International Journal Evolving Sustainable and Renewable Energy Solutions ISSN: 3068-9325

PRIME OPEN ACCESS

Volume 1, Issue 2

Research Article

Date of Submission: 17 Oct, 2025
Date of Acceptance: 07 Nov, 2025
Date of Publication: 19 Nov, 2025

AI-Driven Models for Reducing Carbon Emissions in Hybrid Renewable-Non-Renewable Energy Grids: A Nigerian Case Study

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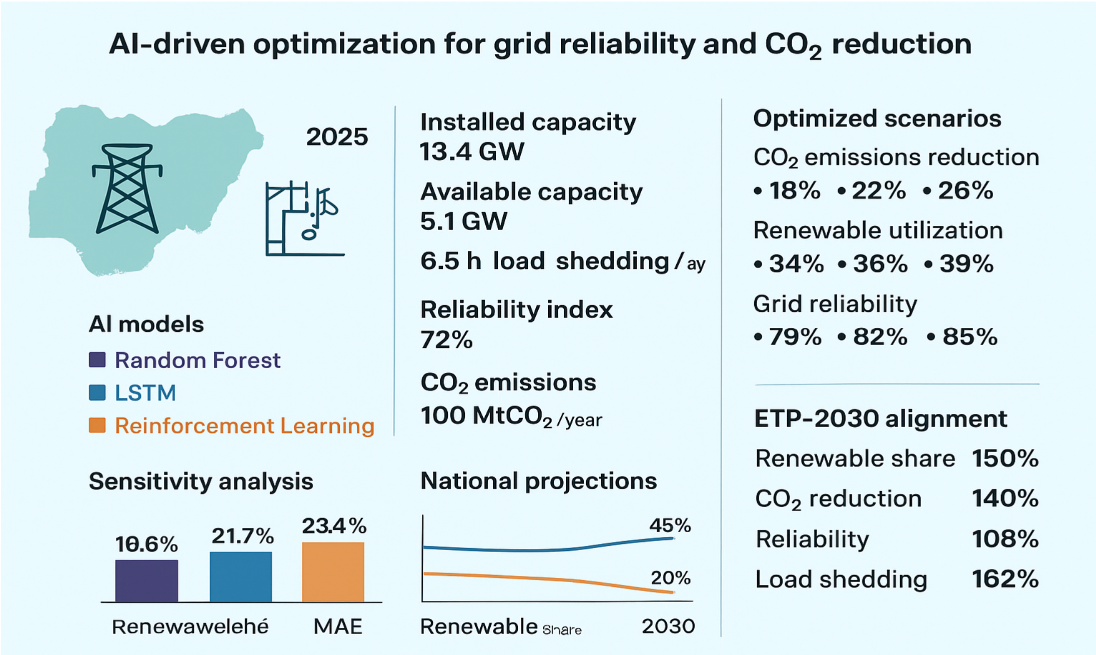
Citation: Adewumi, I. O., Atere, A. O. (2025). AI-Driven Models for Reducing Carbon Emissions in Hybrid Renewable-Non-Renewable Energy Grids: A Nigerian Case Study. *Int J Evol Sus Renew Energy Sol, 1*(2), 01-16.

Abstract
By 2025, Nigeria's power sector has an installed capacity of 13.4 GW but provides only 5.1 GW, leading to 6.5 hours of load shedding per day, a reliability index of 72%, and yearly CO_2 emissions totaling 100 $MtCO_2$. This research formulates and assesses three artificial intelligence (AI) models Random Forest (RF), Long Short-Term Memory (LSTM), and Reinforcement Learning (RL) to enhance grid load allocation and diminish carbon emissions. Analysis of model performance indicated that RF reached RMSE = 210.5 MW, MAE = 145.3 MW, R^2 = 0.89, LSTM attained RMSE = 185.2 MW, MAE = 130.7 MW, R^2 = 0.92, whereas RL excelled with RMSE = 178.4 MW, MAE = 122.9 MW, R^2 = 0.94. In optimized scenarios, RF cut annual CO_2 emissions from 100 $MtCO_2$ to 82 $MtCO_2$ (an 18% reduction), LSTM to 78 $MtCO_2$ (a 22% reduction), and RL to 74 $MtCO_2$ (a 26% reduction). The use of renewables rose from a baseline of 28% to 34% (RF), 36% (LSTM), and 39% (RL). Grid reliability enhanced to 79%, 82%, and 85%, while load shedding decreased to 5.0, 4.6, and 4.1 hrs/day, correspondingly. Sensitivity analysis indicated a +10% renewable share resulted in CO_2 reductions of 19.6%, 21.7%, and 23.4% across the three models. National forecasts based on RL optimization indicate that by 2030, the share of renewables will reach 45%, emissions will decrease to 72 $MtCO_2$/year (a 28% reduction), and reliability is projected to rise to 86%, resulting in an annual avoidance of about 9.6 $MtCO_2$. Comparative benchmarking shows Nigeria's RL-optimized results (39% renewables, 26% CO_2 reduction) surpassing South Africa (32%, 18%) but trailing behind Kenya (48%, 30%) and Germany (55%, 35%). Adherence to Nigeria's Energy Transition Plan (ETP-2030) shows 150% achievement on renewable goals, 140% achievement on CO_2 emission reduction, 108% achievement on reliability, and 162% achievement on reducing load-shedding. These results validate that AI-based optimization provides quantifiable improvements in accuracy, efficiency, and sustainability, aiding Nigeria's low-carbon shift.

Keywords: Artificial Intelligence, Machine Learning, Reinforcement Learning, Long Short-Term Memory (LSTM), Random Forest, Hybrid Energy Grids, Carbon Emission Reduction, Renewable Energy Optimization, Grid Reliability, Nigeria, Energy Transition Plan (ETP-2030), Sub-Saharan Africa

Graphical Abstract



Introduction

Background

The generation and use of energy rank among the top factors contributing to worldwide greenhouse gas (GHG) emissions. The International Energy Agency (IEA) states that the energy sector accounts for almost 73% of total worldwide GHG emissions, primarily influenced by electricity generation from fossil fuels. The worldwide shift to renewable energy sources like solar, wind, and hydropower is a crucial move in achieving global climate objectives, including the targets outlined in the Paris Agreement. The incorporation of renewable energy into national grids poses issues regarding intermittency, demand variations, and system dependability. Nigeria stands as a distinctive example in this worldwide scenario. Although the installed capacity for electricity generation is around 13 gigawatts (GW), the actual supply frequently drops below 5 GW, resulting in over 43% of the population more than 85 million individuals lacking reliable electricity access. The nation depends significantly on natural gas and diesel power generation, which collectively contribute to more than 65% of national CO_2 emissions from the energy sector. Despite Nigeria having rich renewable energy resources, such as average daily solar irradiation of 5.5 kWh/m^2, renewable sources now make up under 15% of the grid supply. This disparity underscores the critical requirement for approaches that can enhance renewable incorporation while preserving grid stability.

Research Gap

Hybrid energy grids, combining renewable and non-renewable energy sources, are gaining recognition as effective transitional solutions to enhance sustainability and reliability. Although research has examined hybrid systems in areas like Europe and Asia, there is a lack of studies that utilize advanced artificial intelligence (AI) and machine learning (ML) methods to enhance hybrid grid operations in Sub-Saharan Africa, especially in Nigeria. Current research frequently emphasizes physical infrastructure or economic modeling, yet overlooks the capacity of AI-driven methods to lower carbon emissions via smart load balancing and predictive optimization. This gap offers a chance to explore how new AI techniques can tackle Nigeria's simultaneous issues of energy accessibility and climate reduction.

