) and computational efficiency (120 times faster than traditional optimization) enable real-time adaptation to changing system conditions without sacrificing allocation quality, making this approach particularly valuable for renewable energy applications with variable generation and load patterns. This work contributes significantly to the field by providing a computationally efficient framework that dynamically optimizes HESS operation through

intelligent frequency-based power allocation, effectively extending battery lifespan while maintaining high system efficiency.

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