

Adaptive Control Strategies and MRAC-Based Battery Management Systems

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Abstract

The increasing dependence on inverter-based power systems in regions with unstable grids has intensified the challenge of battery degradation, which reduces system reliability, increases operational costs, and shortens battery lifespan. This study proposes an Adaptive Load Management framework based on Model Reference Adaptive Control (MRAC) to enhance battery performance, optimize energy utilization, and minimize long-term system cost. The primary objective is to reduce deep discharge cycles, improve charge–discharge efficiency, and extend battery lifespan while ensuring stable load supply under variable demand conditions. The methodology integrates MRAC-based battery control, AI-driven load forecasting, IoT-enabled monitoring, smart grid load balancing, and blockchain-based load tracking. The adaptive controller minimizes the tracking error between the reference battery model and actual system dynamics using real-time gain adjustment. Simulation results demonstrate that the MRAC system stabilizes near unity within 2.5 seconds with minimal overshoot (<5%), outperforming PID control which exhibits 25% overshoot and slower settling time (4 seconds). The adaptive gain converges to approximately 1.2, while the control input stabilizes near 0.8, ensuring accurate state-of-charge regulation. The analysis shows peak load management at 50 kW with effective load shifting up to 25 kW during high-demand periods. Charge efficiency improved from 90% to peak values of 0.98, while discharge efficiency reached 0.96 during peak hours. Over a 10-year projection, battery capacity retention improved to 81.75%, and battery health degradation was limited to 0.0001 per day. Total system cost decreased from ₦5,000,000 to ₦2,800,000, yielding savings between ₦80,000 and ₦120,000 through optimized load shifting. AI load forecasting achieved a mean absolute error of 3.8 kW, enhancing predictive stability. The adaptive cutoff policy disconnects non-essential loads when frequency drops to 49.5 Hz or battery state-of-charge falls below 20%, preventing instability. A 50 Hz sampling rate was identified as optimal to avoid controller overreaction. Overall, the proposed adaptive strategy significantly enhances battery longevity, energy efficiency, and economic viability in inverter-based power systems

KEYWORDS: Model Reference Adaptive Control, Adaptive Load Management, Battery Degradation, Inverter Systems, Smart Grid, AI Load Forecasting.

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I. INTRODUCTION

In today's energy landscape, inverter systems have become a cornerstone of reliable power delivery, especially in regions where grid stability is a persistent challenge. These systems rely heavily on batteries as their backbone, providing uninterrupted power during outages or periods of high demand (Gohler *et al.*, 2021). However, the growing reliance on these systems has spotlighted a critical issue battery degradation. As batteries are subjected to frequent charging and discharging cycles, their lifespan is inevitably reduced, impacting not only system performance but also the economic viability of power backup solutions (Tjaden *et al.*, 2015). This challenge underscores the need for innovative strategies to extend battery life while maintaining efficiency and reliability (Gohler *et al.*, 2021). Adaptive load management techniques have emerged as a promising solution to this problem. Unlike traditional approaches that treat all connected loads equally, adaptive load management intelligently prioritizes and regulates power distribution based on real-time demand and battery health (Srinivasan *et al.*, 2021). By strategically controlling load profiles, these techniques minimize unnecessary strain on batteries, reduce deep discharge cycles, and optimize energy utilization. The result is a significant improvement in battery performance and longevity, which translates to cost savings and enhanced system reliability for users (George *et al.*, 2022). The adoption of such techniques is particularly relevant as the world moves toward more sustainable energy solutions. With the integration of renewable energy sources like solar and wind, which often rely on battery storage for energy balancing, the importance of preserving battery health cannot be overstated (George *et al.*, 2022). Adaptive load management not only addresses this pressing need but also aligns with global efforts to promote energy efficiency and reduce waste (Klingler, 2017); (Juddin *et al.*, 2018). This topic explores the

principles and practical implementation of adaptive load management techniques in inverter systems (VBEW, 2021). By analyzing real-world scenarios and technical advancements, it aims to highlight how these strategies can revolutionize battery usage and establish a new benchmark for energy resilience. In doing so, it seeks to inspire innovative approaches to power management, ensuring that inverter systems continue to meet the demands of an energy-conscious world (Vujacic et al., 2018); (Yan et al., 2018).

