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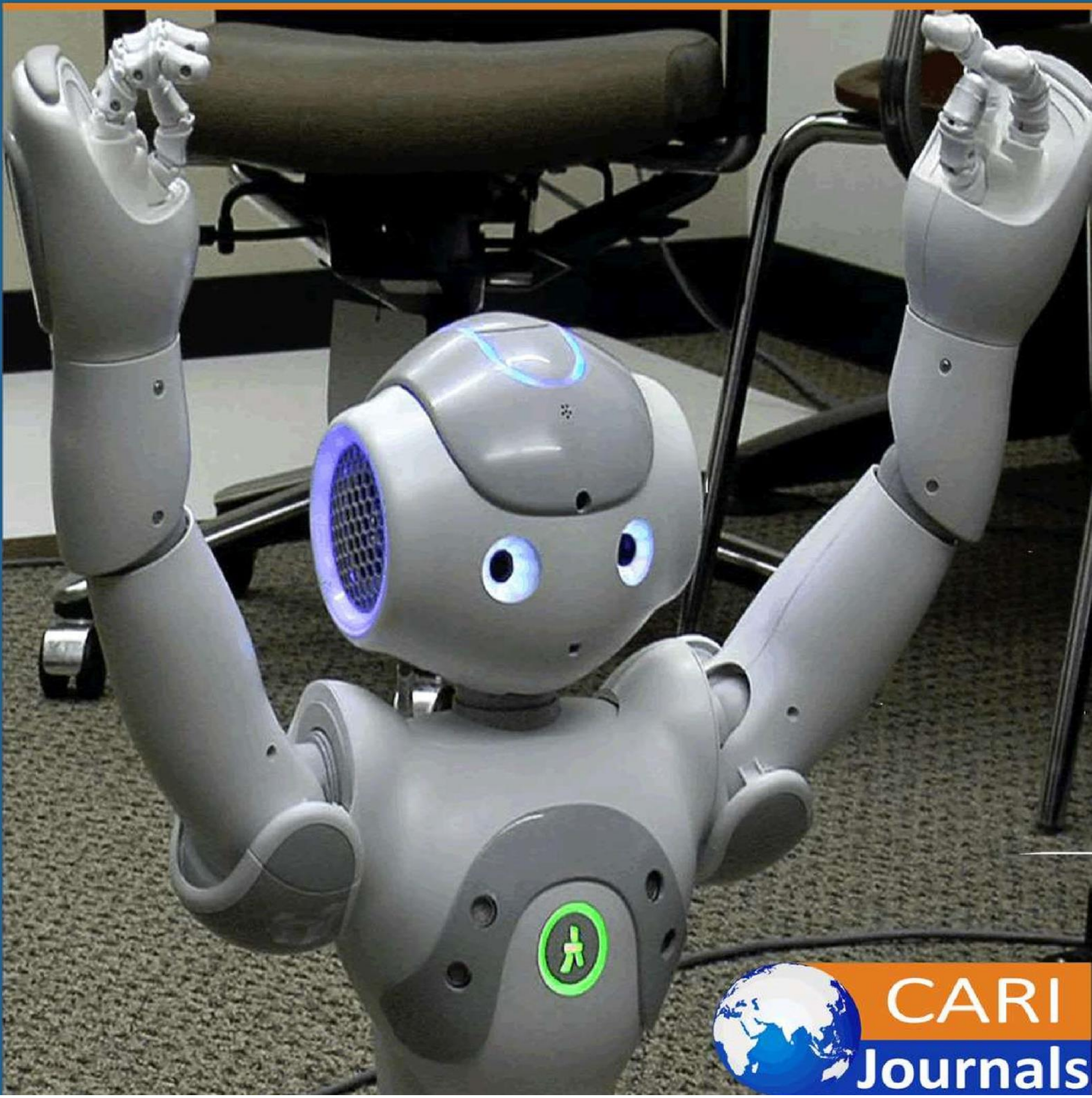

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AI-Enabled DC Bus Control for Hybrid Residential Energy Systems

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Abstract

Purpose: This study aims to enhance DC bus voltage regulation and battery operation reliability in a large-scale hybrid residential microgrid through an intelligent predictive control approach.