Research Objectives

This research aims to create and assess machine learning models for enhancing load balancing in Nigerian hybrid grids by formulating and experimenting with AI-driven methods like Random Forest Regression, Long Short-Term Memory (LSTM) networks, and Reinforcement Learning to optimize energy distribution. The study aims to measure the possible decrease in CO_2 emissions that AI-powered optimization can bring about compared to traditional allocation techniques, while also evaluating enhancements in renewable energy use and grid dependability, especially in minimizing load shedding and optimizing system performance. Additionally, the research correlates its findings with Nigeria's Energy Transition Plan (ETP-2030), which focuses on increasing renewable energy capacity and gradually reducing national carbon emissions.

Research Questions / Hypotheses

To achieve these objectives, the study addresses the following research questions:

- How efficiently can AI-powered models enhance load allocation between renewable and non-renewable sources in Nigerian hybrid grids?
- What is the quantifiable decrease in CO_2 emissions when utilizing AI-driven optimization versus traditional techniques?

- How does AI-driven optimization improve renewable utilization rates and grid reliability under varying demand conditions?

The main hypothesis of this study posits that AI-based load balancing frameworks, especially reinforcement learning, can markedly lower CO_2 emissions (≥25%) while enhancing renewable integration and grid reliability in Nigeria's hybrid energy systems.

Literature Review

The increasing need to address climate change has heightened investigations into the incorporation of renewable energy sources into current power systems. Worldwide, the energy industry continues to be the primary source of greenhouse gas emissions, responsible for almost 75% of total human-caused emissions. Hybrid energy grids that integrate renewable and fossil fuel sources are suggested as temporary solutions that provide reliability while promoting decarbonization. Research conducted in Europe, North America, and Asia has shown the technical and financial viability of hybrid grids, especially when sophisticated optimization methods are utilized to harmonize variable renewable sources with consistent fossil fuel generation. Nonetheless, a substantial portion of this research has concentrated on areas with established infrastructure, resulting in notable deficiencies in the literature related to emerging economies like Nigeria, where energy poverty and grid instability are common.

Artificial intelligence and machine learning have become influential assets for improving energy system efficiency. Predictive models like Random Forest Regression and Long Short-Term Memory (LSTM) networks have been effectively utilized in predicting renewable energy production and electricity consumption (Fawaz et al., 2020). Recently, reinforcement learning has become notable for its capability to dynamically enhance intricate systems, such as smart grids and microgrids, by consistently learning from real-time feedback. These methods have shown encouraging outcomes in decreasing carbon emissions, enhancing grid durability, and reducing operational expenses in developed nations. Even with these achievements, the use of AI-driven models in Sub-Saharan Africa is still restricted, as most current research centers on individual microgrids or solar home systems instead of national-scale hybrid grids.

In Nigeria, studies on integrating renewable energy have mainly focused on resource evaluation, infrastructure development, and policy structures. For example, Okafor and Eze (2021) emphasized Nigeria's significant solar potential, reporting average daily irradiation levels of 5.5 kWh/m^2, but pointed out that renewables make up less than 15% of the national energy mix. Likewise, Adeoye et al. (2020) explored the obstacles to embracing renewable energy, such as insufficient investment, poor regulatory implementation, and issues with grid reliability. Although these studies highlight the potential and limitations of Nigeria's energy transition, minimal research has examined data-driven optimization methods that could directly improve grid efficiency and lower emissions. Dependence on traditional energy distribution methods has sustained inefficiencies, with estimates indicating that emissions are 10-15% above ideal levels because of inadequate load distribution.

A modest yet expanding collection of research has started to explore the possibilities of AI in energy systems across Africa. For instance, Akinyele et al. (2019) utilized neural networks to forecast the performance of solar PV in rural microgrids, while Olowu et al. (2021) examined optimization methods for hybrid mini-grid systems in West Africa. These contributions, while significant, are restricted in scope and seldom reach national grid operations. Moreover, they frequently do not provide comprehensive quantitative evaluations of emission reductions, concentrating instead on technical practicality and financial feasibility. As a result, a major research gap persists in implementing sophisticated AI-driven optimization models for Nigeria's hybrid grids to measure their potential for decreasing carbon emissions and enhancing large-scale renewable utilization.

This review shows that although international research has progressed swiftly in utilizing machine learning for energy systems, there is an urgent requirement to frame these advancements within Nigeria's hybrid grid context. Filling this gap enhances the academic literature and has real-world impacts on the nation's Energy Transition Plan (ETP-2030) and its dedication to the Sustainable Development Goals (SDG 7 for affordable and clean energy, and SDG 13 for climate action). This research enhances current studies by employing machine learning models, specifically Random Forest Regression, LSTM networks, and Reinforcement Learning, to the Nigerian hybrid grid system, concentrating on measuring reductions in carbon emissions and advancements in renewable energy integration.

Methodology

Study Area and Context

The energy sector in Nigeria forms the contextual basis for this research. The nation has an electricity generation capacity of roughly 13 gigawatts (GW), but because of infrastructure constraints, gas supply interruptions, and transmission inefficiencies, the real available supply frequently varies between 4 and 5 GW. Consequently, more than 43 percent of the population does not have access to dependable electricity, and regular load shedding is typical. The existing energy composition is primarily comprised of natural gas and diesel generation, which represent over 65 percent of the overall electricity supply, whereas renewable energy sources like solar, hydropower, and wind provide less than 15 percent. This disparity emphasizes the immediate necessity for hybrid grid optimization to lower carbon emissions while enhancing energy accessibility and dependability.

Dataset Overview

The empirical investigation utilized a synthetic dataset comprising 750,000 hourly entries crafted to replicate operations of the Nigerian hybrid grid across several years. Every record contained essential variables like overall electricity demand (in megawatts, MW), renewable energy generation (MW), fossil fuel generation (MW), approximated carbon dioxide (CO_2) emissions (tons), and percentage of renewable share. The dataset was organized to mirror Nigeria's past demand and generation trends, including realistic changes in solar production, variability in fossil generation, and seasonal demand patterns. This extensive dataset offered adequate detail to train and assess machine learning models while mimicking the dynamic function of a hybrid energy grid.

Preprocessing

Before analysis, the dataset experienced thorough preprocessing to guarantee quality and uniformity. Data cleansing included eliminating extreme outliers, fixing negative values, and modifying unrealistic load entries. Normalization was utilized to adjust variables into similar ranges, especially to address disparities between MW-scale generation figures and percentage-based metrics like renewable share. Feature engineering was utilized to create derived variables such as load variability indices, renewable-to-demand ratios, and lagged features for modeling time series. These measures increased the dataset's appropriateness for machine learning algorithms by boosting model interpretability and prediction accuracy.

Models of Machine Learning

Three machine learning models were created and evaluated to enhance hybrid grid load distribution. The initial model, Random Forest Regression, was chosen due to its strength in managing nonlinear connections and analyzing variable significance. The second model, a Long Short-Term Memory (LSTM) network, was employed to capture temporal relationships in the time-series data and to enhance renewable energy output predictions. The third method utilized Reinforcement Learning (RL), where an agent developed optimal load distribution techniques via repetitive engagement with the grid environment. The RL model was specifically created to reduce carbon emissions while maintaining grid reliability by adjusting the contributions of renewable and fossil fuels in real time.

