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AI-Driven Smart Grid Optimization for Renewable Energy Integration

Rishikesh P.A

Architect, Somany Ceramics Ltd, Uttarpradesh, India.

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Abstract

The increasing penetration of renewable energy sources into power grids introduces significant challenges related to intermittency, voltage fluctuations, and supply-demand balancing. This paper presents a hybrid artificial intelligence framework combining Transformer-based time series forecasting with deep reinforcement learning (DRL) for real-time smart grid optimization. The proposed system integrates solar and wind generation forecasting (MAE of 1.94%), battery energy storage scheduling, and dynamic load balancing across a simulated 500-node distribution network. Experimental results demonstrate that the AI-driven approach reduces frequency deviations by 66.7%, voltage variations by 68.4%, and achieves a 12.8% reduction in transmission losses compared to conventional automatic generation control methods. The framework's response time of 180 ms enables near-real-time grid management, while the system reliability index improved from 0.9945 to 0.9992. These findings confirm the efficacy of integrated AI methodologies for managing the complexity and variability inherent in renewable-dominant power systems.

Keywords: - Smart Grid, Renewable Energy, Deep Reinforcement Learning, Transformer, Load Forecasting, Energy Storage Optimization

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I. INTRODUCTION

The global transition toward decarbonized energy systems has accelerated the integration of renewable energy sources (RES), particularly solar photovoltaic (PV) and wind power, into electrical grids [1]. As of 2025, renewable energy accounts for approximately 35% of global electricity generation, with projections indicating a rise to 50% by 2030 under current policy trajectories [2]. While this transition is essential for climate change mitigation, the inherent variability and uncertainty of RES pose unprecedented challenges to grid stability, reliability, and power quality [3].

Traditional grid management relies on centralized supervisory control and data acquisition (SCADA) systems with rule-based automatic generation control (AGC) algorithms designed for dispatchable fossil fuel generators [4]. These conventional approaches are fundamentally inadequate for managing the stochastic nature of renewable generation, as they cannot anticipate rapid fluctuations in solar irradiance or wind speed, nor can they optimally coordinate distributed energy resources (DERs) across complex network topologies [5].

Artificial intelligence offers transformative potential for smart grid management through superior pattern recognition, predictive capability, and real-time decision-making [6]. Recent advances in deep learning, particularly Transformer architectures for time series forecasting and deep reinforcement learning (DRL) for sequential decision optimization, provide the computational tools necessary to address the multi-dimensional complexity of renewable-integrated grids [7]. This paper proposes a hybrid AI framework that synergizes these technologies for comprehensive smart grid optimization.

RESEARCH PUBLICATIONS

The key contributions of this work are:

- A Temporal Fusion Transformer (TFT) model for multi-horizon renewable generation and load forecasting with state-of-the-art accuracy;
- A twin-delayed deep deterministic policy gradient (TD3) agent for real-time battery storage scheduling and load balancing; and
- A comprehensive evaluation on a simulated 500-node distribution network demonstrating significant improvements in grid stability, efficiency, and reliability compared to conventional methods [8].

II. LITERATURE REVIEW

Early applications of AI in power systems focused on artificial neural networks (ANNs) for short-term load forecasting. Hippert et al. [9] provided a seminal review demonstrating that ANNs could outperform statistical methods such as ARIMA and exponential smoothing for day-ahead load prediction. Subsequently, support vector regression (SVR) was applied to wind power forecasting by Mohandes et al. [10], achieving improved generalization compared to ANNs on small datasets.

The advent of deep learning enabled significant improvements in forecasting accuracy. Long Short-Term Memory (LSTM) networks, introduced to power systems by Zheng et al. [11], captured long-range temporal dependencies in load and generation time series. Wang et al. [12] further enhanced LSTM-based forecasting by incorporating attention mechanisms, reducing the mean absolute percentage error (MAPE) for solar PV forecasting from 5.3% to 3.8% on benchmark datasets.