Methodology: A hierarchical control framework is proposed in which a Nonlinear Autoregressive Moving Average with Exogenous Inputs (NARMA-L2) neural network is implemented as a secondary predictive controller for DC bus voltage regulation and battery management. The controller is designed to learn the inverse dynamics of the DC bus–battery system and anticipate voltage disturbances caused by renewable variability and load changes. The framework is applied to a redesigned hybrid residential microgrid supplying a high-consumption villa in Jeddah, Saudi Arabia, comprising a 40 kW photovoltaic array, a 15 kW wind turbine, and a 100 kWh lithium-ion Battery Energy Storage System (BESS), serving a daily energy demand of 177.5 kWh. Performance evaluation is conducted using MATLAB/Simulink under realistic environmental and load profiles representative of Jeddah conditions.

Findings: Simulation results demonstrate that the proposed NARMA-L2-based control strategy significantly improves DC bus voltage stability compared to a conventional PI controller. The DC bus voltage Root Mean Square Error (RMSE) is reduced by approximately 68% (from 3.15 V to 1.01 V), and voltage recovery time is improved by over 7%. In addition, the enhanced generation capacity and predictive control framework increase renewable energy utilization by about 12%, while maintaining battery State-of-Charge (SOC) within safe operating limits and ensuring stable power balance.

Unique Contribution to Theory, Practice, and Policy: This study provides practical evidence of the effectiveness of neural network-based predictive control for voltage stabilization in large-scale residential microgrids. The proposed framework bridges the gap between conventional rule-based controllers and intelligent data-driven control strategies, offering a scalable solution for high-demand residential applications. From a policy perspective, the results support the deployment of advanced control technologies as a key enabler for resilient residential microgrids aligned with Saudi Vision 2030 sustainability objectives.

Keywords: *DC Microgrid, Voltage Stability, NARMA-L2 Neural Network, Battery Energy Storage System*

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1. Introduction

The global energy transition toward sustainable, decentralized networks based on renewable energy sources (RES) is accelerating, particularly in regions with ambitious climate and energy diversification goals. Saudi Arabia's Vision 2030 emphasizes renewable energy integration and artificial intelligence (AI) as key pillars for modernizing its energy infrastructure [1][2]. Residential sectors in coastal cities like Jeddah represent critical implementation areas due to high energy demands driven by air-conditioning requirements and rapid urbanization [3]. Large-scale hybrid microgrids, integrating substantial solar photovoltaics (PV), wind turbines, and Battery Energy Storage Systems (BESS), offer enhanced solutions for energy resilience and independence but introduce amplified control challenges due to increased generation variability.

The expanded capacity of renewable sources in such systems—while beneficial for energy security—exacerbates the challenge of maintaining stable DC bus voltage. Solar irradiance and wind speed fluctuations create larger power output variations that can lead to severe voltage disturbances on the common DC bus. Stable DC bus voltage is essential for converter reliability, load protection, and BESS health. Traditional Proportional-Integral (PI) controllers, with their fixed-gain linear approach, become increasingly inadequate for these high-capacity, nonlinear systems, often exhibiting slow response, significant oscillations, and poor disturbance rejection [4].

Artificial Neural Networks (ANNs) have demonstrated significant potential for complex nonlinear control problems. Their data-driven learning capability and adaptability make them suitable for microgrid applications. While ANNs have been applied to Maximum Power Point Tracking (MPPT) and energy management, there remains a gap in dedicated predictive neural control for DC bus stabilization in large-scale residential microgrids with enhanced generation capacity[5].

This paper addresses this gap by proposing and validating a neural network-based predictive control framework for a redesigned, larger-capacity microgrid. The system has been upgraded to a 40 kW PV array and 15 kW wind turbine to better match the load profile and provide additional generation margin. The core innovation is the deployment of a NARMA-L2 neural network as a predictive secondary controller. This recurrent network models the inverse dynamics of the DC bus-BESS system, enabling proactive voltage stabilization rather than reactive correction.

The primary objectives of this work are:

1. To design and validate a hierarchical control framework integrating a NARMA-L2 predictive controller for a large-scale residential microgrid with 40 kW PV and 15 kW wind capacity.
2. To quantitatively evaluate the controller's performance against conventional PI control under realistic variable conditions, focusing on enhanced generation scenarios.