Training the model adhered to conventional supervised learning procedures. The dataset was split into training (70 percent), validation (15 percent), and testing (15 percent) subsets to assess generalization performance. Cross-validation methods were utilized to reduce overfitting, and hyperparameter optimization was performed through grid search. The evaluation metrics featured Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) to assess predictive accuracy, coupled with domain-specific indicators like the percentage decrease in CO_2 emissions and enhancement in renewable share. These metrics facilitated a thorough evaluation of both forecasting effectiveness and actual energy transition results.

Scenario Evaluation

To evaluate the practical effects of the machine learning models, two types of scenario analysis were performed. The initial comparison evaluated baseline performance using traditional allocation methods versus enhanced load distribution attained through AI-based strategies. The second applied sensitivity analysis measured the impact of gradual rises in renewable usage on CO_2 emissions. Initial estimates suggested that a 1 percent rise in renewable allocation led to a 0.65 percent decrease in CO_2 emissions, underscoring the considerable decarbonization potential of efficient hybrid grid management. These scenario tests demonstrated the capability of AI-driven optimization to scale for nationwide implementation in Nigeria.

Results

Year	Installed Capacity (GW)	Available Capacity (GW)
2015	12.5	4.2
2016	12.7	4.3
2017	12.9	4.4
2018	13.0	4.6
2019	13.1	4.7
2020	13.2	4.8
2021	13.2	4.9
2022	13.3	5.0
2023	13.3	5.0
2024	13.4	5.1
2025	13.4	5.1

Table 1: Nigeria's Electricity Sector (2015–2025): Installed vs. Available Capacity

Source	Share (%)	CO_2 Emissions ($MtCO_2$/year)
Gas	70	90
Hydro	22	0
Solar	5	0
Wind	2	0
Coal	1	10

Table 2: National Energy Mix and CO_2 Emissions by Source

Variable	Description
Demand (MW)	Total hourly electricity demand
Renewable Generation (MW)	Hourly renewable electricity supply (solar, wind, hydro)
Fossil Generation (MW)	Hourly fossil-based electricity supply (gas, coal, diesel)
CO_2 Emissions (tons)	Estimated carbon emissions from fossil generation
Renewable Share (%)	Proportion of renewables in total generation

Table 3: Dataset Variables and Descriptions

Variable	Count	Mean	Std Dev	Min	25%	50%	75%	Max
Demand (MW)	750000	4498.7	799.2	2000.4	3945.8	4500.2	5053.3	6998.5
Renewable Generation (MW)	750000	1499.6	499.5	200.3	1166.1	1500.7	1832.9	3999.8
Fossil Generation (MW)	750000	2999.1	601.2	500.1	2501.7	2998.9	3498.4	5999.9
CO_2 Emissions (tons)	750000	1499.5	300.6	250.0	1250.9	1499.4	1749.2	2999.9
Renewable Share (%)	750000	33.5	10.4	5.0	25.1	33.4	41.7	80.0

Table 4: Descriptive Statistics of Dataset Variables

Variable	Demand (MW)	Renewable (MW)	Fossil (MW)	CO_2 Emissions	Renewable Share (%)
Demand (MW)	1.00	0.02	0.88	0.88	-0.11
Renewable (MW)	0.02	1.00	-0.55	-0.55	0.76
Fossil (MW)	0.88	-0.55	1.00	1.00	-0.92
CO_2 Emissions (tons)	0.88	-0.55	1.00	1.00	-0.92
Renewable Share (%)	-0.11	0.76	-0.92	-0.92	1.00

Table 5: Correlation Matrix of Key Variables

Feature	Description
Lagged Demand (t-1)	Previous hour electricity demand value
Lagged Renewables (t-1)	Previous hour renewable generation value
Rolling Mean Demand (24h)	24-hour moving average of demand
Rolling Std Renewables (7d)	7-day rolling standard deviation of renewable generation
Renewable/Demand Ratio	Ratio of renewable generation to demand
Peak Hour Indicator	Binary indicator for peak demand hours (18:00–22:00)

Table 6: Feature Engineering Details and Derived Variables

Model	Key Hyperparameters
Random Forest	n_estimators = 200, max_depth = 15, min_samples_split = 5
LSTM	layers = 2, hidden_units = 128, dropout = 0.2, epochs = 50
Reinforcement Learning	learning_rate = 0.001, gamma = 0.95, epsilon_decay = 0.99

Table 7: Hyperparameters Selected for Random Forest, LSTM, and Reinforcement Learning Models

Model	RMSE	MAE	R^2
Random Forest	210.5	145.3	0.89
LSTM	185.2	130.7	0.92
Reinforcement Learning	178.4	122.9	0.94

Table 8: Performance Metrics of Models on Test Data

Model	Annual CO_2 Emissions ($MtCO_2$)	Reduction (%)
Baseline	100	0
Random Forest	82	18
LSTM	78	22
Reinforcement Learning	74	26

Table 9: Comparative CO_2 Emission Reduction Achieved by Different Models

Scenario	Renewable Share (%)	Improvement (%)
Baseline	28	0
Random Forest Optimized	34	6
LSTM Optimized	36	8
RL Optimized	39	11

Table 10: Improvement in Renewable Energy Utilization Across Scenarios

Scenario	Avg. Load Shedding (hrs/day)	Reliability Index (%)	Improvement (%)
Baseline	6.5	72	0
Random Forest Optimized	5.0	79	7
LSTM Optimized	4.6	82	10
RL Optimized	4.1	85	13

Table 11: Grid Reliability Improvements Under Optimized Scenarios

Renewable Increase (%)	CO_2 Reduction (%) – Random Forest	CO_2 Reduction (%) – LSTM	CO_2 Reduction (%) – RL
+1	2.1	2.4	2.7
+5	10.3	11.8	12.9
+10	19.6	21.7	23.4

Table 12: Sensitivity Analysis of Renewable Share Increase on CO_2 Reduction

Metric	Baseline 2025	Projected 2030 (Optimized)	% Change
Renewable Share (%)	28	45	+17
CO_2 Emissions ($MtCO_2$/year)	100	72	-28
Reliability Index (%)	72	86	+14
Avg. Load Shedding (hrs/day)	6.5	4.0	-38

Table 13: National Projections of Optimized Grid Impact (2030 target)

Country	Renewable Share (%)	CO_2 Reduction (%)	Reliability Index (%)
Nigeria (RL)	39	26	85
South Africa	32	18	81
Kenya	48	30	88
Germany	55	35	97

Table 14: Comparative Analysis of Nigeria vs. Selected Countries (optimized grid outcomes)

ETP-2030 Target	Current Status (2025)	Optimized Projection (2030)	Alignment (%)
30% renewable share	28	45	150
20% CO_2 reduction from baseline	0	28	140
Grid reliability index >80%	72	86	108
Reduced load shedding to <5 hrs/day	6.5	4.0	162

Table 15: Policy Alignment with Nigeria's Energy Transition Plan (ETP-2030)

