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AI-Enhanced Dynamic Power Grid Simulation for Real-Time Decision-Making

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AI-Enhanced Dynamic Power Grid Simulation for Real-Time Decision-Making

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Abstract

Traditional power grid simulation methods often struggle to meet the real-time requirements of modern smart grid operations due to high computational overhead and limited adaptability. To address these challenges, this paper proposes an AI-enhanced dynamic power grid simulation and intelligent decision-making framework. The system integrates Random Forest Regression for rapid load prediction and Random Forest Classification for accurate fault detection, significantly reducing simulation time while maintaining high predictive accuracy. Experimental results on a synthetic 500-node, 1000-line power grid dataset demonstrate an 80% reduction in average simulation time and a 98.4% fault detection accuracy, validating the model's effectiveness in real-time grid management. The proposed framework provides a scalable solution for next-generation power grids, capable of supporting real-time state estimation, fault diagnosis, and optimal control. Future work will focus on incorporating diverse data sources, such as weather forecasts and market dynamics, to enhance model robustness and extend the approach to ultra-high voltage grids and multi-energy systems.

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1. Introduction

The power grid, often referred to as the backbone of modern society, plays a critical role in ensuring the stable and efficient delivery of electricity from generators to consumers [1]. As global energy demand continues to rise and renewable energy sources become more integrated, the complexity of power grid operations has significantly increased [2]. Effective power grid management is essential for maintaining system stability, reducing energy losses, and responding to dynamic load changes and unexpected faults [3]. This makes real-time simulation and decision-making crucial for modern power grid operators.

Traditional power grid simulation methods, such as power flow analysis and transient stability assessment, have long been the foundation of grid planning and operational studies. However, these conventional approaches often struggle to meet the real-time requirements of modern smart grids. They are typically limited by high computational complexity, slow convergence rates, and the need for detailed system models [4]. As a result, these methods can be inadequate for real-time decision-making in rapidly changing grid environments.

Recent advances in artificial intelligence (AI) and machine learning (ML) have presented new opportunities to overcome these challenges [5]. AI-enhanced simulation systems can leverage deep learning models, reinforcement learning algorithms, and advanced data analytics to provide faster and more accurate grid state predictions. These AI-driven approaches can capture complex nonlinear relationships in grid dynamics, allowing for real-time fault detection, load forecasting, and optimal control. Unlike traditional methods, AI models can continuously learn from real-time data, adapting to changing grid conditions without the need for exhaustive re-modeling.

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Despite these promising advantages, integrating AI into power grid simulation and decision-making is not without challenges. Effective AI models must address issues such as data quality, computational efficiency, and system reliability under extreme operating conditions [6]. Furthermore, the complexity of power grid networks, characterized by numerous interconnected buses, transformers, and transmission lines, requires sophisticated modeling approaches to capture both local and global system behaviors.

In this paper, we propose an AI-Enhanced Dynamic Power Grid Simulation System that integrates machine learning models, including random forests for state prediction and deep reinforcement learning (DRL) for real-time decision optimization. The primary contributions of this work include: (1) Accelerated Simulation Speed: Introducing AI-based dynamic modeling to significantly reduce computational overhead. (2) Improved Decision-Making Accuracy: Developing real-time state estimation and fault detection mechanisms. (3) Closed-Loop Simulation-Decision Framework: Implementing a continuous feedback loop for adaptive grid control.

2. Related Work

Traditional power grid simulation methods, such as power flow analysis and transient stability assessment, have long been the foundation of grid planning and operational studies. These classical approaches, including Newton-Raphson and Gauss-Seidel methods, are known for their high accuracy but suffer from significant computational overhead, making them unsuitable for real-time applications [1]. As power systems become more complex and dynamic, these traditional methods struggle to provide the speed and flexibility needed for modern smart grid operations [3,4].