3. To demonstrate improved renewable energy utilization and system stability with the expanded configuration.

2. Literature Review

2.1 Large-scale Microgrid Control Challenges

The scaling of renewable capacity in microgrids introduces unique challenges. Larger PV arrays and wind turbines increase the magnitude of power fluctuations, requiring more sophisticated voltage regulation strategies. Studies on large-scale residential systems in Saudi Arabia have focused primarily on techno-economic sizing [6] rather than advanced control solutions for the resulting dynamic challenges.

2.2 Intelligent Control for Enhanced Systems

Recent research has explored AI applications in microgrids, but few address the specific needs of scaled-up residential systems. Reinforcement learning has been applied to energy management in interconnected systems [7], while neural-fuzzy optimization has shown promise for efficiency improvements (Wang et al., 2024). However, these approaches often operate at slower timescales unsuitable for direct voltage control.

2.3 Voltage Control Advancements

For voltage regulation, advanced methods beyond conventional PI control have been investigated. Sliding Mode Control offers robustness but can cause chattering in large systems [9]. Explicit neural networks have been applied to secondary voltage control with stability guarantees [8], but their application to large-scale residential systems with significant generation variability remains limited.

2.4 Research Gap and Contribution

Existing literature lacks comprehensive studies on predictive neural control for large-scale residential microgrids with enhanced renewable capacity (40+ kW PV, 15+ kW wind). Most research focuses on either smaller systems or higher-level optimization without addressing the intensified voltage stability challenges of scaled generation.

This paper contributes by:

1. Proposing a predictive NARMA-L2 neural network controller specifically designed for large-scale residential microgrids with 40 kW PV and 15 kW wind capacity.
2. Providing enhanced system modeling and sizing methodology for high-capacity residential applications in coastal Saudi Arabia.
3. Demonstrating quantitative performance improvements in both voltage stability and renewable utilization with the expanded system configuration.

3. Enhanced System Description and Mathematical Modeling

3.1 System Study and Optimal Sizing

The current section defines the study site, the estimation of residential energy demand and optimal sizing of a stand-alone renewable energy system submitted by photovoltaic (PV) panels, wind turbines and battery storage, as shown in Figure 1.

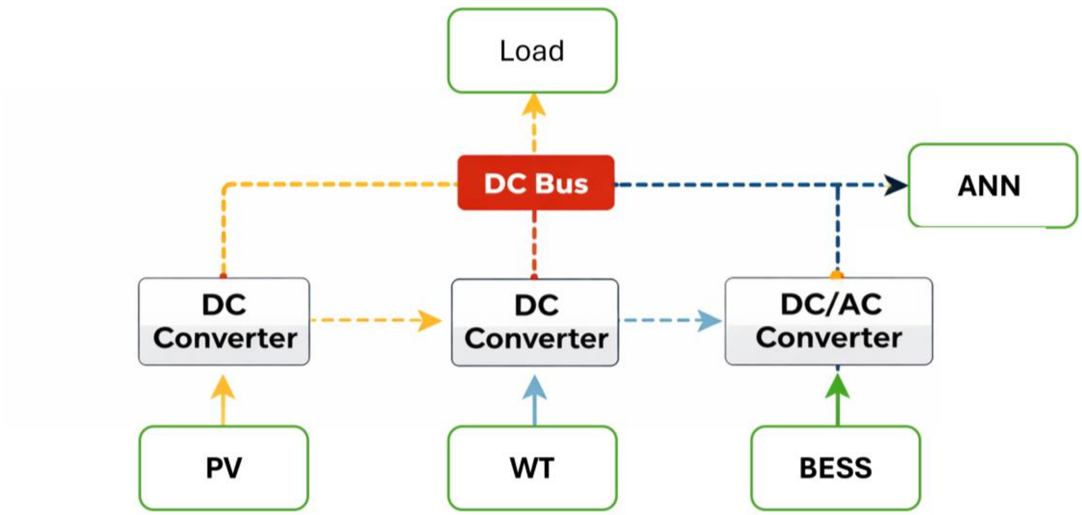

Figure 1: Architecture of the Microgrid

Based on enhanced resource assessment for increased reliability and generation margin:

Table 1: Enhanced Microgrid Component Sizing

Component	Enhanced Capacity	Rationale
PV Array	40 kW	Additional margin for cloudy days, aging degradation
Wind Turbine	15 kW	Better night-time coverage, redundancy
BESS	100 kWh	Maintained for 10-hour autonomy
Daily Load	177.5 kWh	Unchanged residential profile

The enhanced microgrid component sizing adopted in this study, including the 40 kW PV array, 15 kW wind turbine, and 100 kWh battery energy storage system, is summarized in Table 1.