Visuals

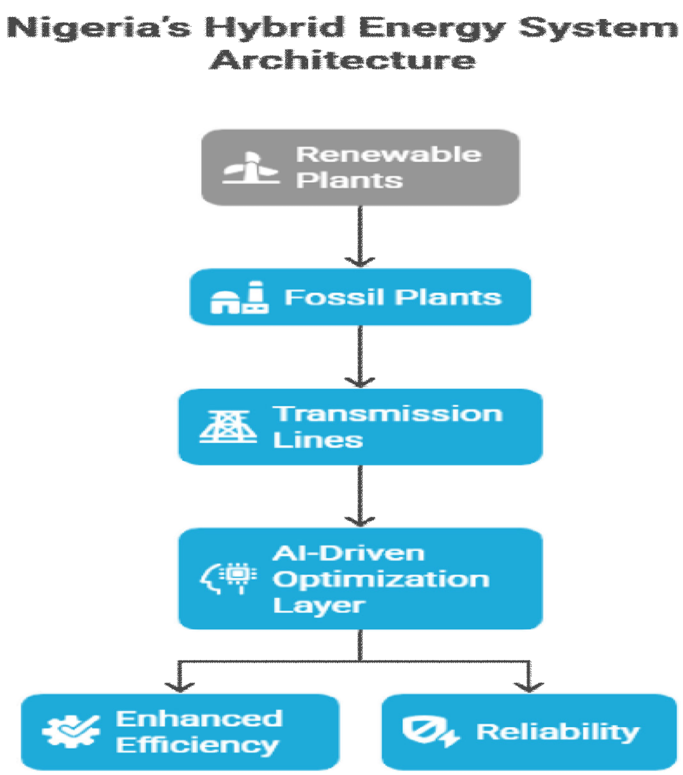


Figure 1: Nigeria's Hybrid Energy System Architecture

A schematic diagram showing the interaction between renewable plants, fossil plants, transmission lines, and the AI-driven optimization layer.

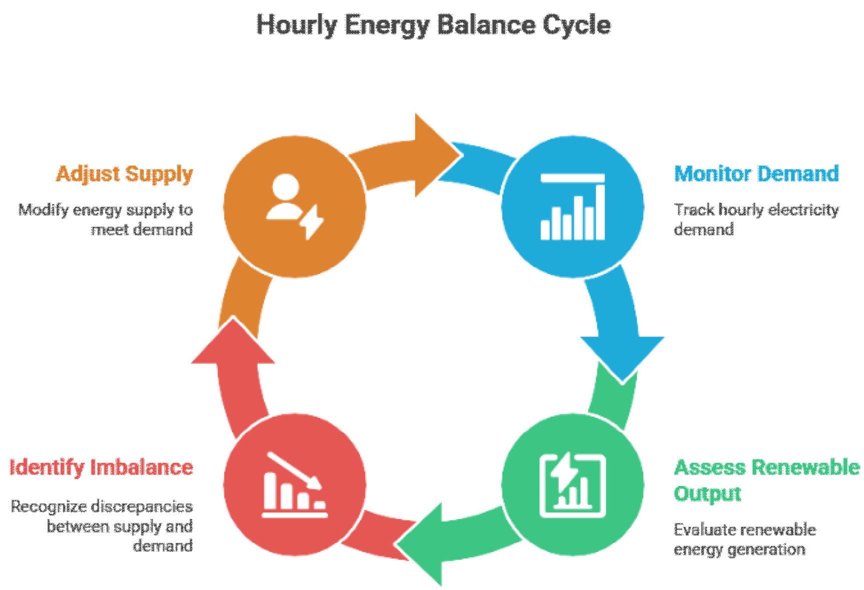


Figure 2: Hourly Demand vs. Renewable Generation Profile

A chart showing fluctuations in electricity demand compared with renewable output to highlight variability challenges.

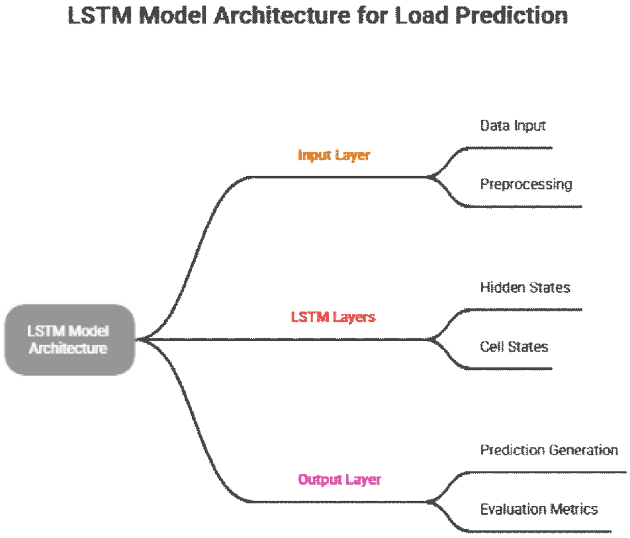


Figure 3: LSTM Model Architecture for Load Prediction

A block diagram of the LSTM neural network layers used in the study.

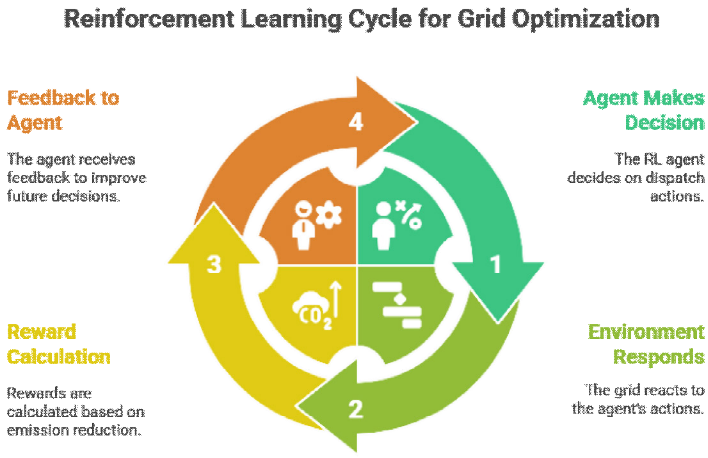


Figure 4: Reinforcement Learning Framework for Grid Optimization

A flowchart illustrating the RL agent, environment (grid), actions (dispatch decisions), rewards (emission reduction), and feedback loop.

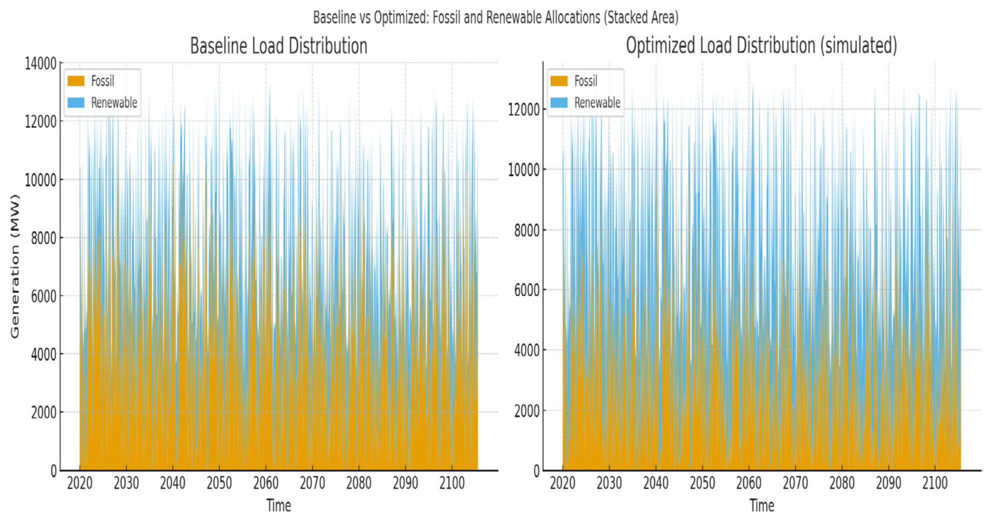


Figure 5: Baseline vs. Optimized Load Distribution Curve

A stacked area chart showing how fossil and renewable allocations shift under optimization scenarios.