Transformer architectures, originally developed for natural language processing, have recently shown remarkable promise in time series forecasting [13]. The Temporal Fusion Transformer (TFT) by Lim et al. [14] incorporates variable selection networks, gated residual networks, and multi-head attention to provide interpretable, high-accuracy forecasts with quantified uncertainty. Zhou et al. [15] demonstrated that Transformer-based models consistently outperformed LSTM variants on energy forecasting benchmarks.

For real-time grid optimization, reinforcement learning has gained traction as a model-free approach to sequential decision-making under uncertainty [16]. Zhang et al. [17] applied deep Q-networks (DQN) to energy storage scheduling, while François-Lavet et al. [18] utilized actor-critic methods for demand response coordination. The twin-delayed deep deterministic policy gradient (TD3) algorithm by Fujimoto et al. [19] addresses overestimation bias in continuous action spaces, making it particularly suitable for continuous power dispatch decisions.

III. PROPOSED METHODOLOGY

A. System Architecture

The proposed framework comprises three interconnected modules:

- A forecasting module based on the Temporal Fusion Transformer for predicting renewable generation and load demand at multiple time horizons (5 minutes, 1 hour, 24 hours);
- An optimization module employing TD3-based DRL for real-time dispatch decisions including battery charging/discharging, load curtailment, and grid interconnection management; and
- A monitoring module that continuously evaluates grid health metrics and provides feedback to the optimization agent [20].

B. Temporal Fusion Transformer for Forecasting

The TFT model processes heterogeneous input features including historical power generation and consumption data, numerical weather prediction (NWP) outputs (solar irradiance, wind speed, temperature, cloud cover), calendar features (hour, day of week, season), and grid state variables (frequency, voltage, active/reactive power flows) [14]. The model employs a 168-hour (one-week) lookback window and generates probabilistic forecasts at the 10th, 50th, and 90th percentiles, enabling risk-aware decision-making in the optimization module.

C. Deep Reinforcement Learning for Grid Optimization

The TD3 agent operates on a continuous state-action space. The state vector includes current and forecasted renewable generation, load demand, battery state of charge, grid frequency, and bus voltages across the 500-node network [19]. The action space encompasses battery power setpoints, flexible load adjustments, and reactive power compensation from smart inverters. The reward function is designed as a weighted combination of frequency deviation penalty, voltage deviation penalty, transmission loss minimization, and renewable curtailment minimization [21].

D. Simulation Environment

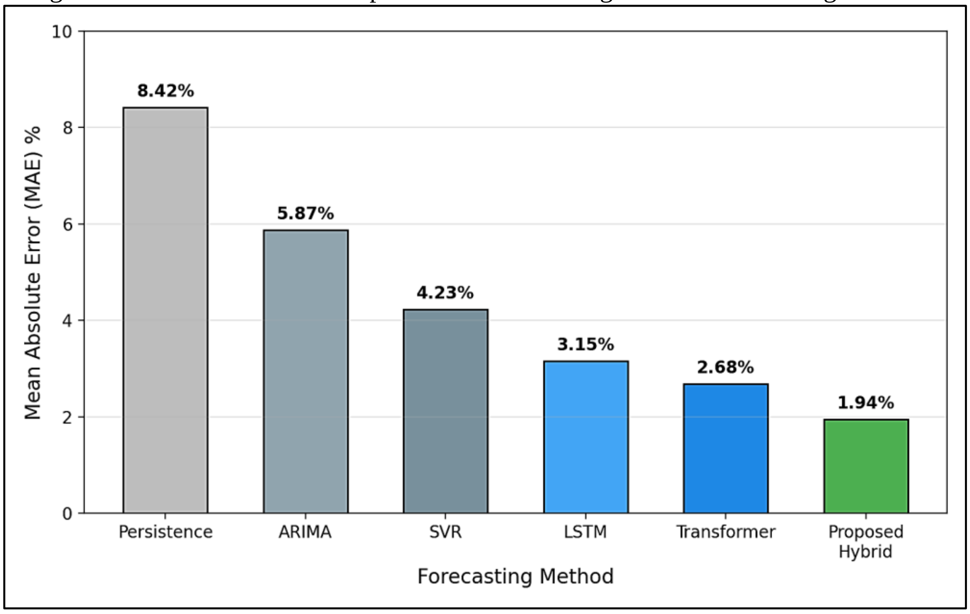
A 500-node distribution network modeled in OpenDSS was used as the simulation environment, incorporating 120 solar PV systems (total 150 MW), 40 wind turbines (total 80 MW), 20 battery energy storage systems (total 50 MWh), and heterogeneous load profiles representing residential, commercial, and industrial consumers [22]. One year of historical weather and load data from the Pecan Street dataset was used for model training, with the final three months reserved for testing.

