ISSN: 6314 -6515
Volume 10, Number 2, 2026
International Journal of Innovations in Engineering and Environmental Science

AI-DRIVEN OPTIMIZATION OF RENEWABLE ENERGY SYSTEMS: BRIDGING THE TECHNOLOGY-SUSTAINABILITY NEXUS IN EMERGING ECONOMIES

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ABSTRACT
The global energy transition demands not only the widespread deployment of renewable energy technologies but also their intelligent management and optimization to deliver reliable, efficient, and cost-effective power. Artificial intelligence (AI) — encompassing machine learning, reinforcement learning, and digital twin technologies — is increasingly recognized as a critical enabler of this optimization challenge, particularly for complex, heterogeneous energy systems such as solar-wind-storage microgrids that predominate in off-grid and weak-grid contexts common in emerging economies. This paper provides a comprehensive review and analysis of AI-driven optimization methodologies for renewable energy systems, with a dual focus on global technological frontiers and applications in the Nigerian and broader African context. Through systematic literature review, comparative case study analysis, and a techno-economic modeling exercise for a hypothetical Nigerian rural microgrid, the study demonstrates that AI-optimized energy management systems can reduce operational costs by 18 to 34%, increase renewable energy utilization by 20 to 42%, and significantly enhance system reliability compared to conventional rule-based control approaches. The paper also identifies key barriers to adoption in emerging economy contexts — including hardware costs, connectivity requirements, and digital literacy gaps — and proposes a practical framework for context-appropriate AI integration in renewable energy projects. The findings have implications for energy system designers, project developers, policymakers, and investors engaged in the clean energy transition across Africa and other developing regions.

Keywords:*Artificial intelligence, renewable energy optimization, microgrid, energy management system, machine learning, reinforcement learning, Nigeria, digital twin, clean energy transition*

INTRODUCTION
The global imperative to decarbonize energy systems while expanding access to affordable electricity presents a profound engineering and management challenge, particularly in emerging economies where energy poverty, infrastructure deficits, and climate vulnerability intersect. Renewable energy technologies — principally solar photovoltaic, wind power, and battery storage — offer an increasingly cost-competitive pathway to address both challenges

simultaneously. However, the intrinsic variability of solar and wind resources, combined with the complexity of balancing supply and demand across spatially distributed systems, imposes significant optimization challenges that conventional engineering control approaches address only partially.

Artificial intelligence has emerged in the past decade as a transformative toolkit for energy systems optimization. The ability of machine learning algorithms to learn from large operational datasets, identify nonlinear patterns, forecast energy generation and demand with high accuracy, and make real-time control decisions that account for multiple competing objectives — including cost minimization, reliability maximization, battery lifetime extension, and grid stability — substantially exceeds the capabilities of traditional rule-based energy management systems (Antonanzas et al., 2020).

In emerging economies like Nigeria, where approximately 40% of the population (over 80 million people) lacks grid electricity, solar-battery microgrids and mini-grids are the primary near-term solution for rural electrification. The economic viability and long-term sustainability of these systems is critically dependent on their operational efficiency. Suboptimal control of a solar-battery system — for instance, charging batteries at the wrong time or curtailing surplus solar generation instead of storing it — can reduce the effective life of the system and inflate the levelized cost of electricity by 15–25% (Renewable Energy For Africa Foundation, 2023).

This paper addresses the question of how AI-driven optimization can improve the performance of renewable energy systems in emerging economy contexts, with particular attention to the practical constraints — connectivity, hardware, data availability, and human capacity — that shape the feasibility and scalability of these approaches. The paper makes three principal contributions: (i) a structured synthesis of AI optimization methodologies and their demonstrated performance gains; (ii) a techno-economic analysis of AI-optimized versus conventional energy management in a Nigerian rural microgrid scenario; and (iii) a context-appropriate framework for integrating AI optimization into renewable energy projects across Africa.

LITERATURE REVIEW

The AI techniques applied to renewable energy optimization can be broadly organized into four categories. Supervised learning methods, including artificial neural networks (ANNs), support vector machines (SVMs), and gradient boosting algorithms, are primarily used for forecasting tasks such as solar irradiance prediction, wind power forecasting, and load demand estimation. These forecasting capabilities are foundational to optimal scheduling decisions in energy management systems (EMS).

Reinforcement learning (RL) and deep reinforcement learning (DRL) represent a second and particularly powerful category. RL agents learn optimal control policies through iterative interaction with an environment, receiving reward signals that encode operational objectives. Deep Q-Networks (DQN) and Proximal Policy Optimization (PPO) algorithms have been successfully applied to microgrid energy management, demonstrating the ability to adaptively optimize dispatch decisions in real time under highly variable conditions (Perera et al., 2021).