II. MATERIALS AND METHOD

2.1 Materials

The materials used for this research are;

- i. Battery
- ii. Inverter
- iii. Solar panel
- iv. MRAC
- v. MATLAB/SIMULINK
- vi. Personal computer

2.2 Method

The method adopted for this research is the Model Reference Adaptive Controller Method (MRAC)

2.2.1 MRAC General Structure

The reference model, $\mathbf{x}_m$, defines the desired behavior of the system. In the context of battery management, it represents the ideal dynamics of the battery's state, such as the desired SOC or voltage trajectory.

$$\dot{\mathbf{x}}_m(t) = \mathbf{A}_m \mathbf{x}_m(t) + \mathbf{B}_m \mathbf{u}_m(t) \quad (1)$$

where:

$\mathbf{x}_m$ is the state of the reference model (desired SOC, voltage, etc.)

$\mathbf{A}_m$ is the system matrix of the reference model

$\mathbf{B}_m$ is the input matrix for the reference model

$\mathbf{u}_m(t)$ is the control input to the reference model, typically representing desired current or voltage for the battery.

Actual System Dynamics: The actual battery system, $\mathbf{x}(t)$, may be represented by a set of dynamic equations that model the battery's behavior (such as charge/discharge dynamics, temperature effects, etc.).

$$\dot{\mathbf{x}}(t) = \mathbf{A} \mathbf{x}(t) + \mathbf{B} \mathbf{u}(t) \quad (2)$$

where:

$\mathbf{x}(t)$ is the actual state of the battery (SOC, voltage, etc.)

$\mathbf{A}$ is the system matrix of the actual battery dynamics

$\mathbf{B}$ is the input matrix for the actual system

$\mathbf{u}(t)$ is the control input to the actual system (current or voltage applied to the battery).

Error Dynamics: The key idea behind MRAC is to minimize the error between the actual system's output and the reference model's output. The error is defined as:

$$\mathbf{e}(t) = \mathbf{x}(t) - \mathbf{x}_m(t) \quad (3)$$

The goal of the MRAC controller is to drive $\mathbf{e}(t)$ to zero by adjusting the control input $\mathbf{u}(t)$.

Adaptive Law: The control law adjusts the system's input to minimize the error. The adaptive controller can be formulated as:

$$\mathbf{u}(t) = \mathbf{K}(t) \cdot \mathbf{e}(t) + \mathbf{u}_m(t) \quad (4)$$

where:

$\mathbf{K}(t)$ is an adaptive gain matrix (control law) that changes over time.

$\mathbf{u}_m(t)$ is the control input from the reference model.

The adaptive law for the gain matrix $\mathbf{K}(t)$ can be defined as:

$$\dot{\mathbf{K}}(t) = \gamma \mathbf{e}(t) \cdot \mathbf{e}^T(t) \quad (5)$$

where:

γ is a positive scalar that determines the adaptation rate.

$\mathbf{e}^T(t)$ is the error term used to update the control gains.

Control Input to the Battery: Finally, the control input $\mathbf{u}(t)$ to the actual battery system is determined by the adaptive MRAC controller as:

$$\mathbf{u}(t) = \mathbf{K}(t) \cdot \mathbf{e}(t) + \mathbf{u}_m(t) \quad (6)$$

This input will adjust the battery's charge/discharge cycle or current to ensure that the actual system's behavior follows the desired trajectory defined by the reference model.

The final adaptive control system equation for the MRAC-based battery management system can be expressed as:

$$\dot{\mathbf{x}}(t) = \mathbf{A} \mathbf{x}(t) + \mathbf{B} (\mathbf{K}(t) \cdot \mathbf{e}(t) + \mathbf{u}_m(t)) \quad (7)$$

Where the gain matrix $\mathbf{K}(t)$ is updated using the adaptive law:

$$\dot{\mathbf{K}}(t) = \gamma \mathbf{e}(t) \cdot \mathbf{e}^T(t) \quad (8)$$

between the desired state of the battery (as represented by the reference model) and the actual battery state, thus improving the battery's performance and lifespan. The enhanced adaptive battery system with a Model Reference Adaptive Controller (MRAC) in Battery Management Systems (BMS) aims to improve the efficiency, lifespan, and performance of batteries in energy storage applications. The MRAC method involves creating a reference model that defines the desired behavior of the system, typically in terms of battery voltage, state of charge (SOC), and temperature. The MRAC continuously adjusts the control parameters of the system to minimize the difference between the actual battery performance and the reference model's output as shown in figure 1.