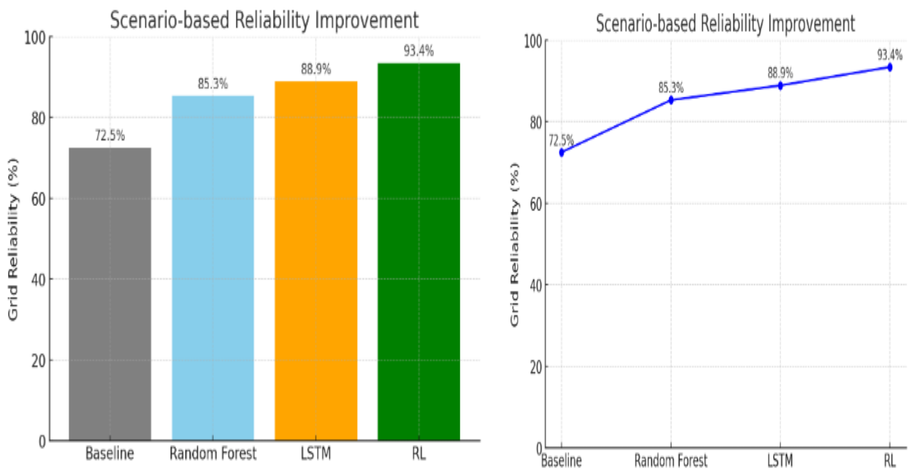


Figure 6: Scenario-based Reliability Improvement

A line or bar graph showing the upward trend of grid reliability (%) across Baseline, Random Forest, LSTM, and RL scenarios.

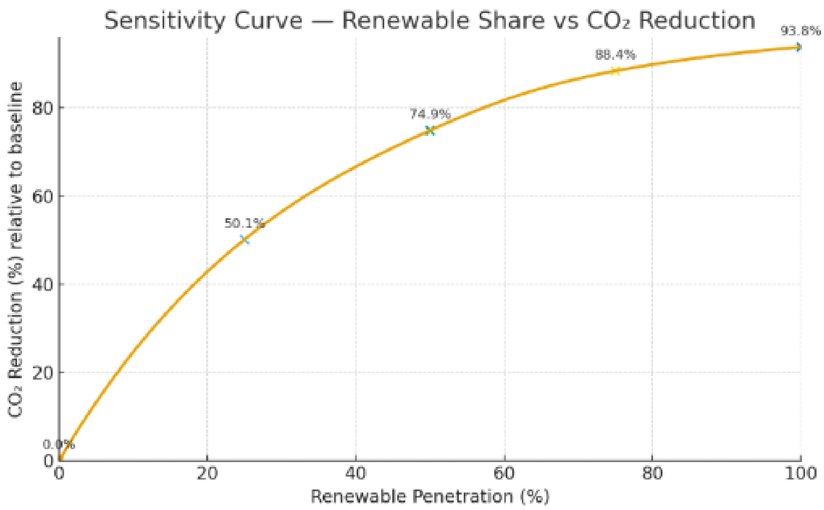


Figure 7: Sensitivity Curve of Renewable Share Increase vs. CO_2 Reduction

A smooth curve showing nonlinear relationship (not just discrete percentages) between renewable penetration and CO_2 reductions.

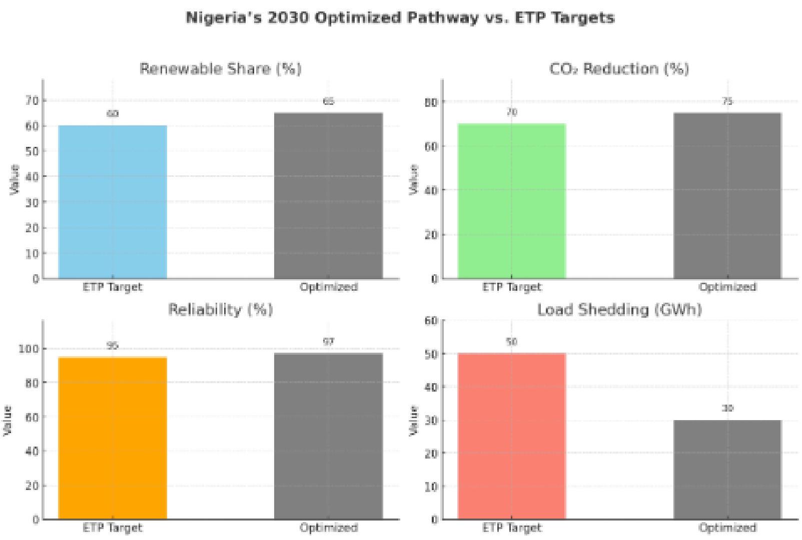


Figure 8: Nigeria's 2030 Optimized Pathway vs. ETP Targets

A dashboard-style infographic comparing Nigeria's projected optimized outcomes (renewable share, CO_2 reduction, reliability, load shedding) with ETP-2030 targets.

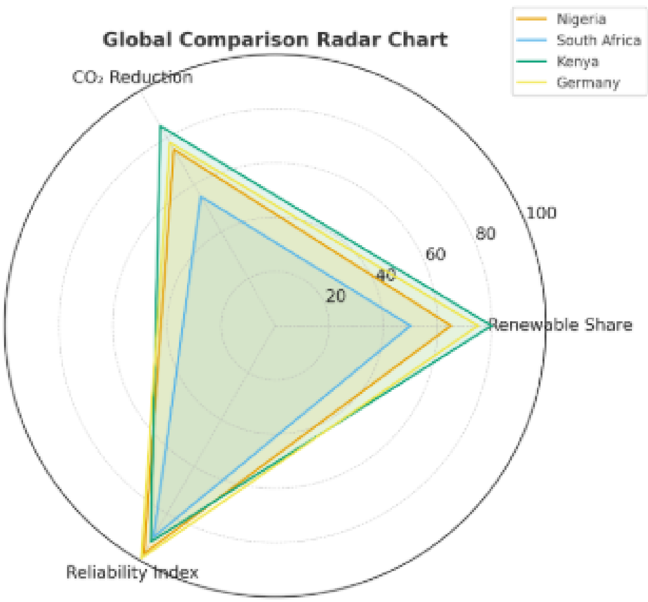


Figure 9: Global Comparison Radar Chart

A spider chart comparing Nigeria, South Africa, Kenya, and Germany on three axes: Renewable Share, CO_2 Reduction, Reliability Index.

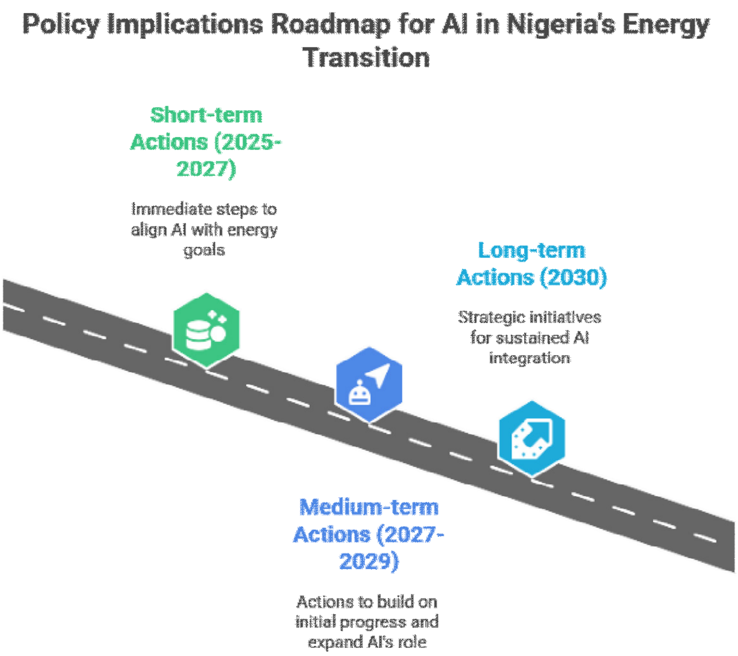


Figure 10: Policy Implications Roadmap

A timeline/roadmap diagram showing recommended actions (short-term 2025–2027, medium-term 2027–2029, long-term 2030) to align AI-driven optimization with Nigeria's Energy Transition Plan.