Multi-objective optimization metaheuristics — including genetic algorithms, particle swarm optimization, and ant colony optimization — constitute a third category, commonly applied to the planning and sizing of renewable energy systems to identify Pareto-optimal configurations that balance cost, reliability, and emissions objectives. Finally, digital twins — virtual replicas of physical energy systems that integrate real-time sensor data with physics-based simulation — represent an emerging frontier that enables predictive maintenance, scenario testing, and AI training in a risk-free virtual environment (Grieves, 2022).

The empirical performance literature on AI-driven energy management systems is growing rapidly. A meta-analysis by Luo et al. (2022) of 47 studies on AI-based microgrid control found median cost reductions of 23.7% and renewable energy utilization improvements of 31.4%

compared to conventional rule-based control. Particularly strong results were reported for hybrid solar-wind-battery-diesel systems — precisely the configuration most common in emerging economy off-grid applications — where AI dispatch optimization can dramatically reduce diesel generator runtime.

Studies from Africa and Asia provide contextually relevant evidence. Olatunde et al. (2023) demonstrated that a fuzzy-logic enhanced energy management system for a Nigerian university campus microgrid reduced diesel consumption by 38% while maintaining the same level of power reliability. In Kenya, a solar-battery mini-grid operated by a rural cooperative that adopted ML-based load forecasting and adaptive tariff mechanisms achieved a 29% reduction in operational costs over two years, making the system financially self-sustaining for the first time.

Despite the compelling performance evidence, the literature documents significant contextual barriers to AI optimization deployment in emerging economies. Connectivity constraints — particularly the limited and unreliable internet access in rural areas where most off-grid systems are deployed — complicate the use of cloud-based AI platforms and require edge computing solutions that can operate autonomously with intermittent connectivity (Ocheje& Ibrahim, 2022). Hardware costs for smart meters, IoT sensors, and edge computing units add to upfront project costs and may not be justifiable for smaller systems.

The availability of historical operational data — essential for training ML models — is often limited for newly deployed systems. Transfer learning approaches, which adapt models trained on data-rich contexts to new deployments, represent a promising solution but require validation across diverse system configurations and geographic contexts. The shortage of engineers with both renewable energy and AI expertise is an additional structural constraint that limits the effective implementation and maintenance of AI-EMS solutions.

METHODOLOGY

A systematic review of peer-reviewed articles and technical reports on AI optimization for renewable energy systems was conducted, covering publications from 2015 to 2025. Searches were conducted across Scopus, IEEE Xplore, Web of Science, and Google Scholar using Boolean queries combining AI/ML terms with renewable energy, microgrid, energy management, and optimization keywords. Of 2,341 initial records identified, 94 studies met inclusion criteria and were retained for analysis. Data extraction focused on AI method, application type, system configuration, geographic context, and quantitative performance metrics.

A hypothetical Nigerian rural mini-grid scenario was modeled to compare the performance of AI-optimized versus conventional rule-based energy management. The modeled system consists of 100 kW solar PV, 200 kWh lithium iron phosphate (LiFePO4) battery storage, and a 50 kW backup diesel generator, serving a cluster of 300 households and 20 small commercial enterprises in Kogi State, North-Central Nigeria. Load profiles were constructed using the HOMER Pro demand estimation tool calibrated with data from similar-scale rural electrification projects in North-Central Nigeria.

Solar resource data were obtained from NASA POWER (Prediction of Worldwide Energy Resources) at 0.5° resolution for the study location. Two EMS scenarios were simulated: (i) a conventional rule-based EMS using fixed state-of-charge thresholds for battery charge/discharge decisions; and (ii) an AI-EMS using a DRL-based controller trained on 12 months of simulated operational data and optimized for minimum lifecycle cost. MATLAB-Simulink was used for simulation, and system performance was evaluated over a 25-year project lifetime using standard techno-economic indicators including levelized cost of electricity (LCOE), renewable energy fraction (REF), battery cycle life, and diesel fuel consumption.

RESULTS AND FINDINGS

The reviewed literature reveals consistent and substantial performance improvements attributable to AI optimization across system configurations and geographies. Deep reinforcement

learning approaches demonstrated the largest performance gains overall, with median cost reductions of 28.4% and renewable fraction improvements of 36.1%. Supervised learning approaches for forecasting, when integrated into EMS scheduling, contributed median cost reductions of 15.7%. The combination of accurate ML forecasting with DRL-based dispatch optimization in integrated AI-EMS architectures delivered the strongest overall results.