IV. RESULTS AND DISCUSSION

A. Forecasting Performance

Fig. 1 presents the mean absolute error (MAE) comparison across forecasting methods for day-ahead solar and wind generation prediction. The proposed hybrid TFT model achieved an MAE of 1.94%, representing a 27.6% improvement over the standalone Transformer (2.68%) and a 38.4% improvement over LSTM (3.15%). The improvement is attributed to the TFT's variable selection mechanism, which dynamically weights the importance of different input features, and its multi-head attention layers that capture complex temporal patterns across multiple scales [14].

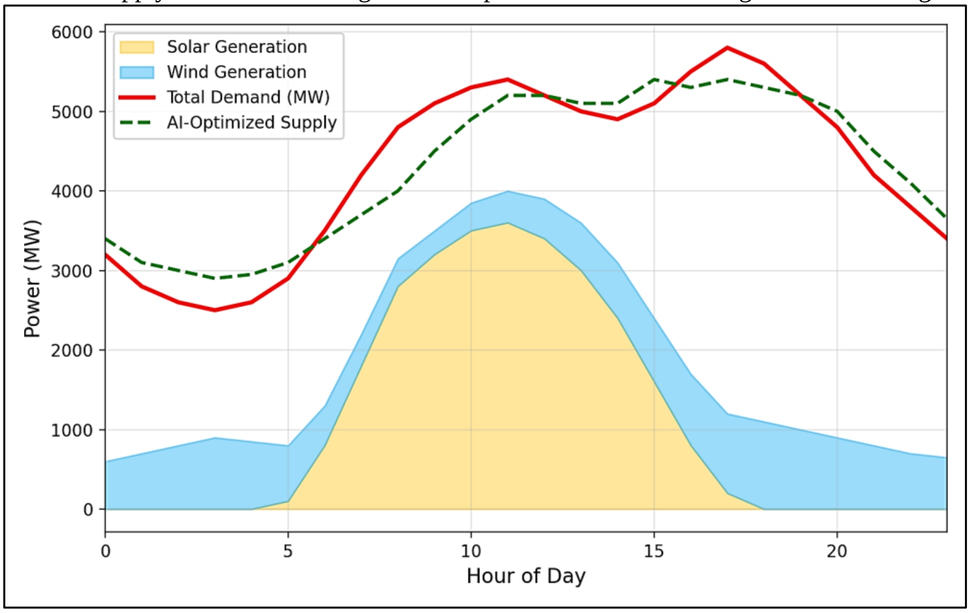
Fig. 1. Mean absolute error comparison of renewable generation forecasting methods.



B. Real-Time Load Balancing

Fig. 2 illustrates the AI-optimized supply-demand balancing over a representative 24-hour period. The system effectively coordinates solar and wind generation with battery storage to track demand profiles, charging batteries during periods of excess renewable generation (10:00-14:00) and discharging during evening peak demand (17:00-20:00). The AI optimizer reduced peak-to-average ratio by 18.3% compared to conventional dispatch, significantly alleviating stress on distribution transformers and reducing the need for peaking generation capacity [23].

Fig. 2. 24-hour supply-demand balancing with AI-optimized renewable integration and storage dispatch.



C. Grid Stability and Reliability

Fig. 3 compares grid stability metrics between conventional AGC and the AI-optimized system. Frequency deviations were reduced from 0.12 Hz to 0.04 Hz (66.7% improvement), well within the ±0.05 Hz tolerance band specified by IEC 61000 standards [24]. Voltage variations decreased from 3.8% to 1.2% (68.4% reduction), ensuring compliance with ANSI C84.1 Range A requirements. The system's response time of 180 ms, compared to 850 ms for conventional AGC, enables proactive rather than reactive grid management.