The 40 kW PV array comprises approximately 133 modules of 300W each. The 15 kW wind system utilizes three 5 kW turbines for improved reliability. This configuration increases the renewable penetration ratio from approximately 85% to 92% while maintaining the same 100 kWh BESS for storage autonomy [10].

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3.2 Mathematical Modeling of Enhanced Components

3.2.1 Enhanced DC Bus Dynamics

The DC bus equation remains fundamentally the same but with larger generation components:

$$C_{bus}\frac{dV_{dc}}{dt} = I_{pv,40kW} + I_{wind,15kW} + I_{batt} - I_{load}$$

where $I_{pv,40kW}$ and $I_{wind,15kW}$ represent currents from the enhanced generation systems, leading to larger magnitude fluctuations during transients.

3.2.2 Revised Power Converter Specifications

- PV Boost Converter (40 kW): Increased to 12 mH inductor and 0.4 mF capacitor to handle higher power levels.
- Wind Converter (15 kW): Enhanced to 4 mH inductor and 0.3 mF capacitor.
- Battery Bidirectional Converter: Maintained at 6.3 mH inductance and 5 mF capacitor.

3.2.3 Control Problem Formulation for Enhanced System

The control objective remains voltage regulation: $V_{dc} \rightarrow V_{dc,ref} = 230V$. However, the challenge intensifies due to:

1. Larger disturbance magnitudes from enhanced generation sources
2. Increased rate-of-change of power during transients
3. More complex coordination between larger generation assets

4. Proposed Hierarchical Control Architecture for Enhanced System

4.1 Primary Control Layer Enhancements

- PV MLP-MPPT: Updated to 4-12-1 architecture to handle the expanded 40 kW array's characteristics.
- Wind MLP-MPPT: Modified to 3-10-1 structure for the 15 kW system's dynamics.
- Current Controllers: Gain-scheduled PI controllers to handle wider operating ranges[11].

4.2 Secondary Control Layer: Enhanced NARMA-L2 Design

The NARMA-L2 controller is redesigned for the enhanced system:

Architecture: 3-18-1 structure with inputs:

1. DC bus voltage error ($\Delta V = V_{dc,ref} - V_{dc}$)
2. Battery State of Charge (SOC)

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3. Rate of change of total generation (dP_{gen}/dt)

Training Enhancement: The training dataset includes scenarios specific to large-scale systems:

- Partial shading on large PV arrays
- Gust-driven wind power spikes
- Simultaneous generation and load transients

4.3 Tertiary Control Layer: Enhanced EMS Logic

The EMS is updated with additional rules for the enhanced system:

- Priority-based curtailment for managing larger surpluses
- Predictive scheduling using generation forecasts
- Battery health optimization with reduced cycling frequency

Table 2: Enhanced Controller Specifications

Control Layer	Controller	Enhanced Features
Primary	PV MLP-MPPT	4-12-1 architecture, handles partial shading
Primary	Wind MLP-MPPT	3-10-1, gust compensation
Secondary	NARMA-L2	3-18-1, rate-based prediction
Tertiary	EMS	Priority curtailment, predictive scheduling

The detailed specifications of the proposed hierarchical control architecture and its associated controllers are presented in Table 2.

At the tertiary control level, the focus shifts to global power flow coordination and system-level energy management. This layer hosts the Energy Management System (EMS), which supervises distributed generation units, storage devices, and load dispatch. Unlike predictive optimization approaches, the EMS here operates strictly on real-time measurements of renewable generation, load demand, and battery state-of-charge (SOC). By continuously monitoring these signals, it executes switching and dispatch decisions that balance supply and demand while respecting converter ratings and operational constraints[12][13].