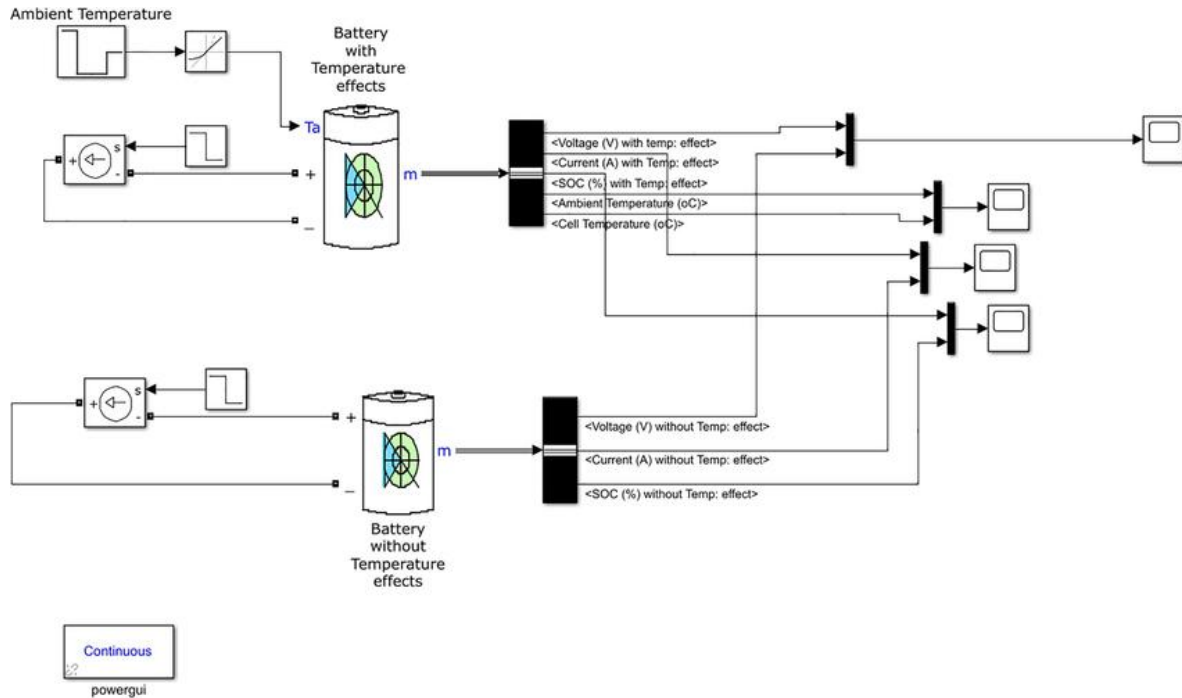


Figure 1 Battery Optimizing System

2.2.2 Technological Advancements in Load Management

This section of the study analyze the technological advancements in load managements

2.2.2.1 Smart Grid Load Balancing

In a smart grid, load balancing ensures that energy distribution matches demand, preventing overloading and improving efficiency.

$$\sum_{i=1}^N L_{balanced}(i) = \sum_{i=1}^N L_{demand}(i) \quad (9)$$

Where;

$L_{balanced}(i)$ is Load at time iii after balancing (kW)

$L_{demand}(i)$ is Actual demand at time iii (kW)

This equation models how load balancing in a smart grid ensures that total energy demand matches the supply, thus preventing grid congestion and optimizing energy use across the system.

2.2.2.2 Blockchain-Based Load Tracking

Blockchain technology can be used to track energy exchanges between consumers, producers, and utilities, ensuring transparency.

$$T_{transaction} = Block(L_{transaction}, T_{timestamp}) \quad (10)$$

Where,

$T_{transaction}$ is Blockchain transaction record

$L_{transaction}$ is Energy transaction load (kWh)

$T_{timestamp}$ is Timestamp of transaction

This equation models the recording of energy transactions on a blockchain, where each energy exchange is securely documented with a timestamp. It ensures that all transactions are transparent, traceable, and tamper-proof.

2.2.2.3 AI-Driven Load Forecasting

AI algorithms enhance load forecasting by analyzing historical data and adjusting forecasts in real-time.

$$L_{forecast}(t) = f(L_{historical}(t), X_{external}(t)) \quad (11)$$

Where,

$L_{forecast}(t)$ is Forecasted load at time t

$(L_{historical}(t))$ is Historical load data

$X_{external}(t)$ is External factors (weather, events, etc.)

