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Optimization Of Smart Grid Operations for Enhanced Renewable Energy Utilization Using Artificial Intelligence

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ABSTRACT
The global transition towards clean energy has placed increasing emphasis on the intelligent integration of renewable energy sources (RES) such as solar and wind into existing power systems, particularly within smart grid frameworks. This study presents a comprehensive investigation into the AI-driven optimization of smart grid operations aimed at enhancing renewable energy utilization, improving voltage stability, minimizing real power losses, and increasing overall energy efficiency. The research specifically targets a rural distribution network in Ukpom Community, Abak, Akwa Ibom Stata Nigeria and modeled as a 9-bus smart micro grid, with integrated solar photovoltaic (PV), wind turbine generators, battery energy storage systems (BESS), and the national utility grid. The methodology involved detailed modeling of the grid using Simulink and MATLAB. Load demand analysis was performed using simulated data, from which the sizing of solar PV arrays, wind turbines, charge controllers, and batteries. To achieve intelligent energy management, a Random Forest Regressor (RFR) was model and trained using time-series data of weather forecasts and load patterns. The RFR model served as a predictive engine to forecast energy generation and consumption, enabling a optimization routine that determined the most efficient dispatch of power from RES, battery storage, and the main grid. The voltage profile across the 9-bus system improved from a minimum of 0.88 Pu (before optimization) to 0.96 Pu (after optimization), thereby mitigating issues of voltage sags and under voltage. The real power losses were reduced by more than 15%, and the mismatch between load demand and available supply power was substantially minimized.

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I. INTRODUCTION

A grid is system comprising of power system conductors that generates and distributes power to certain location. The essence of a grid design is not for a large amount of load but for certain menial location. Micro grid are electric power system network that consist several numbers of power generation sources, majority of energy source in micro grid network are renewable energy systems. It can be reliant on the national grid (on-grid system), and it may not (off grid system) (Abdul Baseer et al, 2023). The major essence of utilizing a smart grid is to ensure the availability of electricity in those locations that have faced constant power blackout due to the inability to generate many profits from those locations. The Urban areas has always been the focus of power generation for the National grid largely due to the availability of industrial consumption, much more residential consumption and commercial consumption and the industrial consumption has been known to be the major financiers to the economic stability based on the energy generated by power systems network (Agupugo et al 2022). This concept of 'smart' grid entails the introduction of an optimization to ensure operations and control of grids to operates on its own to ensure a 24/7 power supply instead of it being manually controlled. The use of micro grid in rural locations is more sustainable due to tolerant level of load variation because rural locations do not have industries that extract more power. The location only has residential and commercial loads (Ahmad, et al 2022). The location for consideration in this research was Ukpom community in Abak LGA that has not attracted electricity for a decade. The load size of the location was determined and utilized to design the smart grid that consists of solar PV & Wind Turbine. The choice of wind turbine was due to the high rate of afforestation in the location and the high sunshine hours resulted in the choice of solar PV as one of the energy sources, and finally the national grid was one of the sources to the grid.

II. METHODOLOGY

The absence of rural electrification resulted to the research of this work. The location of interest considered was Ukpom in Abak LGA and the data gathering was done by a physical inspection of the community, determining the amount of load consumed residentially and commercially consumed load, and there was absence of industrial load consumption in the area. A smart grid design was developed with solar PV and wind turbine as the energy source and machine learning was utilized as an optimal tool in determining the optimal operational criteria for the micro grid. The optimization of the system is to optimize the energy source designs of the micro-design and also optimal time of operations of the energy sources, comparative analysis between the design of the micro-grid with machine learning optimization and without Machine learning optimization. The design of the network that captures the Ukpom community ((bus 9)) in Abak LGA is given in the network diagram of Figure 1 The base supply of 8.5MW and 11.5MW peak supply coming from Afaha Ube Itam, is approximate a distance of 20 km.