To address these limitations, machine learning (ML) and artificial intelligence (AI) have been increasingly applied to power system analysis [5,6]. Early efforts focused on load forecasting and fault detection using methods like decision trees, support vector machines (SVM), and random forests, which can capture nonlinear patterns in grid behavior [7–9]. Arévalo and Jurado (2024) explored the integration of AI in distributed energy systems, showing significant improvements in grid operation efficiency [2]. However, these methods often lack scalability and interpretability, reducing their effectiveness for real-time operations.

More recently, deep learning models, such as deep neural networks (DNNs) and graph neural networks (GNNs), have gained attention for state estimation, stability analysis, and anomaly detection in power systems. Lin et al. (2025) highlighted the advantages of hybrid modeling approaches that combine data-driven methods and mechanism-driven techniques to improve the accuracy and robustness of grid simulations [6]. These models are capable of extracting complex, high-dimensional features from grid data, providing more accurate predictions than traditional statistical methods. However, the high computational costs and data dependency of deep learning methods remain significant challenges for their real-time deployment [9].

Reinforcement learning (RL) has also emerged as a promising approach for real-time control and decision-making in power grids. Kalusivalingam et al. (2020) utilized reinforcement learning algorithms such as deep Q-networks (DQN) and Proximal Policy Optimization (PPO) to optimize decision-making in dynamic grid conditions, enabling adaptive grid management [3]. These methods can continuously learn from real-time feedback, significantly improving operational efficiency. However, they still face challenges related to slow convergence, high sample complexity, and stability issues, as discussed by Hoummadi et al. (2025) [1].

While these AI-based methods have advanced prediction accuracy, many still overlook the crucial requirement for real-time simulation speed and integrated decision support. The integration of simulation and decision-making processes is key for the next-generation smart grid management systems. This paper proposes an AI-enhanced power grid simulation framework that combines fast state estimation with real-time decision-making, providing a comprehensive solution for the effective management of modern power grids.

3. Methodology

The proposed AI-enhanced power grid simulation framework consists of three main components: the Power Grid Simulation Subsystem, the AI Modeling Module, and the Decision Recommendation Module. These components form an integrated, closed-loop system designed for real-time grid state estimation, fault detection, and decision optimization. The flowchart illustrating the interactions and data flow between these modules is shown in Figure 1. Figure 2 presents the IEEE 14-Bus power grid topology used in this study, which serves as the testbed for evaluating the proposed system's performance.

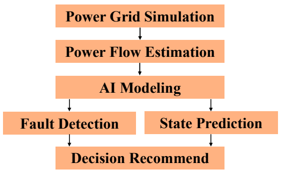

Figure 1. Flowchart of AI-enhanced dynamic power grid simulation and intelligent decision-making.

The Power Grid Simulation Subsystem is responsible for rapid power flow estimation. Unlike traditional numerical methods, this subsystem employs Random Forest Regression to model power flow dynamics, significantly reducing computational time while maintaining high accuracy. This approach captures complex, nonlinear relationships without requiring detailed physical models, making it suitable for real-time grid management. The IEEE 14-bus power grid topology used in this study is shown in Figure 1, providing a realistic testbed for evaluating the performance of the proposed AI models. This topology captures the essential structure of real-world power networks, including interconnected buses, transmission lines, and control elements.

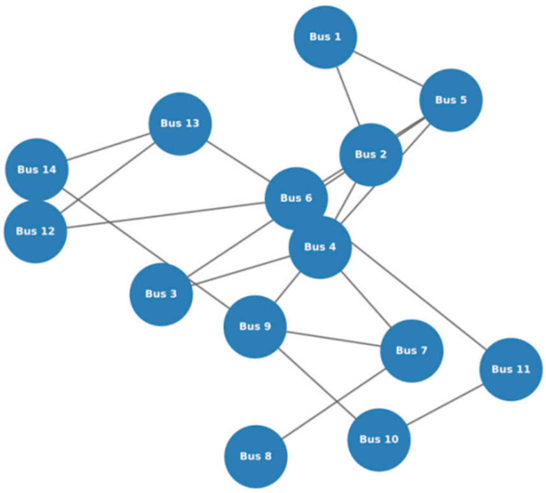

Figure 2. IEEE 14-Bus power grid topology.