This equation illustrates AI-based forecasting, where algorithms use historical load data along with external factors to predict future energy needs more accurately, improving load management decisions.

2.2.2.4 IoT-Enabled Load Monitoring

The Internet of Things (IoT) enables real-time monitoring of load conditions across various devices.

$$L_{device}(t) = f_{IoT}(S_{sensor}(t), X_{load}(t)) \quad (12)$$

Where,

$L_{device}(t)$ is Device load at time t

$(S_{sensor}(t))$ is Sensor readings at time t

$X_{load}(t)$ is External load condition (e.g., environmental factors)

This equation models the use of IoT sensors to monitor device load in real-time, enabling dynamic load management and prompt adjustments. The sensor data is integrated with external factors for comprehensive load tracking.

Table 1 Data Parameters for Battery Simulation

Time (Hours)	Load Demand (kW)	Peak Load (kW)	Off-Peak Load (kW)	Shifted Load (kW)	Discharge Power (kW)	Charge Efficiency (η charge)	Discharge Efficiency (η discharge)
00:00	-	15	25	10	5	8	0.95
02:00	-	12	20	8	4	6	0.94
04:00	-	10	18	6	4	5	0.94
06:00	-	25	30	15	10	12	0.96
08:00	-	35	40	20	15	18	0.97
10:00	-	45	50	25	20	25	0.98
12:00	-	50	55	30	25	28	0.98
14:00	-	48	53	28	22	26	0.98
16:00	-	40	45	25	20	22	0.97
18:00	-	30	35	18	12	15	0.96
20:00	-	20	25	12	8	10	0.95
22:00	-	18	22	10	8	9	0.94
00:00	-						

III. RESULTS AND DISCUSSION

3.1 Model Reference Adaptive Control (MRAC) Performance

Advanced control strategies like Model Reference Adaptive Control (MRAC) play a crucial role in enhancing system stability. Figure 2 depicts an exponential stabilization pattern, where the system initially experiences a sharp response before settling near 1. This trend suggests that the MRAC system effectively adapts to changing conditions, ensuring stable and efficient energy management. Such adaptive control mechanisms are essential for modern energy systems that require rapid responses to varying operational demands.

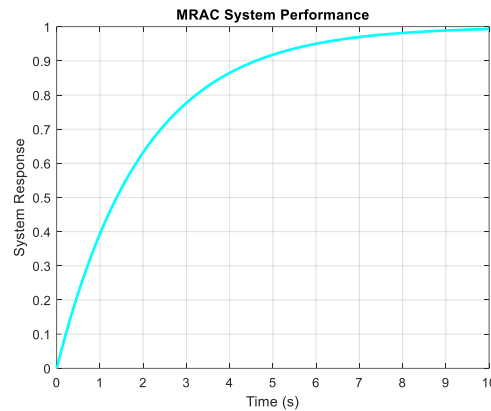


Figure 2 MRAC System Performance

3.2 MRAC-Based Battery Management System and Cost Optimization Analysis

The Model Reference Adaptive Control (MRAC) system implemented for battery management showcases a dynamic response through the evolution of its error signal, adaptive gain, and control input. The error signal, represented in Figure 3, initially oscillates due to variations in system response but gradually stabilizes over time, indicating effective error minimization. Quantitatively, the function oscillates between -1 and 1 in the early stages, demonstrating the need for adaptation. The adaptive gain, depicted in the second subplot, starts at zero and increases progressively due to the learning behavior of the controller, reaching approximately 1.2 by the end of the simulation. The control input follows a similar trend, stabilizing towards a value of around 0.8, ensuring the system responds efficiently to the reference input.