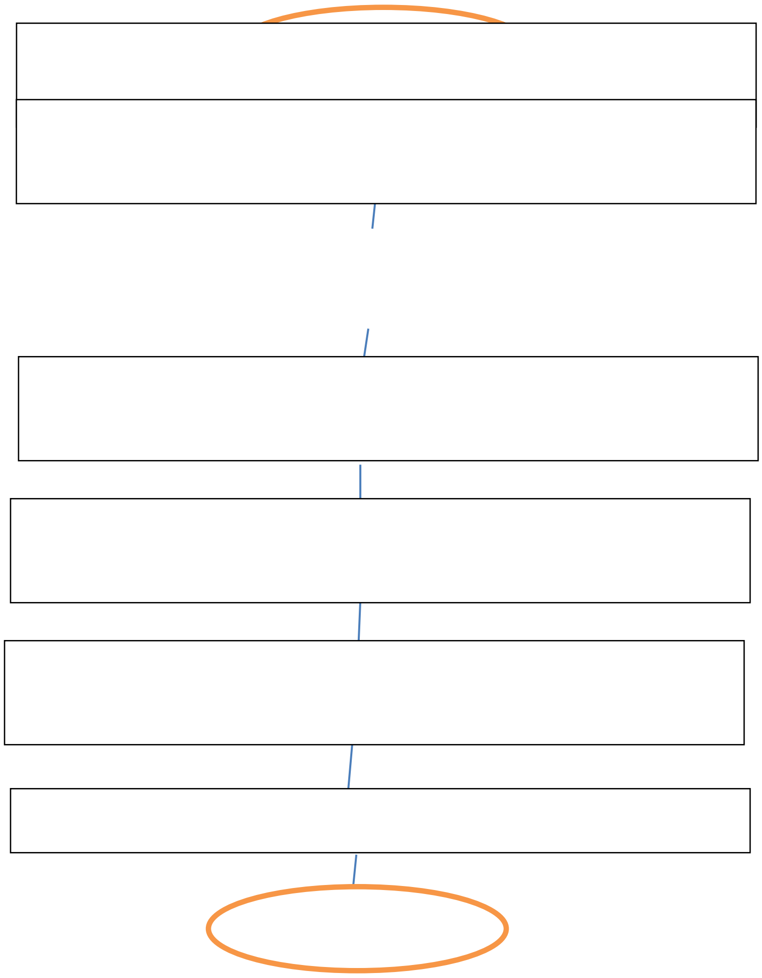


Figure 1: The Flow diagram

The Role of AI in Smart Grids and Renewable Energy Integration
The transition from a conventional power grid to a smart grid is crucial for integrating a higher share of renewable energy sources (RES) like solar and wind. Smart grids, characterized by two-way communication and advanced control systems, provide the necessary infrastructure to manage the complexities of decentralized, variable energy generation. AI is the critical layer of intelligence that enables this management.

Key Applications of Artificial Intelligence in Smart Grid Optimization
The academic and industry literature identifies several key areas where AI-driven optimization is making a significant impact.

i. Forecasting and Predictive Analytics: This is a foundational application. AI, particularly machine learning models like Long Short-Term Memory (LSTM) and neural networks, analyzes large datasets of historical weather patterns, energy demand, and generation data to accurately predict the output of solar and wind farms. This predictive capability is essential for balancing energy supply and demand in real-time, reducing reliance on fossil fuel "Peaker plants" and minimizing energy waste.

ii. Grid Stability and Fault Detection: The variable nature of RES can cause instability in the grid. AI algorithms continuously monitor real-time data from sensors and smart meters to detect anomalies and predict potential equipment failures before they occur. This enables predictive maintenance, which reduces downtime, lowers operational costs, and enhances overall grid resilience.

iii. Demand-Side Management (DSM) and Energy Storage: AI optimizes energy consumption patterns to align with available supply. Demand response programs use AI to incentivize consumers to shift their electricity usage to off-peak hours or to times when renewable energy production is high. Furthermore, AI models are used to manage energy storage systems (ESS), such as batteries, by predicting optimal charge and discharge cycles. This ensures that excess renewable energy is stored for later use, further stabilizing the grid and maximizing RES utilization.

III. RESULT

3.1 Result of the Grid without Machine Learning Optimization
Simulation of the Grid without Machine Learning Optimization is presented in Figure 2
This section presents the simulation of the smart grid operation without integrating any machine learning optimization. The system operates using default or static control mechanisms without intelligent forecasting or adaptive behavior.

