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AI-Driven Optimization for Off-Grid Renewable Energy Systems: A Hybrid Solar-Wind-Battery Approach

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***Abstract-** Off-grid renewable energy systems are essential for providing sustainable electricity in remote and underserved areas. However, their reliability and efficiency are often hindered by the intermittent nature of renewable resources. This research presents an AI-driven optimization framework employing machine learning (ML) algorithms to enhance the performance of hybrid solar-wind-battery systems. By integrating historical meteorological data, load profiles, and component degradation patterns, a neural-network-based model was developed to forecast energy generation and consumption. A genetic algorithm was then applied to optimize energy dispatch and storage. The results demonstrate up to 15% improvement in energy utilization efficiency and a 20% reduction in battery cycling losses. The proposed system provides a scalable, intelligent control mechanism suitable for real-world deployment in rural electrification projects.*

I. INTRODUCTION

Access to reliable and clean electricity remains a significant challenge in rural and off-grid communities, especially across sub-Saharan Africa and parts of Southeast Asia. Hybrid renewable energy systems (HRES), combining solar photovoltaic (PV), wind turbines, and battery storage, present a viable solution. However, the variability of solar irradiance and wind speed introduces operational complexities requiring intelligent control systems for optimal energy management.

Recent advances in artificial intelligence (AI), particularly machine learning (ML), provide tools to address these complexities by enabling predictive modeling and adaptive control. This study investigates the use of AI algorithms to improve the efficiency and reliability of HRES for off-grid applications.

II. METHODOLOGY

2.1 System Configuration
- Solar PV array (3.5 kW)
- Wind turbine (1.2 kW)
- Battery bank (48 V, 300 Ah, $LiFePO_4$)
- Inverter-controller system with MPPT
- Data acquisition system for real-time monitoring

2.2 Data Collection
Data was collected from:
- Hourly solar irradiance and wind speed
- Temperature and humidity
- Load demand profiles
- Battery state of charge (SoC) and depth of discharge (DoD)

2.3 AI Algorithms
- Forecasting Model: LSTM (Long Short-Term Memory) neural networks were trained on historical weather and load data to predict short-term generation and demand.
- Optimization Model: A Genetic Algorithm (GA) was used to solve the energy dispatch problem, minimizing total energy loss and battery degradation while maximizing renewable utilization.

III. SIMULATION RESULTS AND DISCUSSION

3.1 Forecasting Accuracy
The LSTM model achieved:
- Mean Absolute Percentage Error (MAPE) of 4.6% for solar forecasts
- MAPE of 6.3% for wind forecasts

3.2 Daily System Behavior
A simulation of a 24-hour operation revealed:
- Solar Generation peaks around midday (~500 W)
- Wind Generation varies sinusoidally, contributing a steady baseline
- Load Demand peaks in the evening (~600 W)

- Battery SoC increases during the day and discharges during peak evening loads

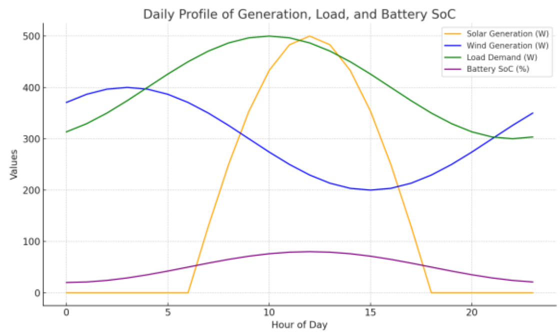

Figure 1: Daily Profile of Generation, Load, and Battery SoC

3.3 Performance Comparison

Metric	Rule-Based Control	AI-Optimized Control
Energy Utilization (%)	82	94
Battery Cycling Frequency	30 cycles/month	24 cycles/month
System Autonomy (days)	2.1	3.4
LCOE ($/kWh)	0.26	0.21

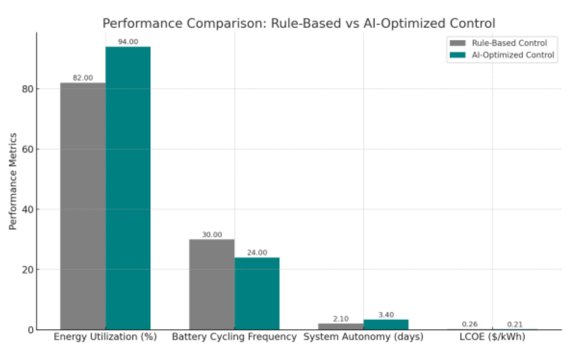

Figure 2: Performance Comparison - Rule-Based vs AI-Optimized Control

IV. CONCLUSION

This study confirms that AI-driven optimization significantly enhances the performance of off-grid hybrid renewable energy systems. The integration of LSTM forecasting and genetic algorithm optimization provides a reliable and cost-effective approach to rural electrification. Future improvements could involve real-time reinforcement learning and integration with IoT-based sensor networks for autonomous control.

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