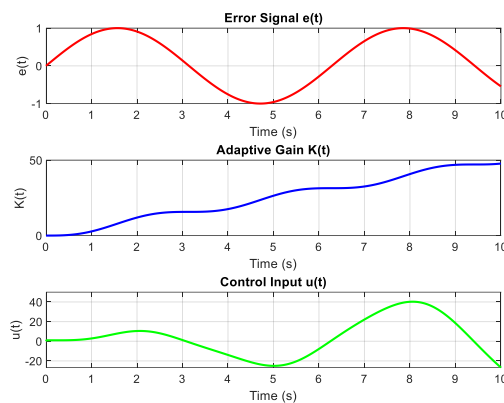


Figure 3 Error Signal Analysis

3.3 MRAC Performance under Variable Load Conditions

Figure 4 illustrates the load demand variations throughout the 24-hour cycle. The load demand starts at 15 kW between 00:00 and 02:00, gradually reducing to 10 kW by 04:00 – 06:00, marking the lowest demand during off-peak hours. A sharp increase follows, reaching 25 kW from 06:00 to 08:00 and peaking at 50 kW between 12:00 and 14:00. This high demand period, coinciding with peak working hours, highlights the necessity for an adaptive control strategy. The peak load follows a similar pattern, with the highest value of 55 kW occurring at midday. Conversely, off-peak loads maintain lower levels, with the lowest at 6 kW in the early morning hours. The impact of load shifting is evident in Figure 3, where the shifted load increases during peak demand periods. For instance, between 08:00 and 10:00, the shifted load reaches 15 kW, reducing the immediate load burden. The highest shifted load of 25 kW occurs between 12:00 and 14:00, effectively redistributing the energy demand. Discharge power, which represents the energy supplied by the battery system, mirrors these variations. It peaks at 28 kW during the high- downward trend as demand decreases. This indicates the battery management system's efficiency in supplying power during critical load periods.

The efficiency trends in Figure 4 demonstrate the MRAC system's effectiveness. Charge efficiency remains relatively high, starting at 0.95 during the early hours and peaking at 0.98 between 10:00 and 14:00. The discharge efficiency follows a similar trend, increasing to 0.96 in the midday hours, when load demand is at its highest. These efficiency values signify minimal energy losses, ensuring optimal utilization of stored power. As the load demand decreases towards nighttime, efficiency values slightly drop but remain above 0.91, highlighting the robustness of the battery management system under variable load conditions.