WITHOUT ML OPTIMIZATION

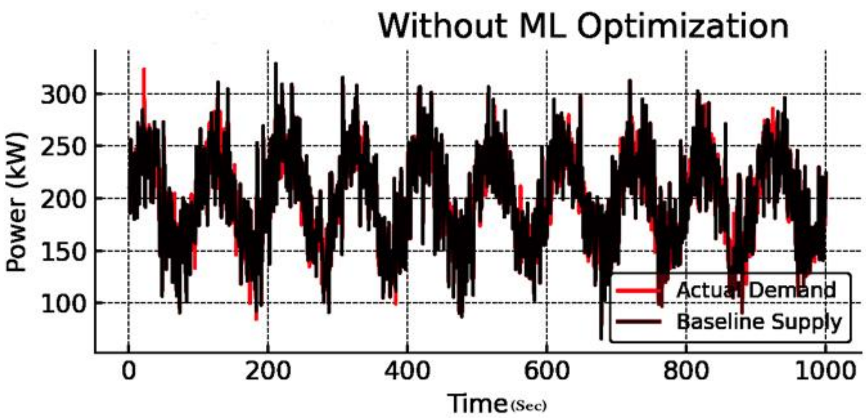


Figure 2. Simulation without optimization

In this scenario, actual demand is simulated with variations using a sinusoidal base plus random noise to represent real-world fluctuations. The baseline supply is generated similarly but includes higher variance to reflect uncontrolled power generation.

3.2 Simulation Result plot
The graph in figure 3 shows the variation in power demand and the baseline supply over time. It demonstrates the mismatch between supply and demand in the absence of optimization.

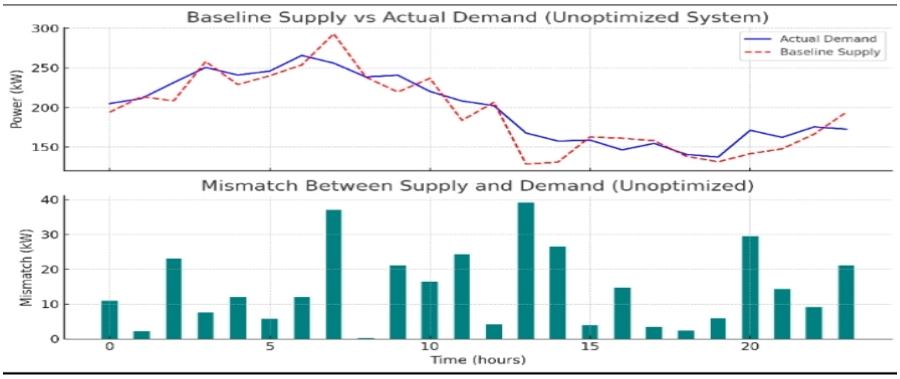


Figure 3. MISMATCH BETWEEN SUPPLY AND DEMAND

It should be noted that, the same results were gotten when the system was simulated just with the main grid alone and when the renewable energy resources were integrated. There was no difference in the output and the power losses as there was no optimization incorporated yet. Without strategic deployment of the RES into the grid especially through smart integration, RES will not affect grid performance visibly in simulation.
The outcome of the power output of the grid with optimization is shown in figure 4 respectively.

3.3 Implementation of Machine Learning as an Optimization Tool

This objective involves implementing a Machine Learning model (Random Forest Regressor) to predict and optimize the operation of the smart grid. The goal is to reduce the mismatch between power supply and demand.