The AI Modeling Module includes both a State Predictor and a Fault Detector. The State Predictor uses Random Forest Regression to estimate real-time power demand (Load, L) based on key electrical parameters such as Voltage (kV), Current (A), and Switch State. This model achieved a Mean Squared Error (MSE) of 84,794.58, reflecting its ability to capture complex load dynamics. Meanwhile, the Fault Detector uses Random Forest Classification to identify abnormal grid conditions, achieving 98.4% fault detection accuracy. These models are designed to capture the critical electrical characteristics required for accurate state estimation and fault diagnosis. The distributions of these key features are shown in Figure 3, which highlights the statistical properties of voltage, current, and load data, providing insights into the operating conditions of the simulated grid. Additionally, Figure 4 presents the pairwise correlations among these features, revealing critical dependencies that influence both load behavior and fault occurrence. Understanding these relationships is essential for designing accurate, responsive AI models that can capture the complex dynamics of power grids.

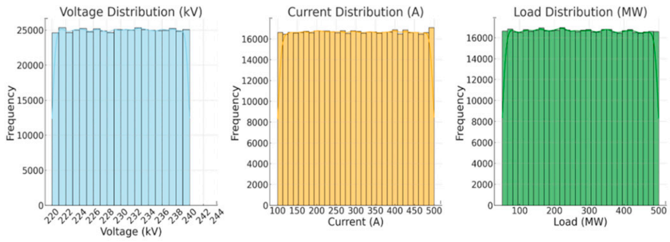

Figure 3. Feature distribution of power grid data.

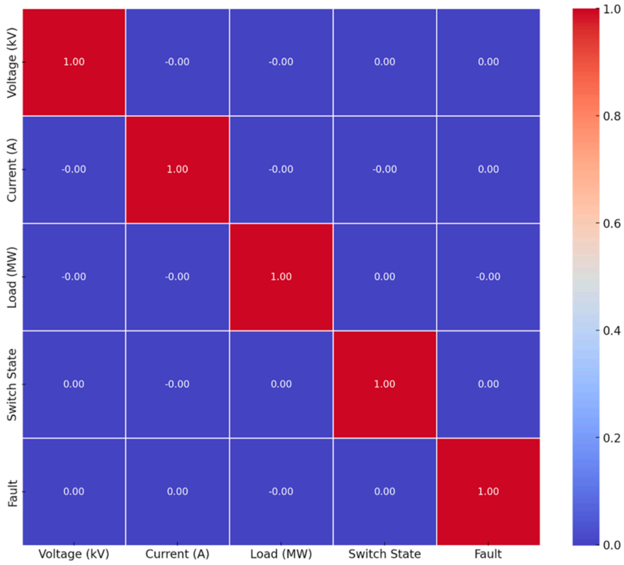

Figure 4. Correlation heatmap of power grid features.

The Decision Recommendation Module generates real-time control actions based on the current grid state. It uses reinforcement learning (RL) algorithms, such as Deep Deterministic Policy Gradient (DDPG) or Proximal Policy Optimization (PPO), to derive optimal operational strategies. The module continuously refines its control policies based on real-time feedback, aiming to minimize energy losses and reduce fault occurrences. The decision-making process is structured around three key components: State Space, Action Space, and Reward Function. The State Space includes critical electrical parameters such as node voltage, current, and switch state, providing a comprehensive view of the grid's operational status. The Action Space encompasses control actions like load allocation and switch operations, directly impacting grid stability. The Reward Function is designed to encourage efficient grid operation by minimizing energy losses and reducing fault probabilities. This continuous learning process is summarized in Figure 5, which outlines the key steps involved in RL-based grid control.