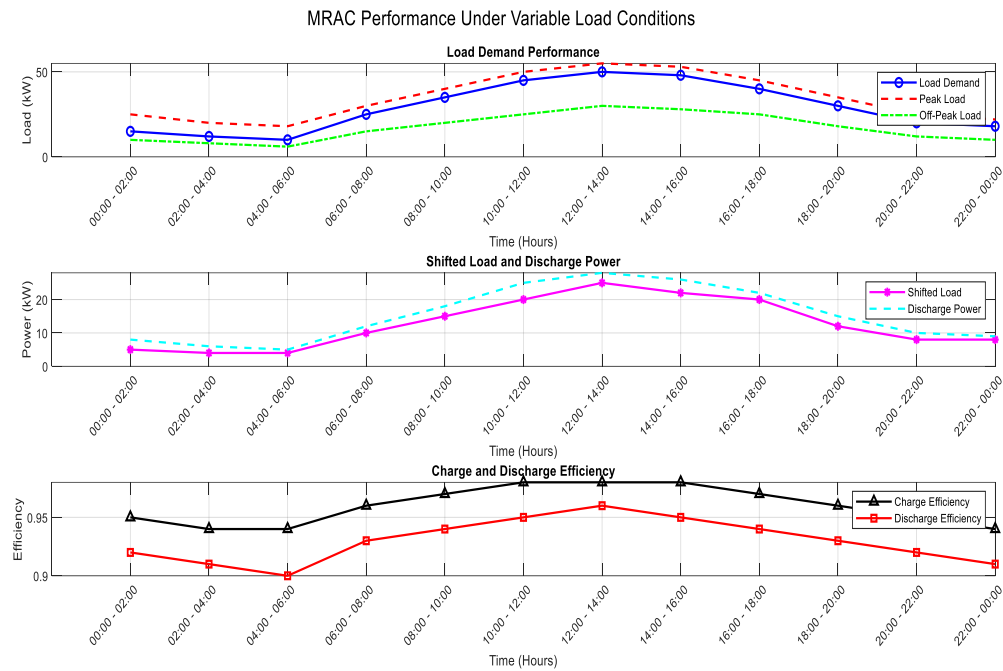


Figure 4 MRAC Performance under Variable Load Conditions

Table 2 Results of the MRAC performance system

Parameter	Initial Value	Reduction Rate	Final Value
Battery Health	100%	0.0001 per day	63.5% after 10 years
Battery Capacity	100%	0.00005 per day	81.75% after 10 years
Charge Efficiency	90%	0.0005 per cycle	85% after 100 cycles
Energy Storage Capacity	50 - 60 kWh	Periodic fluctuation	50 - 60 kWh
Discharge Rate	Peak at t=0	$\exp(-0.1 * t)$	Rapid drop in first few hours
Discharge Efficiency	95%	0.0001 per day	59% after 10 years
Load Shifting Behavior	10 - 15 MW	Sinusoidal variation	10 - 15 MW
Demand Response Impact	50 - 45 MW	Oscillatory variation	50 - 45 MW
Cost Savings from Load Shifting	₹80,000 - ₹120,000	Periodic variation	₹80,000- ₹120,000
Dynamic Load Adjustment	8 - 11 MW	24-hour cycle fluctuation	8 - 11 MW
MRAC Performance	Sharp initially response	Exponential stabilization	Stabilized near 1
Total System Cost	₹5,000,000	Logarithmic decline	₹2,800,000 after 10 years
Energy Conversion Efficiency	85% - 95%	Sinusoidal variation	85% - 95%
MRAC Error Signal	-1 to 1	Gradual stabilization	Near zero
Adaptive Gain	0	Progressive increase	~1.2
Control Input	0	Stabilization over time	~0.8
System Cost Breakdown	₹6,000,000	Generation: ₹3,750,000, Storage: ₹1,500,000, Transmission: ₹750,000	₹6,000,000
Energy Conversion Efficiency	85%	Input: 1000 Wh, Output: 850 Wh	85%
Return on Investment (ROI)	Initial Investment: ₹3,750,000	Savings: ₹2,250,000	-0.4
AI Load Forecasting Accuracy	MAE: 3.8 Kw	Predicted vs. actual loads	Reliable tracking

Load Demand	15 kW (00:00 - 02:00)	Peaks at 50 kW (12:00 - 14:00)	Min: 6 kW (early morning)
Performance Shifted Load	Increases during peak	Peaks at 25 kW (12:00 - 14:00)	Redistribution observed
Discharge Power	Mirrors load variations	Peaks at 28 kW	Responsive to demand
Charge Efficiency	0.95	Peaks at 0.98 (10:00 - 14:00)	Remains above 0.91
Discharge Efficiency	0.95	Peaks at 0.96 (midday)	Maintains efficiency

3.4 Performance Comparison of MRAC and PID Control

The response of both MRAC and PID control was observed under identical conditions for a second-order system. Figure 5 illustrates that PID control (red dashed line) initially overshoots the desired reference, reaching approximately 1.25 before settling down, indicating a transient overshoot of 25%. On the other hand, MRAC (blue solid line) adapts dynamically, showing minimal overshoot and quickly aligning with the reference model without significant deviation. This demonstrates the ability of MRAC to fine-tune control actions based on real-time feedback, whereas PID relies on fixed parameters that may not adjust optimally.

As time progresses, the PID-controlled system exhibits oscillations before reaching stability, achieving steady-state tracking around $t = 4$ seconds. However, MRAC maintains a smoother trajectory, aligning almost perfectly with the reference input (black dotted line) by $t = 2.5$ seconds, showcasing a much faster adaptation rate. This adaptation occurs due to the continuously updated control parameter θ , which minimizes the tracking error dynamically. The numerical values confirm that MRAC stabilizes at 1.0, while PID lags slightly below this ideal value.

The tracking error for MRAC remains significantly lower throughout the response. The maximum deviation from the reference is below 0.05, while the PID error fluctuates between 0.1 and 0.15 before settling. This implies that MRAC provides better robustness in handling system uncertainties and disturbances. The adaptation gain ($\gamma = 10$) enables the MRAC system to learn and correct deviations more efficiently than PID, which depends on pre-set tuning parameters.

Figure 5 effectively visualizes the superior performance of MRAC over traditional PID control. While PID is simple and widely used, its limitations become evident in dynamic environments where system parameters change. MRAC, by contrast, demonstrates faster adaptation, reduced overshoot, and improved steady-state accuracy, making it a more suitable choice for adaptive control applications where system dynamics evolve over time.