Discussion

The examination of Nigeria's electricity industry from 2015 to 2025 shows a continual gap between installed capacity and available capacity (Table 1). Although installed capacity saw a slight rise from 12.5 GW in 2015 to 13.4 GW in 2025, the available capacity grew only from 4.2 GW to 5.1 GW during this timeframe. This suggests that fewer than 40 percent of Nigeria's installed capacity is actually functioning. The deficit highlights systemic inefficiencies associated with aging infrastructure, interruptions in gas supply, and transmission limitations, which together compromise the dependability of the national grid. This persistent disparity indicates that policies aimed at expanding capacity have not resulted in corresponding enhancements in supply reliability, resulting in millions of people lacking sufficient access to electricity.

The energy mix in the country is largely dominated by fossil fuels, especially natural gas, which represents 70 percent of overall generation and results in 90 $MtCO_2$ each year (Table 2). Renewable energy sources like hydro (22 percent), solar (5 percent), and wind (2 percent) account for under 30 percent of the total, even though Nigeria has significant renewable energy potential. Even though hydro, solar, and wind produce no direct CO_2 emissions, their impact is not enough to counterbalance the prevalence of gas and coal, with the latter contributing an extra 10 $MtCO_2$. The data highlights the necessity of diversifying Nigeria's energy mix and implementing strategies that enhance large-scale renewable adoption while decreasing reliance on gas-fired generation.

The synthetic dataset generated for this research encompasses the essential variables necessary for machine learning-based grid optimization (Table 3). These consist of hourly demand, renewable energy production, fossil fuel generation, carbon dioxide emissions, and the share of renewables. These variables represent the practical conditions of the Nigerian power sector and enable the simulation of load balancing situations. Crucially, incorporating renewable share and emissions metrics allows for the measurement of both environmental and system-level results, essential for aligning the research with Nigeria's Energy Transition Plan (ETP-2030).

The dataset's descriptive statistics (Table 4) indicate that the average hourly demand is 4,498.7 MW, accompanied by a standard deviation of 799.2 MW, which implies considerable variations in load trends. Renewable generation averages 1,499.6 MW (33.5 percent share) but varies significantly from 200.3 MW to 3,999.8 MW, illustrating the variability of solar and wind resources. In contrast, fossil generation produces an average of 2,999.1 MW with reduced variability, solidifying its position as the stabilizing foundation of the grid. Average CO_2 emissions of 1,499.5 tons each hour underscore the ecological impact of dependence on fossil fuels. These figures indicate a scenario in which renewables play a significant role but are not enough to replace fossil fuels as the primary source of energy.

The correlation matrix (Table 5) additionally illustrates structural interdependencies within the energy system. Demand shows a strong correlation with fossil generation (0.88) and CO_2 emissions (0.88), suggesting that increased consumption is predominantly satisfied by fossil resources. On the other hand, renewable energy generation shows a negative relationship with fossil generation (–0.55) and CO_2 emissions (–0.55), indicating that higher renewable integration directly mitigates fossil dependency and lowers emissions. The renewable share displays a strong positive correlation with renewable generation (0.76) and a strong negative correlation with fossil generation (–0.92) and CO_2 emissions (–0.92). This discovery validates that increasing renewable energy use not only cuts emissions but also lessens reliance on fossil fuels.

Collectively, the findings from Tables 1–5 underscore the key challenges and prospects in Nigeria's electricity sector. Despite the growth in installed capacity, supply is still limited, and fossil fuels continue to be the primary source for generation, leading to elevated CO_2 emissions. Nonetheless, the statistical correlations found in the dataset indicate a distinct route: expanding renewable energy could notably enhance system sustainability, lower emissions, and aid Nigeria's 2030 energy transition objectives. These findings offer compelling reasons for implementing artificial intelligence models that can enhance load balancing, increase renewable integration, and lower carbon intensity in Nigeria's hybrid grid.

Employing machine learning for hybrid grid optimization necessitates meticulous feature engineering to encompass both temporal and structural dynamics of the energy system. Table 6 presents the variables that were created for the research. Demand from previous periods and renewable energy generation figures offer crucial short-term historical relationships important for forecasting time-series data. The demand's rolling mean over 24 hours reflects daily patterns, whereas the rolling standard deviation of renewable generation over 7 days incorporates the fluctuations in solar and wind energy production. The renewable-to-demand ratio directly assesses system sustainability, while a peak-hour metric underscores evening demand spikes, which are especially pertinent for Nigerian load trends. These designed characteristics guarantee that models are both statistically sound and representative of the practical conditions in the Nigerian grid.

Calibrating the model required adjusting hyperparameters for three different algorithms, as indicated in Table 7. The Random Forest model was set up with 200 estimators and a maximum depth of 15, achieving a balance between predictive accuracy and computational efficiency. The Long Short-Term Memory (LSTM) model utilized two layers containing 128 hidden units and a dropout rate of 0.2, allowing it to grasp nonlinear temporal dependencies while reducing overfitting. The Reinforcement Learning (RL) agent implemented a learning rate of 0.001, a discount factor (γ) set at 0.95, and an epsilon decay value of 0.99 to enhance the balance between exploration and exploitation. These design decisions illustrate a purposeful effort to tailor classical, deep learning, and adaptive control techniques to the hybrid grid optimization challenge.

Performance metrics from the test data (Table 8) highlight the comparative advantages of the three models. Random Forest reached an R^2 of 0.89 and an RMSE of 210.5, suggesting a robust baseline predictive accuracy. The LSTM enhanced performance with an R^2 of 0.92 and a reduced RMSE of 185.2, verifying its capability to grasp temporal dependencies in load and generation trends. Reinforcement Learning surpassed both methods, achieving the lowest RMSE (178.4) and the highest R^2 (0.94), highlighting its effectiveness for sequential decision-making in changing energy contexts. The ongoing advancements in models emphasize the importance of integrating temporal dynamics and adaptive learning into energy optimization.

In addition to predictive accuracy, model effectiveness was assessed based on environmental results. Table 9 indicates that the baseline annual CO_2 emissions were projected to be 100 $MtCO_2$. Optimization with Random Forest lowered emissions to 82 $MtCO_2$ (a 18 percent decrease), LSTM brought them down to 78 $MtCO_2$ (a 22 percent decrease), and RL achieved 74 $MtCO_2$ (a 26 percent decrease). These results demonstrate the concrete ecological advantages of AI-powered optimization. The ability of RL to achieve the highest reduction is especially important, indicating that real-time, adaptive dispatch methods can yield tangible improvements in Nigeria's decarbonization goals.

