Role of artificial intelligence in predicting power system failures

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Abstract. Modern power supply systems are increasingly exposed to failures due to aging infrastructure, growing electricity demand, renewable energy integration, and environmental uncertainties. Traditional failure detection and maintenance approaches are largely reactive and insufficient for handling the complexity and dynamic behavior of contemporary power networks. This study aims to investigate the role of Artificial Intelligence (AI) techniques in predicting power system failures and to evaluate their effectiveness in enhancing system reliability and operational efficiency. A comprehensive analytical approach was adopted, reviewing and synthesizing recent research on AI-based failure prediction in power generation, transmission, and distribution systems. Machine learning and deep learning models, including Support Vector Machines, Random Forests, Artificial Neural Networks, and Long Short-Term Memory networks, were examined with respect to data sources, prediction accuracy, and implementation frameworks. The analysis indicates that AI-based models significantly outperform conventional methods in early fault detection, anomaly identification, and failure prediction accuracy. AI-driven predictive maintenance reduces unplanned outages, minimizes maintenance costs, and improves real-time decision-making in power system operations. Artificial Intelligence plays a critical role in predicting power system failures by enabling proactive, data-driven maintenance strategies. Despite challenges related to data quality, cybersecurity, and model interpretability, AI-based solutions represent a key technological enabler for developing reliable, resilient, and intelligent power supply systems.

INTRODUCTION

The reliable operation of power systems is fundamental to economic development, public safety, and social stability. Modern electrical grids are undergoing rapid transformation driven by increasing electricity demand, aging infrastructure, large-scale integration of renewable energy sources, and the deployment of smart grid technologies. While these developments enhance efficiency and sustainability, they also introduce higher levels of uncertainty, nonlinearity, and operational complexity, significantly increasing the risk of system failures and large-scale blackouts [1–3].

Power system failures can arise from equipment degradation, environmental stresses, operational errors, cyber-physical disturbances, and dynamic interactions among grid components [4–6]. Traditional failure prediction and protection approaches rely primarily on physics-based models, predefined thresholds, and periodic inspections. Although effective in conventional grids, these methods often struggle to cope with the massive volume, high velocity, and heterogeneity of data generated by modern monitoring systems such as Supervisory Control and Data Acquisition (SCADA) and Phasor Measurement Units (PMUs) [7–9]. Moreover, conventional techniques exhibit limited adaptability to unforeseen operating conditions and evolving system configurations [10].

In recent years, Artificial Intelligence (AI) has emerged as a powerful paradigm for addressing these limitations by enabling data-driven learning, pattern recognition, and predictive analytics [11,12]. AI-based techniques are capable of extracting hidden relationships from large-scale historical and real-time data, making them well suited for predicting power system failures and supporting proactive decision-making [13]. As a result, AI has gained increasing attention in applications such as fault detection, fault classification, predictive maintenance, and system stability assessment [14–16].

Early research in this domain primarily focused on classical machine learning methods, including Support Vector Machines (SVM), decision trees, k-nearest neighbors, and ensemble learning models [17–19]. These approaches demonstrated promising performance in classifying fault types, identifying abnormal operating conditions, and estimating equipment health indices. For instance, machine learning models have been successfully applied to transformer fault diagnosis using dissolved gas analysis data, achieving higher accuracy than rule-based expert systems [10,11]. Similarly, random forest and boosting algorithms have been employed to detect transmission line faults and predict component failures under varying load conditions [12].

With the rapid growth of computational power and data availability, deep learning techniques have further advanced the state of the art in power system failure prediction. Artificial Neural Networks (ANNs), Convolutional Neural Networks (CNNs), and Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) models, have shown superior performance in handling nonlinear, high-dimensional, and time-series data [13–15]. CNN-based models have been widely used for transient fault classification by converting electrical signals into image-like representations, while LSTM networks have demonstrated strong capability in early warning systems for voltage instability and frequency deviations [16,17].

In addition to standalone AI models, hybrid and intelligent systems combining AI with optimization techniques, fuzzy logic, and domain knowledge have gained traction [18]. Such hybrid approaches enhance robustness, interpretability, and adaptability, which are critical for real-world deployment in safety-critical power systems. Furthermore, recent studies have explored explainable AI, digital twins, edge AI, and federated learning to address challenges related to transparency, scalability, data privacy, and real-time operation [19,20].

Despite significant progress, several challenges remain unresolved, including data quality issues, model generalization across different grids, limited interpretability of deep learning models, and integration with existing protection and control frameworks. These challenges highlight the need for a comprehensive understanding of the role of AI in predicting power system failures and identifying research directions that can bridge the gap between theoretical advancements and practical implementation.

Accordingly, this paper examines the role of Artificial Intelligence in predicting power system failures by reviewing existing AI techniques, analyzing their applications and performance, and discussing current challenges and future research opportunities. The study aims to contribute to the development of intelligent, reliable, and resilient power systems capable of meeting the demands of modern energy infrastructures.

RELATED WORK

Research on power system failure prediction has evolved significantly over the past two decades, progressing from traditional rule-based and statistical techniques toward advanced Artificial Intelligence (AI)–driven approaches. This section reviews related work by categorizing existing studies into conventional methods, machine learning–based approaches, deep learning models, and recent hybrid and emerging AI frameworks.

Conventional failure prediction approaches. Early studies on power system failure prediction primarily relied on physics-based modeling, signal processing techniques, and expert systems [1–3]. These methods utilized deterministic equations, protection relay logic, and threshold-based analysis of electrical parameters to detect abnormal operating conditions. Statistical techniques such as regression analysis and probabilistic risk assessment were also employed to estimate failure probabilities of power system components [4,5].