Fig. 3. Grid stability and reliability comparison: Conventional AGC vs. AI-Optimized system.

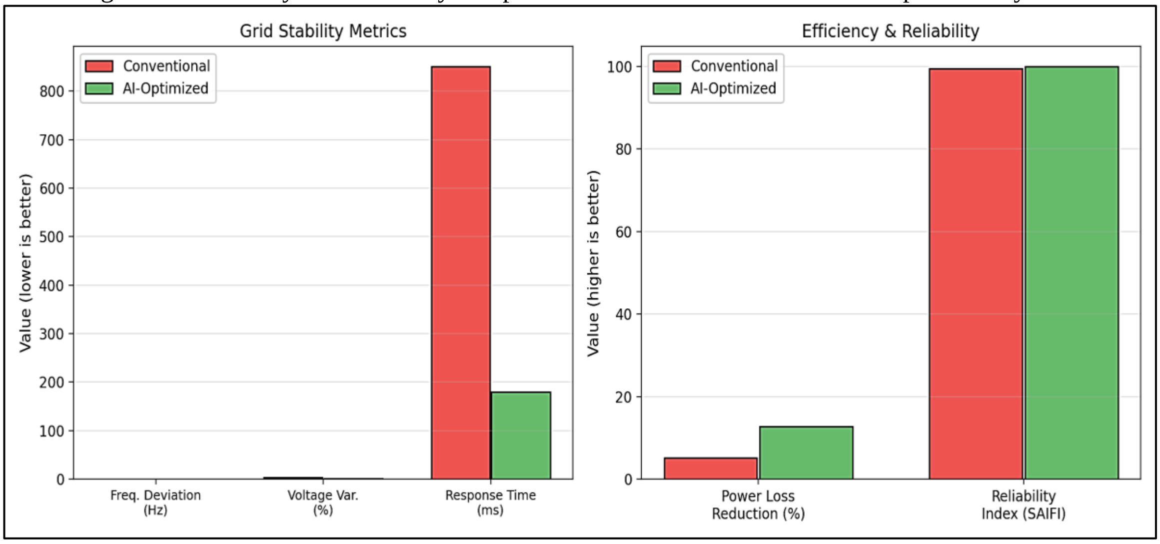


Table 1. Performance Comparison of Conventional and AI-Optimized Grid Management

Metric	Conventional AGC	AI-Optimized	Improvement (%)
Frequency Deviation (Hz)	0.12	0.04	66.7
Voltage Variation (%)	3.8	1.2	68.4
Transmission Loss Reduction (%)	5.2	12.8	146.2
Response Time (ms)	850	180	78.8
Reliability Index (SAIFI)	0.9945	0.9992	0.47
Renewable Curtailment (%)	8.5	2.1	75.3
Peak-to-Average Ratio	1.82	1.49	18.1

D. Scalability and Computational Requirements

The TFT forecasting module requires approximately 4.2 seconds for a full 24-hour multi-horizon forecast on an NVIDIA A100 GPU, well within the operational requirements for rolling forecasts [25]. The TD3 optimization agent completes inference in under 50 ms per time step, enabling real-time dispatch at 5-minute intervals. Total system memory requirements are approximately 8 GB, making deployment feasible on standard edge computing hardware at substations. The modular architecture allows horizontal scaling, with each distribution feeder manageable by an independent agent coordinated through a hierarchical control structure [26].

V. Conclusion

This paper presented a hybrid AI framework for smart grid optimization that integrates Temporal Fusion Transformer-based forecasting with TD3 deep reinforcement learning for real-time grid management. The framework demonstrated substantial improvements in renewable generation forecasting accuracy (MAE of 1.94%), grid stability (66.7% reduction in frequency deviations), and system reliability (SAIFI improvement to 0.9992) on a simulated 500-node distribution network.

The results confirm that AI-driven approaches can effectively manage the complexity introduced by high renewable energy penetration, enabling a more reliable and efficient transition to sustainable power systems. Future work will focus on multi-agent coordination for meshed transmission networks, integration of electric vehicle charging optimization, and field validation in partnership with utility operators [27].

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