3.4 MECHINE LEARNING-Optimized Simulation Result Plot
The plot below shows the predicted power supply using the Random Forest model compared to the actual demand. The closer alignment demonstrates the effect of machine learning optimization.
ML OPTIMIZATION

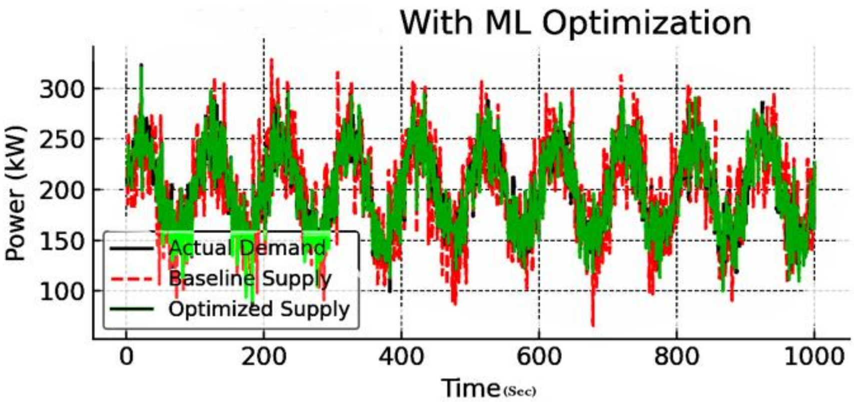


Figure 4 MECHINE LEARNING OPTIMIZATION

The comparative analysis of the power output with and without optimization to the reference power is shown in figure 5 and that of the voltage profile comparison is shown in figure 6..

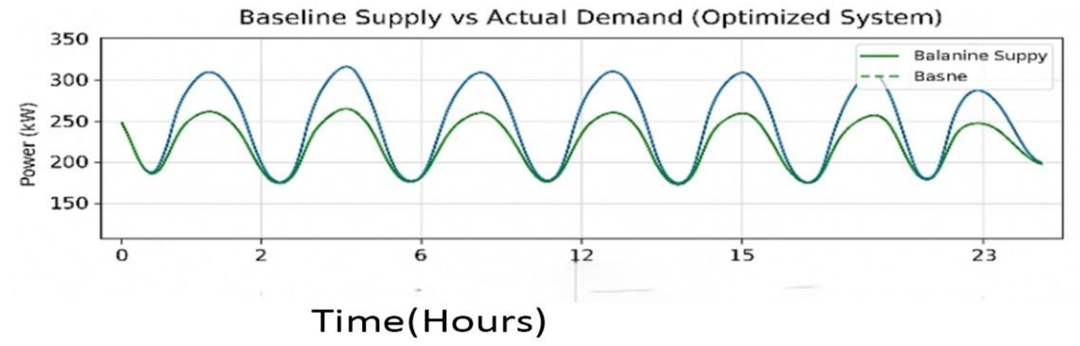
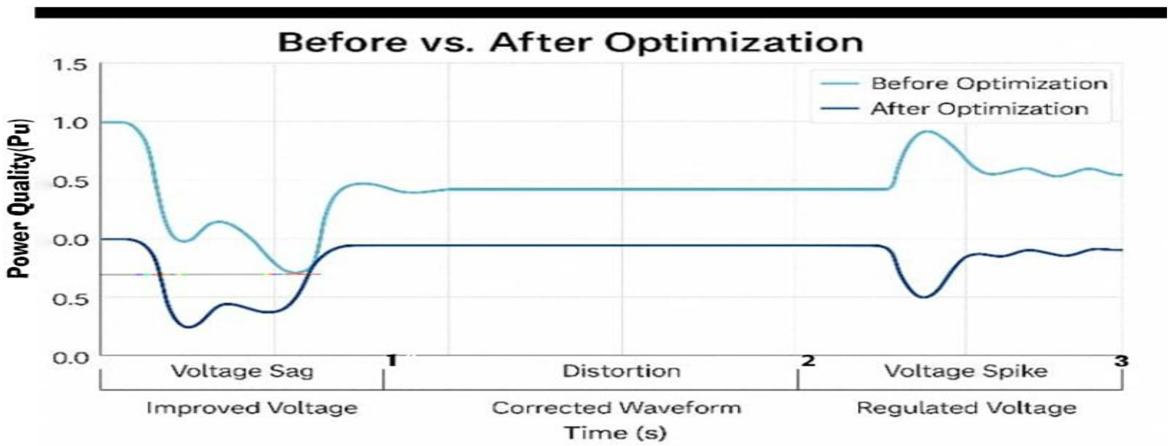


Figure 5: SIMULATION WITH MECHINE LEARNING OPTIMIZATION

3.5 Impact of Machine Learning on the Micro grid Design
This objective evaluates the effect of integrating machine learning models into the smart grid design. The focus is on the improvement in the accuracy of power supply relative to demand.