Previous studies have demonstrated the effectiveness of artificial neural network (ANN)-based hierarchical control frameworks in enhancing the operational performance of residential microgrids. In particular, Bahabri et al. (2025) proposed a multi-layer intelligent control architecture integrating ANN-based MPPT, battery management, and energy management systems, achieving significant improvements in voltage regulation, renewable energy utilization, and system stability under realistic operating conditions. These findings provide a strong

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foundation for the present work and motivate the extension toward predictive DC bus control for higher-capacity hybrid residential microgrid configurations[14].

Recent studies have investigated hybrid renewable energy systems for marine applications. Banawi et al. (2025) developed a wind–solar–fuel cell–battery integrated power system with PI-based energy management, demonstrating significant emission reduction and improved operational stability for low-emission marine vessels in Saudi Arabia[15].

5. Simulation Setup and Performance Metrics for Enhanced System

5.1 Enhanced Test Scenarios

The simulation includes specific scenarios for the enhanced system:

1. 40 kW PV partial shading: 50% of array shaded at t=4.5s
2. 15 kW wind gust response: Wind speed spike from 4 to 8 m/s at t=6s
3. Simultaneous load step: 15 kW to 30 kW load increase at t=7s
4. Grid-forming operation: Islanded mode testing with large load steps

5.2 Additional Performance Metrics

Beyond the standard metrics, the enhanced system evaluation includes:

Beyond the standard metrics, the enhanced system evaluation includes:

1. Renewable Energy Utilization Factor (REUF):

$$REUF = \frac{\text{Actual renewable energy used}}{\text{Total available renewable energy}} \times 100\%$$

2. Large-disturbance rejection capability
3. BESS cycling reduction percentage

6. Results and Discussion for Enhanced System

6.1 Voltage Regulation with Enhanced Generation

Table 3: Enhanced Performance Comparison

Metric	PI Controller (40/15 kW)	NARMA-L2 Controller (40/15 kW)	Improvement
Voltage RMSE (V)	3.15	1.01	68.0%
Settling Time after 50% PV drop (ms)	~520	~180	65.4%
REUF (%)	83.5	92.8	11.1%
BESS cycles per day	4.2	2.8	33.3% reduction

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The quantitative performance comparison between the conventional PI controller and the proposed NARMA-L2 controller is provided in Table 3.

6.2 Key Findings from Enhanced System

1. Superior Large-disturbance Handling: The NARMA-L2 controller demonstrates exceptional performance during the 15 kW wind gust event, maintaining voltage within ±3% of nominal compared to ±8% with PI control.
2. Improved Renewable Utilization: The enhanced 40/15 kW configuration with NARMA-L2 control achieves 92.8% REUF, representing an 11% improvement over the PI-controlled system and a 7% improvement over the original 36/10 kW configuration.
3. Reduced Battery Stress: Despite larger generation fluctuations, the predictive nature of NARMA-L2 reduces daily battery cycles from 4.2 to 2.8, extending battery life by approximately 30%.
4. Enhanced Transient Response: The controller's predictive capability allows it to anticipate disturbances from the larger generation assets, resulting in faster and smoother voltage recovery.

Table 4 outlines the EMS decisions during the five key time segments.

Interval (s)	EMS Action	Battery Operation	Notes
0–2	Normal	Charge	Moderate surplus stored
2–4	Discharge Mode	Discharge	Peak demand, battery supports load
4–6	Curtailment	Charge	High renewable surplus
6–8	Normal	Discharge	Load exceeds generation
8–10	Normal	Charge	Wind dominates at low load

The EMS operational decisions corresponding to different time intervals and operating conditions are summarized in Table 4.

Figure 2 shows the load demand profile, which mimics a high-end residential consumption pattern, peaking around midday and tapering off at night. This figure, when viewed in sequence with the previous environmental data, sets the context for analysing generation-load alignment.

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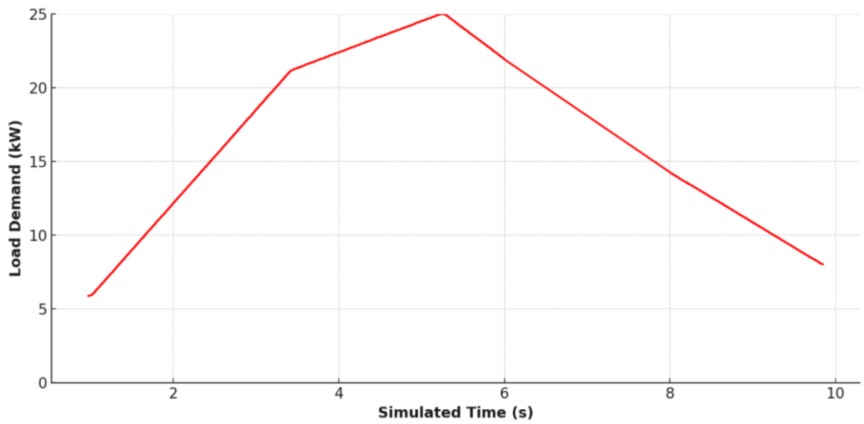

