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INTELLIGENT PREDICTIVE CONTROL OF MICROGRID BY AI LOAD FORECASTING

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Abstract — *This paper presents an intelligent energy management system for microgrids that integrates AI-based load forecasting with predictive and adaptive control strategies. The proposed framework combines demand estimation, proactive scheduling, and real-time dispatch optimization within a unified hierarchical architecture. Evaluated over a 6-hour control horizon, the system achieves a 93% reduction in operating cost compared to conventional rule-based methods and 75% reduction compared to scheduling-only approaches, while attaining a renewable self-sufficiency rate of 78.8%.*

I. INTRODUCTION

The global drive toward decarbonization has accelerated the deployment of distributed microgrid installations that rely on solar photovoltaic (PV) panels and wind turbines as primary energy sources. These systems offer significant benefits — including localized supply, improved grid resilience, and reduced transmission losses — but the inherently stochastic and weather-dependent nature of renewable generation introduces substantial operational challenges for energy dispatch and management.

Conventional rule-based controllers, while simple to implement, are reactive by design and cannot anticipate future system states. This leads to suboptimal renewable utilization and excessive dependence on grid imports. More advanced scheduling approaches address this by optimizing dispatch decisions over a rolling future horizon, but their effectiveness depends critically on the availability of accurate short-term load and generation forecasts. Machine learning techniques, particularly artificial neural networks (ANNs), have proven well-suited for this forecasting task in power systems.

Adaptive real-time control through reinforcement learning (RL) has also emerged as a powerful complement to model-based scheduling. RL agents learn optimal sequential dispatch policies through interaction with the system environment, enabling adaptive corrections that are difficult to anticipate in advance. Prior work has demonstrated that combining forecasting, scheduling, and real-time RL control can unlock compounding efficiency gains — yet the full integration of all three layers within a single-microgrid architecture has received limited investigation. The present study addresses this gap.

II. PROPOSED FRAMEWORK OVERVIEW

The proposed system manages four physical assets — a solar PV array, a wind turbine, a battery energy storage system (BESS), and a bidirectional grid connection — through three hierarchical control tiers operating in a coordinated pipeline.

The first tier uses a neural network to estimate near-term electricity demand from recent consumption history and real-time meteorological measurements. These predictions feed into the second tier, which computes an optimized power dispatch schedule across all available sources by minimizing grid cost over a receding planning window while respecting battery safety constraints. The third tier receives this schedule as a reference and applies real-time corrections based on current observed system conditions, enabling adaptive responses to short-horizon price fluctuations and forecast deviations that the scheduler cannot fully anticipate.

This layered design ensures that each component reinforces the others: reliable demand forecasts enable proactive scheduling, which in turn reduces the magnitude of real-time corrections needed, allowing the adaptive controller to focus on marginal refinements rather than gross error recovery. The physical microgrid components are summarized in Table I.

TABLE I. MICROGRID PHYSICAL COMPONENTS

Component	Role in the System
Solar PV Array	Generates DC power proportional to solar irradiance; converted to AC via grid-tied inverter with maximum power point tracking.
Wind Turbine	Supplies AC power varying with wind speed; principal renewable source, delivering 41.33 kWh over the 6-hour evaluation window.
Battery Storage (BESS)	Lithium-ion buffer absorbing surplus generation and supplementing supply during demand peaks; SOC maintained within prescribed safety bounds.

Grid Connection	Bidirectional interface supporting both power import and export; dispatch decisions exploit dynamic tariff structure to minimize cost.

III. SIMULATION RESULTS AND DISCUSSION

All three control strategies — rule-based, scheduling-only, and the full proposed framework — were benchmarked on a common 6-hour simulation running at 1-minute control intervals. A summary of the energy audit for the complete evaluation period is presented in Table II.

TABLE II. SIMULATION ENERGY SUMMARY (6-HOUR HORIZON)

Performance Metric	Value
Total Load Demand	**17.10 kWh**
Solar PV Generation	**4.95 kWh**
Wind Generation	**41.33 kWh**
Grid Imported	**3.63 kWh**
Grid Exported	**51.08 kWh**
Renewable Self-Sufficiency Rate	**78.8%**
Average Battery SOC	**45.3%**
Demand Forecast MAE	**0.293 kW**
Demand Forecast RMSE	**0.377 kW**

The demand forecasting module tracked the measured load profile with high fidelity throughout the evaluation window. Consumption rose steadily from roughly 1.8 kW at the start of the horizon to beyond 4.5 kW by its conclusion. The achieved forecast errors — MAE of 0.293 kW and RMSE of 0.377 kW — are well below the threshold required for reliable scheduling decisions.

Battery management remained consistently within safe operating bounds across the full simulation. Beginning at approximately 52%, the SOC declined to 29.8% as the controller compensated for rising load, with a mean of 45.3%. No SOC limit violations were recorded at any point, confirming the robustness of the joint constraint enforcement mechanism.

The energy balance results highlight the system's strong renewable utilization. Aggregate load demand of 17.10 kWh was met predominantly from wind generation (41.33 kWh) and solar PV (4.95 kWh), with only 3.63 kWh drawn from the grid — yielding a renewable self-sufficiency rate of 78.8%.

The operational cost comparison across strategies is presented below:

Control Strategy	Total Cost	Reduction vs Rule-Based
Rule-Based Control	$3.3860	—
Scheduling-Only Control	$0.9502	72%
Proposed Framework (Full)	**$0.2356**	**93%**

The proposed framework achieved the lowest expenditure at $0.2356 — a 93% reduction compared to rule-based control and a 75% improvement over scheduling-only approaches. The layered architecture compounds savings at each tier: the forecaster equips the scheduler with reliable forward-looking information, while the adaptive controller exploits residual price fluctuations and minor forecast deviations that the scheduler cannot fully anticipate.

Throughout the simulation, instantaneous power balance was maintained with negligible supply-demand mismatch at every time step, confirming the physical realizability of all dispatch decisions produced by the system.

IV. CONCLUSION

A three-tier intelligent energy management architecture has been presented for microgrid control, integrating AI-based demand forecasting, proactive power scheduling, and real-time adaptive dispatch within a unified hierarchical framework. Each layer reinforces the others, producing compounding efficiency gains that no single component achieves independently.

Over a 6-hour evaluation, the proposed system reduced total operating expenditure by 93% relative to conventional rule-based control and by 75% relative to scheduling-only operation. Battery state-of-charge was maintained within safe limits throughout (mean 45.3%), continuous power balance was upheld, and a renewable self-sufficiency rate of 78.8% was achieved through coordinated solar, wind, and storage dispatch.

These results demonstrate that the proposed architecture is both computationally tractable and broadly applicable to grid-tied and islanded microgrid configurations. Future work will focus on hardware-in-the-loop validation, extension to coordinated multi-microgrid networks, interval-based probabilistic forecasting for improved uncertainty quantification, and integration of demand-response mechanisms to unlock further cost reductions.

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