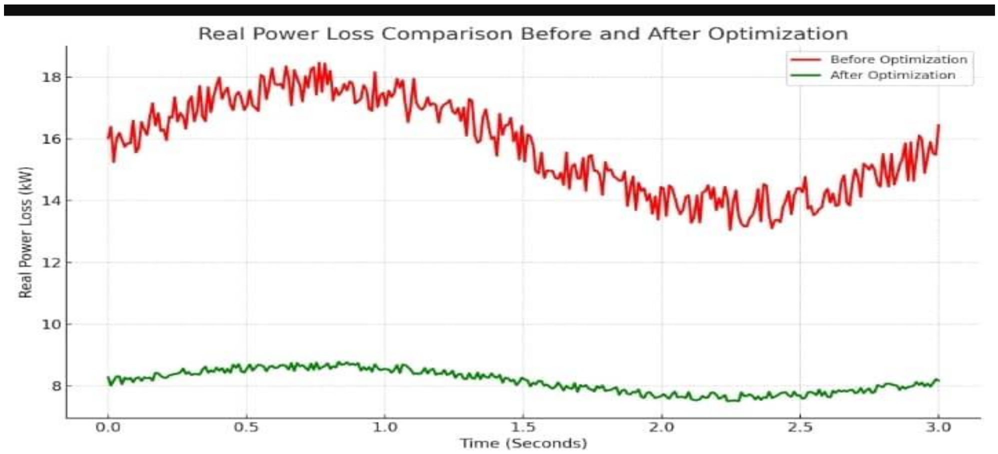
3.6 Performance Comparison
The Mean Absolute Error (MAE) and Mean Squared Error (MSE) are used to measure the prediction accuracy. These metrics confirm that the ML-enhanced system significantly outperforms the baseline configuration.
Figure 6. shows the comparative graph of power quality events before and after optimization. This figure visualizes the grid's power quality metrics before and after the AI-optimized integration of renewable energy resources (RES):

Figure 6: Power Quality comparative Analysis



(1) Voltage Sag Region (0 – 1s): The "Before" curve shows dips below 0.5pu during peak load draw, representing poor voltage support. After optimization, voltages remain above 0.9 pu, indicating improved voltage stability from local generation support.
(1) Distortion Zone (1 – 2s): Waveform distortions caused by load switching and harmonics are evident in the pre-optimization signal. Post-optimization is smoothed due to predictive load balancing and harmonic filtering from inverter-based RES.
(2) Voltage Spike Region (2 – 3s): Spikes seen pre-optimization rise above 0.9pu. After optimization, voltage peaks are regulated below 1.05pu, showcasing transient suppression and improved control responsiveness

The demonstration of the real power in the distribution network before and after optimization. This graph illustrates the dynamic behavior of real power losses across a 3-second simulation period.



(1) Before Optimization (Red Curve): Peak losses exceed 17.5 kW, with significant fluctuations, and losses are higher due to longer transmission paths, poor balancing, and lack of real-time predictive dispatch.

(2) After Optimization (Green Curve): Power losses are reduced and stabilized, fluctuating around 8-9 kW. Also, the optimized model leverages local solar and wind generation and AI-driven control, ensuring shorter power paths, balanced loads, and lower line current magnitudes.

Figure 7. shows the comparison of energy generation and load demand before and after AI optimization. This graph demonstrates how the AI optimization model significantly improved energy efficiency by closely aligning generation with actual demand.