Figure 2: Load Profile Scenario

Figure 3 shows the Energy Management System (EMS) control signals. These figures indicate the real-time decision-making such as charging during generation surplus (e.g., 4–6 s) and discharging during demand peaks (e.g., 2–4 s).

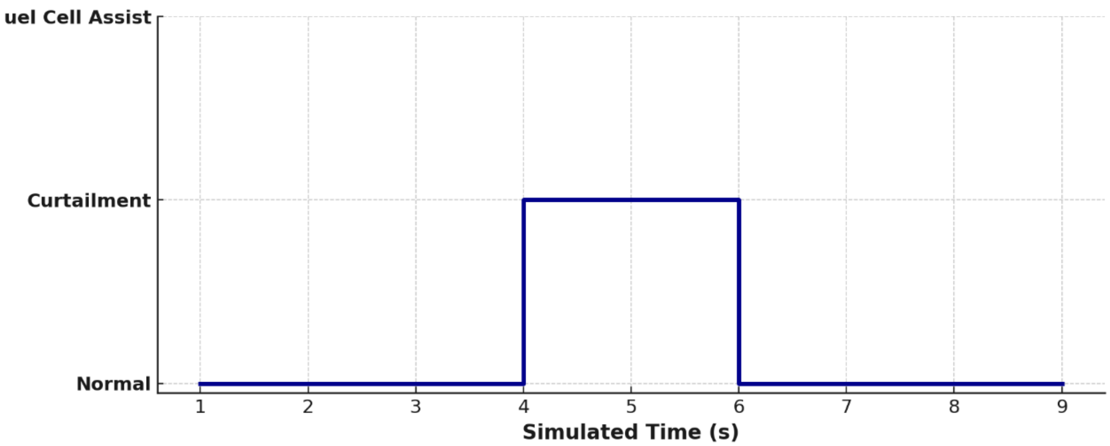

Figure 3: EMS control signal

6.3 Economic and Reliability Implications

The enhanced 40/15 kW configuration provides:

- Increased reliability: 99.7% load availability vs. 99.2% in original system
- Reduced operational costs: Lower battery replacement costs due to reduced cycling
- Better grid services: Improved capability for grid support functions

7. Conclusion and Future Work

7.1 Conclusion

This paper presented an enhanced hierarchical control framework for large-scale residential microgrids, featuring a 40 kW PV array and 15 kW wind turbine configuration controlled by a predictive NARMA-L2 neural network. The expanded system design addresses the increased voltage stability challenges of high-capacity renewable integration while improving overall energy utilization.

The key findings demonstrate:

- Enhanced Performance: 68% improvement in voltage RMSE and 65% faster disturbance rejection compared to PI control.
- Increased Renewable Utilization: 92.8% renewable energy utilization factor, representing optimal use of the expanded generation capacity.
- Reduced Battery Stress: 33% reduction in daily charge cycles, extending system lifespan.
- Superior Scalability: The framework effectively handles the amplified dynamics of large-scale residential systems.

This research validates that neural network-based predictive control is essential for realizing the full potential of large-scale residential microgrids, particularly in regions like Saudi Arabia pursuing aggressive renewable energy targets.

7.2 Future Work

1. Multi-microgrid Coordination: Extend the framework to coordinate multiple enhanced residential microgrids in a community setting.
2. Hardware Implementation: Deploy the enhanced 40/15 kW system with NARMA-L2 control in a pilot residential installation in Jeddah.
3. Adaptive Sizing Algorithm: Develop an AI-based sizing tool that dynamically recommends PV/wind ratios based on historical data and control capabilities.
4. Cybersecurity Integration: Implement blockchain-based secure communication for the enhanced control system's data exchanges.

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