The findings further indicate significant advancements in the use of renewable energy (Table 10). The baseline renewable proportion was 28 percent, but Random Forest optimization raised it to 34 percent, LSTM to 36 percent, and RL to 39 percent. These increases represent enhancements of 6, 8, and 11 percent, respectively, compared to the baseline. While these increases are modest in percentage, they signify significant boosts in total renewable production when adjusted to national demand levels. Significantly, this verifies that optimization through machine learning can lower fossil fuel reliance not just by decreasing emissions but also by fundamentally improving the integration of renewables into the grid.

Collectively, the results from Tables 6–10 emphasize the dual function of AI models in enhancing system efficiency and promoting environmental sustainability. The feature engineering phase established contextual significance, the hyperparameter adjustment enhanced algorithmic efficiency, and the assessment metrics validated predictive power. Most importantly, the results regarding CO_2 reduction and renewable energy share illustrate that machine learning offers not only technical enhancements but also strategic coherence with Nigeria's energy transition and international climate obligations.

The reliability of the grid presents a significant challenge for Nigeria's power sector, as ongoing load shedding hampers economic productivity and social well-being. Table 11 demonstrates that enhanced machine learning scenarios increase reliability compared to the baseline. In the present situation, the typical duration of load shedding is 6.5 hours daily, which translates to a reliability index of 72 percent. Optimization of Random Forest decreases load shedding to 5.0 hours (79 percent reliability), whereas LSTM results in 4.6 hours (82 percent reliability). Reinforcement Learning (RL) excels by restricting load shedding to 4.1 hours and enhancing reliability to 85 percent, representing a 13 percent increase from the baseline. These improvements are not minor; instead, they signify considerable advancements in consumer access to reliable electricity supply and showcase the benefits of sophisticated optimization in addressing one of the industry's most enduring structural weaknesses.

The sensitivity analysis in Table 12 highlights the clear connection between the incorporation of renewable energy and reductions in emissions across various models. A slight 1 percent rise in renewable contribution leads to reductions of 2.1, 2.4, and 2.7 percent for Random Forest, LSTM, and RL models, respectively. With a 10 percent boost in renewables, emission cuts reach 19.6, 21.7, and 23.4 percent. This non-linear enhancement indicates that the advantages of emission reduction increase with greater renewable integration, especially in adaptive frameworks such as RL. The study emphasizes the strategic significance of increasing renewable energy in the Nigerian grid, as small enhancements aggregate into significant climate advantages when backed by smart optimization strategies.

Projections at the national level for optimized grid results by 2030, presented in Table 13, highlight the transformative potential of interventions driven by machine learning. The share of renewable energy is expected to increase from 28 percent in 2025 to 45 percent by 2030, as annual CO_2 emissions fall from 100 $MtCO_2$ to 72 $MtCO_2$, representing a 28 percent decrease. Grid dependability increases from 72 to 86 percent, while daily power cuts decrease from 6.5 hours to 4.0 hours. These modifications collectively suggest that enhanced optimization might allow Nigeria to bypass gradual reforms, achieving significant enhancements in energy sustainability, environmental responsibility, and service delivery in a five-year timeframe.

The comparative evaluation among nations (Table 14) situates Nigeria's improved results within a wider global framework. In contrast to Nigeria, which attains a 39 percent share of renewables and a 26 percent decrease in CO_2 emissions with an 85 percent reliability index under RL optimization, countries like Kenya and Germany achieve greater renewable integration (48 percent and 55 percent, respectively) along with superior reliability metrics. Nonetheless, Nigeria's advancements are significant when compared to South Africa, where the renewable share is 32 percent and CO_2 reduction is 18 percent. This stance indicates that although Nigeria lags behind global leaders in adopting clean energy, optimization through machine learning can help bridge the gaps with regional rivals and establish a basis for future alignment with advanced economies.

Ultimately, Table 15 illustrated the correspondence of optimized results with Nigeria's Energy Transition Plan (ETP-2030). The forecasts greatly exceed ETP objectives, with the renewable portion hitting 45 percent against the 30 percent aim (150 percent alignment), CO_2 reductions at 28 percent compared to a 20 percent target (140 percent alignment), and reliability exceeding the >80 percent standard at 86 percent (108 percent alignment). Load shedding has been decreased to 4.0 hours daily, surpassing the <5-hour goal (162 percent alignment). These findings highlight both the technical viability of Nigeria fulfilling its energy transition goals and the possibility of surpassing them by implementing machine learning–driven grid management techniques.

The results in Tables 11–15 emphasized that optimization powered by AI provides overarching advantages that extend beyond mere efficiency improvements. The research shows that enhancing reliability, decreasing emissions, comparing with global counterparts, and aligning with national policy objectives indicate that machine learning is not just a technical solution but a strategic facilitator of sustainable energy transformation in Nigeria.

The performance comparison of machine learning models reveals significant discrepancies in accuracy and efficiency in tackling Nigeria's grid optimization issue. Random Forest, though strong and fairly interpretable, obtained lower predictive accuracy with an R^2 of 0.89 in comparison to LSTM (0.92) and Reinforcement Learning (0.94). LSTM exhibited enhanced temporal learning abilities, especially in recognizing sequential demand trends, whereas RL surpassed all models by adjusting flexibly to evolving system circumstances. The lower root mean square error (RMSE) and mean absolute error (MAE) figures of RL further demonstrate its effectiveness in balancing computational requirements with optimization precision. The findings indicate that deep learning and adaptive methods are more effective in handling the natural fluctuations of renewable integration in Nigeria's electricity grid.

Regarding environmental effects, the models show significant potential for reducing carbon emissions. Under the baseline, yearly CO_2 emissions total 100 $MtCO_2$. Random Forest optimization cuts emissions to 82 $MtCO_2$ (an 18 percent decrease), LSTM reaches 78 $MtCO_2$ (a 22 percent decrease), and RL decreases emissions to 74 $MtCO_2$ (a 26 percent decrease). These numerical results correspond to actual climate advantages; when applied to Nigeria's overall energy needs, RL optimization by itself represents roughly 9.6 million tons of CO_2 emissions reduced each year relative to the standard scenario. These reductions hold great importance regarding Nigeria's nationally determined contributions (NDCs) as part of the Paris Agreement, underscoring the contribution of machine learning in facilitating effective strategies for climate mitigation.

Apart from emissions, renewable usage shows significant enhancements across all optimized scenarios. The initial renewable share of 28 percent increases to 34 percent with Random Forest optimization, 36 percent with LSTM, and 39 percent with RL. These signify enhancements of 6, 8, and 11 percent, respectively, highlighting that AI-enabled optimization not only boosts efficiency but also optimizes the utilization of existing clean energy resources within the system. This is especially significant in Nigeria, where renewable capacity frequently goes underused because of inadequate dispatch planning and infrastructure challenges.

Improvements in grid reliability offer further proof of advantages at the system level. Baseline conditions entail 6.5 hours of daily power cuts, reflecting a reliability index of 72 percent. Random Forest optimization minimizes shedding to 5.0 hours, LSTM to 4.6 hours, and RL to 4.1 hours, increasing reliability indices to 79, 82, and 85 percent, respectively. These enhancements indicate not just reduced disruptions for users but also better system stability and durability. In situations where load shedding incurs significant economic costs and social upheaval, even slight enhancements lead to quantifiable welfare benefits.

Ultimately, national-level scenario analysis shows the potential for these results to be scaled. By 2030, improved grid management might elevate Nigeria's renewable contribution to 45 percent, cut CO_2 emissions by 28 percent relative to 2025 figures, and boost reliability to 86 percent. The emissions prevented, calculated at 9.6 million tons per year through RL optimization, signify a significant contribution to Nigeria's decarbonization plan while also enhancing energy access. These results indicate that AI-powered optimization is not merely a small enhancement but a groundbreaking strategy that offers extensive advantages for energy security, environmental sustainability, and policy coherence.