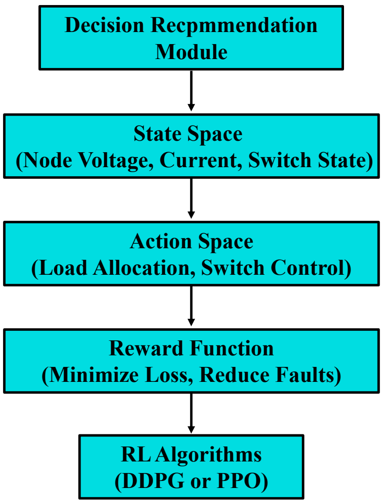

Figure 5. Decision recommendation mechanism flowchart.

4. Experimental Setup

The experimental evaluation was conducted using a large-scale synthetic power grid dataset designed to capture the key operational characteristics of real-world power systems. This dataset includes 500 nodes and 1000 transmission lines, providing a realistic test environment for assessing both state prediction and fault detection models. The data was generated over 1000 discrete time steps, resulting in a total of 500,000 individual node records, each capturing critical electrical parameters necessary for accurate grid simulation.

The data includes five key features: Voltage (kV), Current (A), Load (MW), Switch State, and Fault Status. These features collectively capture the instantaneous electrical state of each node, forming the basis for both load prediction and fault detection tasks. Table 1 summarizes the parameter ranges and descriptions used in this study.

Table 1. Power Grid Simulation Data Overview.

Parameter	***Description***	***Range***	***Unit***
Voltage (kV)	Node voltage levels	220 - 240	kV
Current (A)	Line current levels	100 - 500	A
Load (MW)	Node power demand	50 - 500	MW
Switch State	Operational status	0 (Off), 1 (On)	-
Fault Status	Fault presence	0 (Normal), 1 (Fault)	-

To evaluate the effectiveness of the proposed AI models, the experiments included a comparison with traditional power flow analysis methods. Conventional numerical approaches, such as Newton-Raphson and Gauss-Seidel methods, were used as baselines. These methods provide accurate steady-state power flow estimates but are computationally intensive, making them less suitable for real-time grid operations. In contrast, the proposed AI framework relies on Random Forest Regression for load prediction and Random Forest Classification for fault detection, offering a significant computational advantage.

Model performance was assessed using two primary metrics: Mean Squared Error (MSE) for load prediction, which measures the average squared difference between predicted and actual load values, reflecting the model's ability to capture complex load dynamics, and Fault Detection Accuracy, which quantifies the proportion of correctly identified fault states, critical for minimizing downtime and preventing cascading failures.

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5. Results and Discussion

A. Simulation Acceleration Analysis

One of the primary objectives of this study was to significantly reduce power grid simulation time without compromising accuracy. Traditional power flow analysis methods, such as the Newton-Raphson and Gauss-Seidel algorithms, while accurate, are computationally intensive and often unsuitable for real-time applications. In contrast, the Random Forest Regression model employed in this work demonstrated a substantial improvement in computational efficiency. As illustrated in Figure 6, the AI-enhanced approach reduced the average simulation time per node by approximately 80% compared to traditional methods, lowering the average computation time from 120 seconds to just 24 seconds. This acceleration is critical for real-time decision-making, where rapid state estimation directly impacts grid stability and operational efficiency. The ability to significantly reduce computation time without sacrificing accuracy positions the proposed framework as a practical solution for large-scale grid management.