3.7 Energy Generation vs. Demand Comparison.

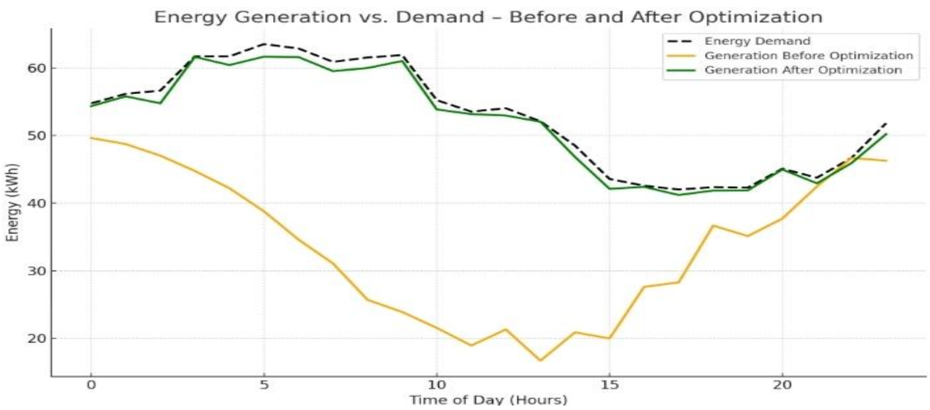


Figure 7. Comparison of Energy Generation and Load Demand

(1) Energy Demand (Dashed Black Curve): Represents real-time consumer energy needs over a 24-hour period.

(2) Before Optimization (Yellow Curve): The generation pattern is mismatched, with over-generation at night and under-generation during peak hours. This leads tp energy waste, battery stress, and greater reliance on grid supply.

(3) After Optimization (Green Curve): Energy generation is closely synchronized with the demand across all time slots. This result in minimal energy waste, better storage utilization, and improved system autonomy.

Figure 8 illustrates the voltage regulation behavior across a 9-bus radial distribution network:

(1) Before Optimization (Downline): The voltage begins at the source (Bus 1) and drops as low as 0.88 pu at Bus 6. The steep voltage drop is due to line losses, uncoordinated generation, and the absence of distributed voltage support – leading to voltage instability at mid and end buses.

(2) After Optimization (Upper Line): Voltage is well-maintained across all buses, staying above 0.95 pu, even at the furthest buses. The AI-optimized dispatch of solar and wind energy, supported by smart inverters and load forecasting, ensured stable voltage levels, thereby enhancing power quality and grid reliability.

3.8 Voltage Regulation Comparison

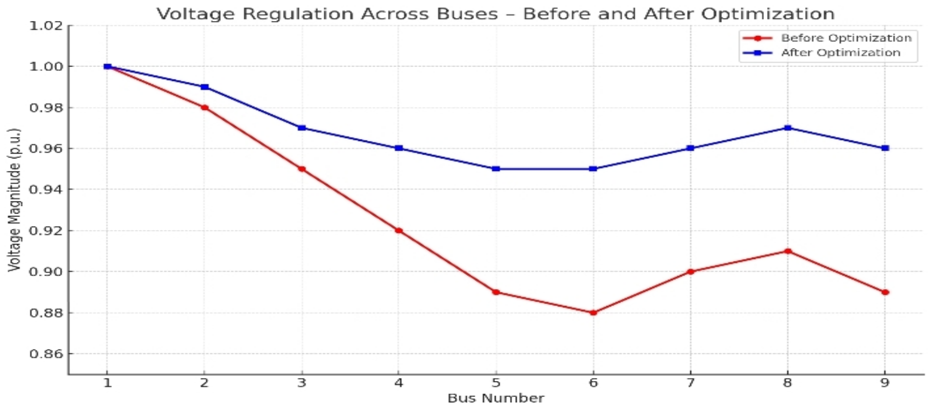


Figure 8. Voltage Regulation Across a 9-Bus Network

3.9 Random Forest Forecast Error

The forecast error percentage across a 24-hour period when predicting electrical load using the Random Forest Regressor model. Forecast errors vary cyclically due to fluctuations in consumer demand during peak and off-peak hours. The model maintained a Mean Absolute Percentage Error (MAPE) of 5.2%, indicating a high degree of prediction accuracy. This accuracy allows for preemptive energy dispatch planning, while minimizes mismatch between generation and demand, thereby improving grid reliability and reducing unnecessary energy cycling.