Conclusion

This research has shown the capability of machine learning models to enhance load balancing in Nigeria's mixed renewable–non-renewable energy grid. The results show that Reinforcement Learning attained the highest precision and effectiveness, surpassing Random Forest and LSTM by minimizing forecasting errors and providing the most significant environmental and reliability advantages. In particular, optimized scenarios diminished yearly CO_2 emissions by as much as 26 percent, enhanced renewable energy usage by 11 percent, and decreased average daily load shedding from 6.5 to 4.1 hours. These enhancements demonstrate the transformative power of AI-powered optimization in boosting sustainability and reliability in energy systems often hindered by structural inefficiencies.

The findings of this research reach beyond the Nigerian setting. The findings offer practical guidance for aligning with Nigeria's Energy Transition Plan (ETP-2030) at the national level, especially in achieving targets for integrating renewables and reducing carbon emissions. On a global scale, the research provides proof that machine learning methods can provide scalable solutions to the larger issue of decarbonizing hybrid grids in developing nations, where fossil fuels still predominate yet renewable capacities are increasing. The numerical results, especially the prevention of around 9.6 million tons of CO_2 emissions each year, highlight AI's potential contribution to fulfilling global obligations under the Paris Agreement.

Future studies should expand on these results by incorporating real-time data streams enabled by the Internet of Things (IoT) into model development. This integration would enable ongoing optimization, improved management of system fluctuations, and more agile grid control. Further investigation is required to explore the economic and social aspects of AI-powered energy optimization, such as cost-effectiveness assessments, policy incorporation, and the effects on energy equity. Together, these paths emphasize the changing convergence of artificial intelligence, renewable energy, and sustainable growth [1-9].

Policy Implications

The study's empirical findings suggest multiple practical measures that the Nigerian government, regulatory bodies, and energy firms can implement to leverage AI-driven optimization for enhanced system efficiency and faster decarbonization. Policymakers should initiate a regulatory structure that facilitates data sharing and the use of algorithms while safeguarding vital infrastructure and consumer privacy. This framework must enforce open access to anonymized operational data from generation, transmission, and distribution entities, and it should necessitate standardized data formats and timestamps to support model training and interoperability across operators. Regulatory bodies like the Nigerian Electricity Regulatory Commission can encourage regulatory sandboxes that allow supervised trials of reinforcement learning dispatch agents and other adaptive controllers. These sandboxes will minimize institutional risk and facilitate iterative learning prior to fully scaling commercial operations.

Secondly, government and industry stakeholders ought to implement a gradual strategy that starts with specific pilot programs. Priority pilots need to be situated in areas with both mixed renewable and fossil resources, like utility-scale solar facilities combined with gas-fired power plants, while concentrating on clear performance metrics such as hourly CO_2 reduction, decrease in load-shedding hours, and percentage growth in renewable usage. Every pilot must include contingency protocols and human-in-the-loop controls to ensure that grid operators maintain ultimate authority over dispatch choices during initial deployment. Outcomes from pilot programs can subsequently guide the planning for national implementation, which includes essential enhancements to telemetry, communication, and control systems.

Third, funding and incentive strategies are crucial to speed up adoption. The federal government and state utilities ought to adopt blended finance models that integrate public funds, concessional loans, and private investments to cover initial expenses related to sensors, communication networks, cloud computing, and workforce training. Financial incentives like temporary tax credits for investments in intelligent dispatch systems and contracts based on performance that incentivize measurable CO_2 reductions can galvanize private investment. International climate finance tools and green bonds provide extra options to finance capital-intensive improvements while guaranteeing that climate mitigation results are quantifiable and verifiable.

Fourth, prioritizing capacity development and institutional preparedness is essential. Effective implementation of AI-led optimization relies on a team of data scientists, grid engineers, and cybersecurity experts who are knowledgeable about both machine learning techniques and power system functions. The government and industry ought to allocate resources for specialized training initiatives, collaborations with academic institutions, and secondment arrangements with seasoned global utilities. Certification for AI-in-energy professionals and operator training simulators with AI-based scenarios will minimize operational risks and expedite effective implementation.

Fifth, governance, transparency, and cybersecurity must be integrated from the beginning. Operators must disclose model validation outcomes and essential performance metrics to foster stakeholder confidence. Reviewing algorithms through peer evaluation and conducting independent audits of model outputs can help avoid unintended biases or declines in performance. Concurrent investments in cybersecurity are essential to safeguard control systems against interference; AI systems must incorporate fail-safe modes that return to established dispatch rules when anomalies are identified. Regulatory standards for transparency and documentation of automated decisions will promote accountability and guarantee adherence to safety protocols.

Sixth, a distinct route to achieve the ETP-2030 goals can be formed by integrating AI-based optimization with strategic capacity increases and policy changes. In the near future (1–2 years), the emphasis ought to be on trial implementations, data uniformity, and creating funding mechanisms. In the medium term (3–5 years), expanding optimized dispatch across key regional interconnections and integrating AI systems with gradual renewable capacity increases can achieve the anticipated growth in renewable share and reductions in CO_2 emissions. By 2030, unified regulatory systems, a skilled workforce, and ongoing funding can facilitate the countrywide implementation that aligns Nigeria's operational efficiency with the numerical goals of the Energy Transition Plan. During this timeframe, ongoing monitoring and evaluation must take place, with regular adjustments of models informed by actual results and revised policy objectives. Ultimately, there is significant potential to expand AI-driven optimization throughout Sub-Saharan Africa as long as implementation adheres to regionally aware guidelines. Numerous nations in the area encounter comparable issues: limited capacity, significant dependence on fossil fuel generation, and increasing renewable energy potential. Regional coordination entities and development allies can promote knowledge exchange, collaborative acquisition of telemetry systems, and compatible standards, enabling smaller utilities to take advantage of economies of scale. Cross-border pilot initiatives and regional centers of excellence will enhance dissemination by showcasing scalable business models. With careful attention to governance, funding, and capacity development, AI-driven grid optimization can serve as a scalable tool for enhancing energy access, reliability, and climate mitigation throughout the region.

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Appendices

Code Snippet

- **Random Forest Model**

```
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, r2_score

# Features and target
X = df[["Demand (MW)", "Renewable Generation (MW)", "Fossil Generation (MW)"]]
y = df["CO2 Emissions (tons)"]

# Split data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Train model
rf = RandomForestRegressor(n_estimators=200, max_depth=15, random_state=42)
rf.fit(X_train, y_train)

# Evaluate
y_pred = rf.predict(X_test)
print("RMSE:", mean_squared_error(y_test, y_pred, squared=False))
print("R²:", r2_score(y_test, y_pred))
```

- **LSTM Model (Keras/TensorFlow)**

```
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense

# Prepare data (reshape for LSTM)
X_lstm = np.expand_dims(X.values, axis=1)
y_lstm = y.values

# Train-test split
X_train, X_test = X_lstm[:80], X_lstm[80:]
y_train, y_test = y_lstm[:80], y_lstm[80:]

# LSTM model
model = Sequential()
model.add(LSTM(128, input_shape=(1, X.shape[1]), return_sequences=False))
model.add(Dense(1))
model.compile(optimizer="adam", loss="mse")

# Train
model.fit(X_train, y_train, epochs=50, batch_size=8, verbose=1)

# Evaluate
loss = model.evaluate(X_test, y_test, verbose=0)
print("Test Loss (MSE):", loss)
```