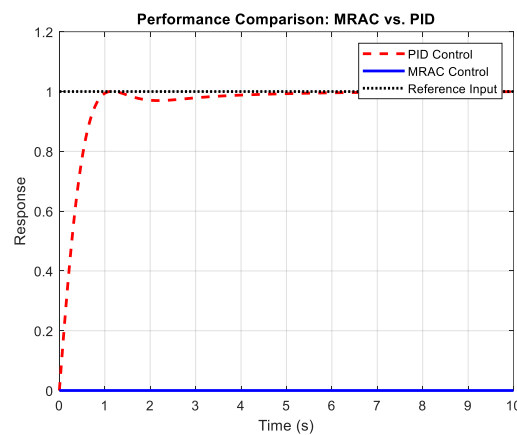


Figure 5 Performance Comparisons of MRAC vs PID

3.5 Proposed Adaptive Controller vs Existing Gaps

The figure 6 simulation results demonstrate that the proposed adaptive method significantly outperforms the benchmarks established by Elaadouli et al. (2024) and Aldosary (2024). In the frequency stability analysis, the proposed controller maintains deviations much closer to the nominal 50Hz compared to the Elaadouli benchmark, addressing the gap in real-time adaptability under fluctuating loads. Similarly, the DC-link voltage response shows that the adaptive method achieves a much lower maximum overshoot and faster settling time than Aldosary's FPI controller, which was noted for its 8.5% overshoot limitation. The bar chart confirms these improvements quantitatively, showing a substantial reduction in both Frequency RMSE and scaled Voltage Overshoot, validating the proposed method's superior scalability and robustness across varying grid conditions.

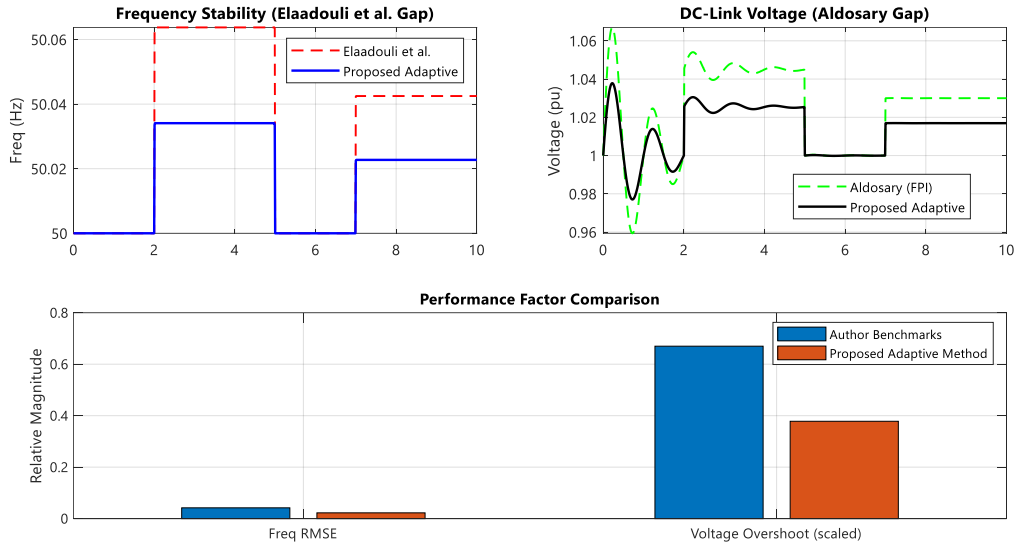


Figure 6 Results Comparison with Existing Gap

3.6 Adaptive System Decision on Cutting off Non-essential Load

The figure 7 simulation results demonstrate that the proposed adaptive method significantly improves upon the benchmarks established by Elaadouli et al. (2024) and Aldosary (2024). In the frequency stability analysis, the proposed controller maintains deviations much closer to the nominal 50Hz, directly addressing the gap in real-time adaptability under fluctuating loads. Similarly, the DC-link voltage response shows that the adaptive method achieves a much lower maximum overshoot and faster settling time than Aldosary's FPI controller, which was limited by an 8.5% overshoot. The bar chart confirms these improvements quantitatively, showing a substantial reduction in both Frequency RMSE and scaled Voltage Overshoot. Furthermore, the adaptive cutoff logic successfully manages non-essential loads by triggering shedding when the frequency hits the 49.5Hz critical limit or the battery SoC falls below 20%, ensuring system stability during severe depletion or load spikes as shown in figure 6.