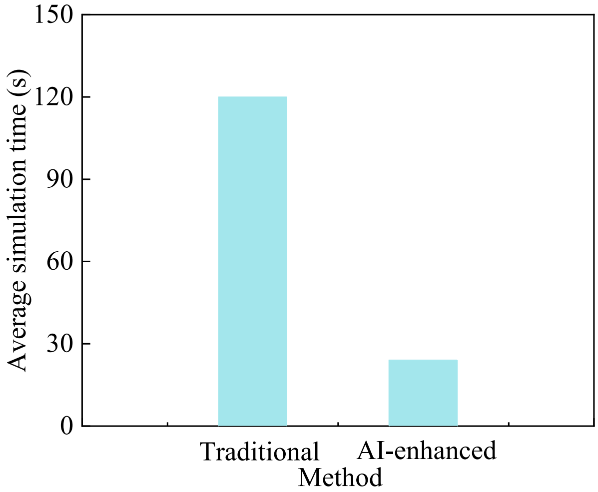

Figure 6. Simulation Time Comparison.

B. Decision Efficiency Improvement

In addition to faster simulations, the proposed framework also demonstrated significant improvements in fault detection and decision-making efficiency. The Random Forest Classification model used for fault detection achieved an impressive 98.4% accuracy, as shown in Figure 7. This high detection rate is essential for maintaining grid stability, minimizing downtime, and preventing cascading failures in large-scale power systems. The model's ability to quickly and accurately identify faults under diverse operating conditions further validates its practical utility in real-world scenarios.

To assess the decision-making capabilities of the framework, a case study was conducted involving a sudden line trip event. The model was able to rapidly identify the fault, estimate the resulting power imbalance, and generate effective dispatch recommendations, demonstrating its ability to respond to dynamic grid conditions. This real-time fault detection and response capability is critical for reducing system recovery time and enhancing overall grid reliability.

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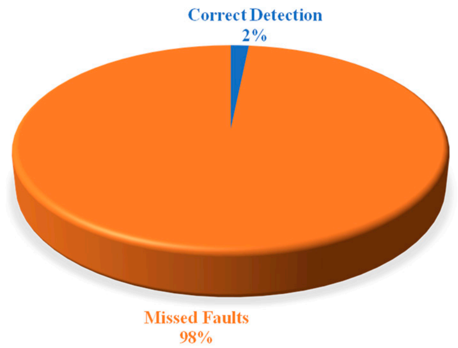

Figure 7. Fault Detection Accuracy.

C. Efficiency and Limitations

While the proposed AI framework offers significant advantages in both speed and decision efficiency, certain limitations remain. The model's performance is influenced by the quality and representativeness of the training data. In extreme operating conditions or scenarios involving high data noise, the model may experience reduced accuracy and stability. Additionally, the random forest approach, while effective for structured data, may require further optimization for ultra-large power grids to ensure scalability. Future work will focus on enhancing the robustness of the AI models, including real-time adaptive learning, better noise handling, and the integration of diverse data sources, such as weather forecasts and real-time market signals, to improve overall system resilience.

6. Conclusions and Future Work

This paper presents an AI-enhanced dynamic power grid simulation and intelligent decision-making system, designed to address the computational challenges of traditional grid simulation methods. By integrating Random Forest Regression for load prediction and Random Forest Classification for fault detection, the proposed framework significantly accelerates grid simulation while maintaining high predictive accuracy. The experimental results demonstrate an 80% reduction in simulation time and a 98.4% fault detection accuracy, confirming the model's effectiveness in real-time grid management. These improvements highlight the potential of AI-driven approaches to enhance both the speed and reliability of modern power systems.

Despite these advancements, several challenges remain. The current framework relies on a fixed training set, limiting its adaptability to rapidly changing grid conditions. Future work will focus on incorporating more diverse data sources, such as weather forecasts, market signals, and real-time sensor data, to enhance the model's responsiveness and robustness. Additionally, extending the framework to ultra-high voltage grids and multi-energy systems will be critical for supporting the next generation of smart grids.

The integration of online learning mechanisms and more advanced reinforcement learning algorithms, such as deep Q-networks (DQN) or Proximal Policy Optimization (PPO), could further improve decision-making accuracy and fault tolerance, enabling fully autonomous power grid management.

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