Studies conducted in African or low-income country contexts (n=18 in the sample) showed performance gains broadly consistent with global averages, though with greater variance attributable to data availability, system heterogeneity, and implementation quality. Critically, all studies reporting AI-EMS results from African deployments reported positive net economic outcomes, indicating that performance gains are sufficient to offset the added costs of AI implementation even in resource-constrained settings.

The techno-economic simulation for the Nigerian rural mini-grid scenario yielded significant performance differentials between the conventional rule-based EMS and the AI-DRL-based EMS. Under the conventional EMS, the system achieved a renewable energy fraction of 68.3%, with diesel generator contributing 31.7% of annual electricity supply, and a simulated LCOE of ₦87.4 per kWh over 25 years. Under the AI-EMS, the renewable fraction increased to 89.1%, diesel contribution fell to 10.9%, and the LCOE declined to ₦71.2 per kWh — a 18.5% reduction. Battery cycle counts under AI-EMS control were 12.3% lower than under rule-based control, translating to a projected battery replacement interval extension of approximately 2.7 years — a significant cost saving in a system where battery replacement is the largest capital maintenance expenditure.

Sensitivity analysis showed that AI-EMS benefits were most pronounced during periods of high load variability and low solar resource, precisely the conditions that challenge conventional fixed-threshold controllers. The analysis also indicated that the incremental hardware cost of edge AI implementation (estimated at approximately ₦1.2 million, or USD 800, per system) was recovered within 3.4 years through reduced diesel costs alone, yielding a positive ROI over the project lifetime under all but the most pessimistic cost scenarios.

DISCUSSION

The convergence of evidence from the literature review and the techno-economic modeling exercise makes a compelling case for the integration of AI-driven optimization into renewable energy systems deployed in Nigeria and comparable emerging economy contexts. The 18.5% LCOE reduction demonstrated in the modeling scenario translates directly into improved project economics: at lower electricity costs, mini-grid operators can attract more customers, offer more affordable tariffs, and achieve financial sustainability more rapidly — all critical factors in the long-term success of rural electrification initiatives.

The extension of battery cycle life through AI-optimized charging is of particular practical significance. Batteries represent 30–40% of total mini-grid capital costs and their premature degradation due to improper charging is one of the most common causes of mini-grid project failure in Sub-Saharan Africa (ARE, 2023). The AI-EMS approach effectively acts as a smart battery management system that continuously adapts to the operational state of the storage asset.

The feasibility of AI-EMS deployment in low-connectivity rural environments, long a technical barrier, has been substantially addressed by advances in edge computing. Single-board computers such as the Raspberry Pi and NVIDIA Jetson Nano can now execute DRL inference and ML forecasting tasks locally, without requiring continuous internet connectivity. This edge-first architecture is well-suited to the infrastructure realities of rural Nigeria and supports the development of locally maintainable, resilient energy management solutions.

The proposed AI integration framework emphasizes four principles: (i) modularity — AI components should be designed for incremental integration into existing EMS architectures; (ii) data frugality — models should be trained to perform well with limited local data, using transfer learning from global datasets; (iii) explainability — AI control decisions should be interpretable to

system operators, building trust and supporting local troubleshooting capacity; and (iv) affordability — hardware and software choices should be optimized for cost in the target deployment context.

CONCLUSION

This paper has synthesized global and regional evidence to demonstrate that AI-driven optimization offers substantial and practically achievable performance improvements for renewable energy systems in emerging economy contexts. The combination of a systematic literature review — documenting median cost reductions of up to 28% and renewable fraction improvements of up to 36% from DRL-based optimization — and a contextualized techno-economic modeling exercise for a Nigerian rural mini-grid scenario provides a robust evidence base for action.

The key message for practitioners and policymakers is that AI optimization is not a luxury technology for data-rich, high-capacity contexts — it is increasingly an accessible and cost-effective tool for improving the economics and reliability of the solar and battery systems that are electrifying rural Africa. Achieving this potential requires targeted action on three fronts: investment in edge computing hardware standards and ecosystems for off-grid applications; curriculum development at technical institutions to build AI-energy engineering competencies; and the integration of AI-EMS performance requirements into rural electrification project standards and developer contracts.

The School of Engineering at Auchi Polytechnic is well-positioned to contribute to this agenda through applied research on AI-EMS architectures tailored to Nigerian energy system conditions, collaborative pilot projects with rural electrification agencies, and the development of AI-for-energy engineering training programs that equip the next generation of Nigerian engineers to lead the clean energy transition.

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