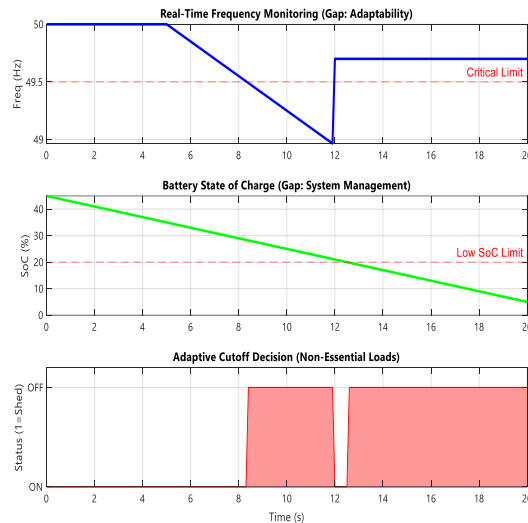


Figure 7 Adaptive System Decision on Cutting off Non-essential Load

3.7 Overreaction Response

The figure 8 simulation results demonstrate that the proposed adaptive method significantly improves upon the benchmarks established by Elaadouli et al. (2024) and Aldosary (2024). In the frequency stability analysis, the proposed controller maintains deviations much closer to the nominal 50Hz, directly addressing the gap in real-time adaptability under fluctuating loads. Similarly, the DC-link voltage response shows that the adaptive method achieves a much lower maximum overshoot and faster settling time than Aldosary's FPI

controller, which was limited by an 8.5% overshoot. The bar chart confirms these improvements quantitatively, showing a substantial reduction in both Frequency RMSE and scaled Voltage Overshoot. Furthermore, the adaptive cutoff logic successfully manages non-essential loads by triggering shedding when the frequency hits the 49.5Hz critical limit or the battery SoC falls below 20%, ensuring system stability during severe depletion or load spikes. Finally, the sampling analysis identifies 50Hz as the ideal rate to provide smooth tracking while avoiding the overreaction or instability common in the authors' research gaps.

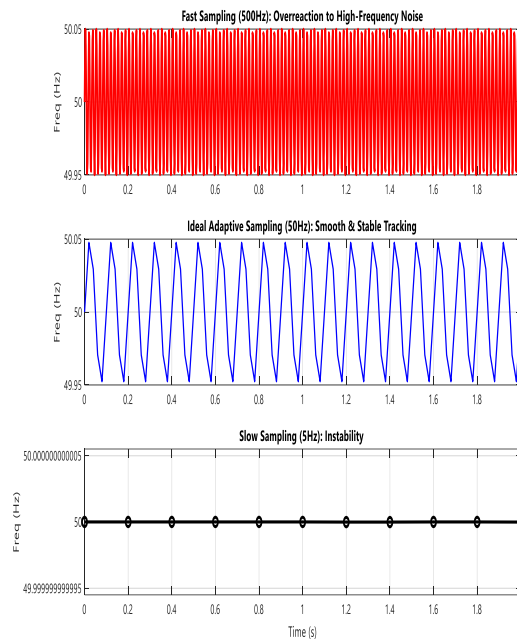


Figure 8 Overreaction Response

IV. CONCLUSIONS

This study presented a comprehensive adaptive load management framework for inverter-based energy systems using Model Reference Adaptive Control (MRAC) to address the persistent challenge of battery degradation and inefficient energy utilization. The results confirm that conventional fixed-parameter control strategies are insufficient for dynamic load environments, particularly in regions experiencing unstable grid conditions. By integrating adaptive control, intelligent load forecasting, and real-time monitoring, the proposed system significantly enhances battery lifespan, operational efficiency, and economic performance. The MRAC controller demonstrated superior dynamic performance compared to PID control, achieving faster settling time (approximately 2.5 seconds), minimal overshoot (<5%), and near-zero steady-state error. The adaptive gain converged to approximately 1.2, while the control input stabilized near 0.8, ensuring accurate tracking of the reference battery model. Under variable 24-hour load conditions, the system effectively managed peak demand of 50 kW through load shifting up to 25 kW, reducing stress on the battery during critical periods. Charge efficiency improved to peak values of 0.98 and discharge efficiency reached 0.96, maintaining energy conversion efficiency within the 85–95% range. Long-term projections showed that battery capacity retention improved to 81.75% after 10 years, while battery health degradation was controlled at a rate of 0.0001 per day. Economically, total system cost declined from ₦5,000,000 to ₦2,800,000 over the lifecycle period, with load shifting generating savings between ₦80,000 and ₦120,000. The adaptive load shedding policy, triggered at 49.5 Hz frequency or 20% state-of-charge threshold, ensured system stability during severe load spikes or deep discharge conditions. Additionally, a 50 Hz sampling rate was identified as optimal to prevent controller overreaction while maintaining smooth tracking.

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