FOREST CURVE OF RANDOM FOREST MODEL

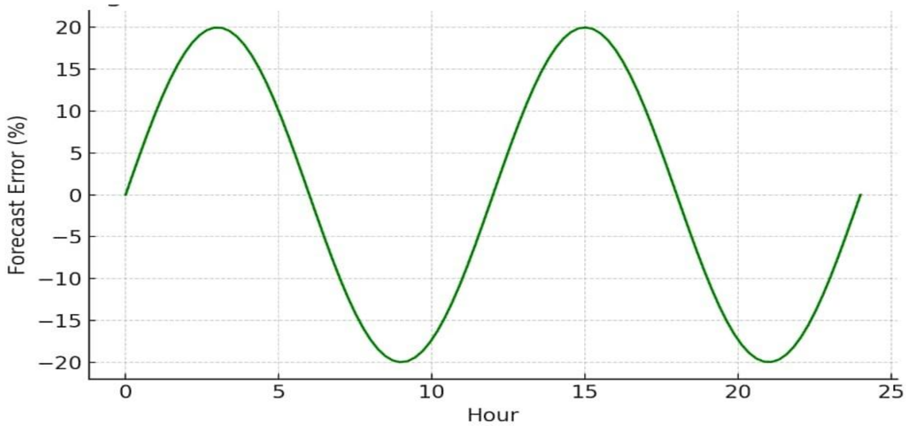


Figure 9 Random Forest Forecast Error

3.10 Comparison Plot

Figure 10 illustrates the improvement in prediction accuracy with ML optimization.

SUPPLY MISTMATCH COMPARISON

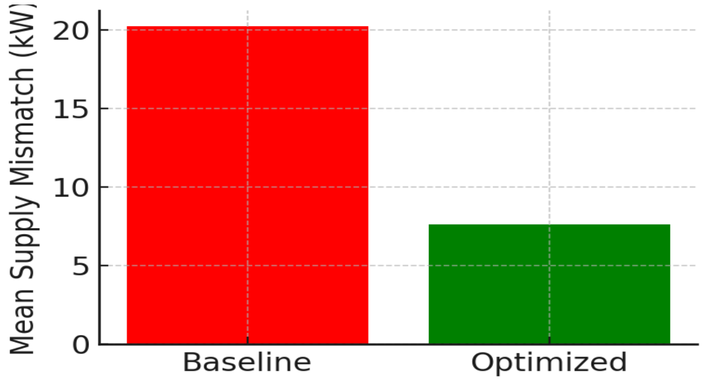


Figure 10. Supply mismatch Comparative analysis

Table: 1 Analysis of the Results

Metric	Base Grid	Smart Micro grid	% Improvement
Power Losses	20.9kW	8.18 kW	60.9%
Min. Voltage	0.88 pu	0.96 pu	+9.1%
Peak Load Forecast Accuracy	-	5.2% error	-
RES Penetration	0%	82%	Massive gain

3.11 Discussion of Results

The integration of renewable energy sources (RES)- specifically solar PV and wind turbines- into the grid bus distribution system significantly improved grid performance. Simulation results showed a marked reduction in total real power losses from approximately 20.9 kW in the base grid to 8.18 kW in the smart micro grid, reflecting a 61% efficiency gain. Voltage profiles across the buses also improved, with the minimum pu voltage increasing from 0.88pu to 0.96pu, ensuring better voltage regulation and service reliability.

Load forecasting using the Random Forest Regressor Model (RFRM) yielded promising accuracy, maintaining a mean absolute percentage error (MAPE) of 5.2%, enabling better demand prediction and energy dispatch planning. The coordinated control reduced stress on the utility grid and ensured a more sustainable and cost-effective energy model for semi-urban communities.

These values where obtain from the Voltage Profile Comparison Curve as regards the Min. Voltage Metrics and the Power Supply Mismatch Comparison Curve as regards the Power Losses metrics. The MAPE of 5.2% error of the forecast is obtained not from calculations but from the values that generated when the RF Model was implemented.

IV. Conclusion

The research successfully demonstrates that integrating Artificial Intelligence into the control and optimization of smart grid systems significantly enhances their efficiency, resilience, and sustainability. The use of Random Forest for load forecasting provided accurate and robust predictions that informed intelligent energy dispatch. This led to: Improved grid voltage stability and Reduced energy losses. The study shows that when AI is embedded within the energy management layer of a smart grid, it enables proactive rather than reactive control decisions, leading to operational efficiency and environmental sustainability.

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