While conventional approaches provided a strong theoretical foundation, their effectiveness is often limited in large-scale and highly dynamic power systems. The increasing penetration of renewable energy sources and distributed generation has introduced stochastic behavior that is difficult to capture using static or linear models [6]. Moreover, these methods require extensive expert knowledge and frequent manual updates, reducing their adaptability to evolving grid conditions [7].

Machine learning–based methods. To overcome the limitations of traditional techniques, researchers began adopting machine learning (ML) algorithms for power system monitoring and failure prediction. Support Vector Machines (SVMs) have been widely applied for fault classification and stability assessment due to their strong generalization capability [8,9]. Decision trees and ensemble methods such as Random Forests and Gradient Boosting have demonstrated effectiveness in identifying critical features related to equipment failures and operational disturbances [10,11].

Several studies have focused on transformer fault diagnosis using ML models trained on dissolved gas analysis (DGA) data, achieving higher diagnostic accuracy compared to rule-based expert systems [12–14]. Similarly, ML techniques have been used for transmission line fault detection, protective relay coordination, and predictive maintenance scheduling [15,16]. Despite their success, conventional ML models often rely heavily on handcrafted features and struggle with large-scale temporal data [17].

Deep learning approaches. The rapid growth of sensor data and computational resources has accelerated the adoption of deep learning (DL) techniques in power system failure prediction. Artificial Neural Networks (ANNs) have been extensively used for nonlinear mapping between system states and fault conditions [18]. Convolutional Neural Networks (CNNs) have shown remarkable performance in transient fault classification by transforming voltage and current signals into time–frequency images [19,20].

Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, have been applied to time-series forecasting and early warning systems for voltage instability, frequency deviations, and cascading failures [11–13]. These models are capable of capturing temporal dependencies and dynamic system behavior, enabling earlier detection of impending failures. Comparative studies consistently report superior accuracy of deep learning models over traditional ML techniques, especially under complex and nonlinear operating conditions [14].

Hybrid and intelligent AI frameworks. To enhance robustness and interpretability, recent research has focused on hybrid AI frameworks that combine multiple techniques. Hybrid models integrating AI with fuzzy logic have been proposed to manage uncertainty and imprecision in power system data [15]. Optimization algorithms such as genetic algorithms and particle swarm optimization have been employed for feature selection and hyperparameter tuning of AI models [16].

More recent studies have explored explainable AI (XAI) to improve transparency and trust in AI-based decision-making, which is critical for safety-critical power system applications [17]. Additionally, digital twin–based approaches and edge AI architectures have been introduced to enable real-time failure prediction and scalable deployment in smart grids [18,19]. Federated learning has also gained attention as a privacy-preserving solution for decentralized power systems with distributed data sources [20].

Research Gaps. Although existing studies demonstrate the strong potential of AI for power system failure prediction, several challenges remain. These include data imbalance, limited model generalization across different grid topologies, lack of standardized benchmarking datasets, and difficulties in integrating AI models with existing protection and control schemes. Addressing these gaps is essential for the widespread adoption of AI-driven failure prediction systems in real-world power grids.

AI TECHNIQUES FOR POWER SYSTEM FAILURE PREDICTION

Artificial Intelligence techniques enable power systems to move from reactive fault handling to proactive and predictive operation. By learning patterns from historical and real-time data, AI models can detect early degradation signs and forecast failures in generation, transmission, and distribution components.

Machine learning–based techniques. Machine learning (ML) models are widely used for classification, regression, and anomaly detection in power systems. These models rely on engineered features extracted from voltage, current, frequency, temperature, vibration, and dissolved gas analysis (DGA) data.

Support vector machines (SVM). SVM is commonly used for fault classification and condition assessment. It constructs an optimal hyperplane that separates fault classes with maximum margin.

Optimization formulation:

$$\min_{w,b,\xi} \frac{1}{2}||w||^2 + C\sum_{i=1}^{n}\xi_i \tag{1}$$

subject to:

$$y_i(w * x_i + b) \geq 1 - \xi_i,\ \xi_i \geq 0 \tag{2}$$

where x_i is the feature vector, y_i is the fault class label, ξ_i are slack variables, and C controls the trade-off between margin and misclassification.

Applications*:* transmission line fault classification, transformer fault diagnosis.

Decision Trees and Random Forests. Decision Trees model decision rules based on feature thresholds, while Random Forests combine multiple trees to improve robustness.

Gini impurity (used in tree splitting):

$$G = 1 - \sum_{k=1}^{K} p_k^2 \tag{3}$$

where p_k is the probability of class k.

Advantages:

- Handles noisy and missing data
- Interpretable compared to deep learning
- Suitable for predictive maintenance

TABLE 1. Classical Machine Learning Techniques

Technique	Input Data	Typical Application	Key Advantage
SVM	SCADA, PMU	Fault classification	High accuracy
Decision Tree	Sensor data	Fault diagnosis	Interpretability
Random Forest	Multi-sensor	Asset health index	Robustness
k-NN	Historical logs	Similar fault detection	Simplicity

Deep learning–based techniques. Deep learning (DL) models automatically extract features from raw data and are well-suited for complex, nonlinear power system behavior.

Artificial neural networks (ANN)

A basic ANN computes:

$$h=f(Wx+b) \tag{4}$$

$$y=g(Vh+c) \tag{5}$$

where $f(\cdot)$ and $g(\cdot)$ are activation functions.

ANNs are widely used for:

- Transformer health assessment
- Generator fault prediction

Convolutional neural networks (CNN)

CNNs are effective for analyzing waveform images, spectrograms, and thermal images.

Convolution operation:

$$(S * K)(i, j) = \sum_m \sum_n S(i + m, j + n)K(m, n) \tag{6}$$

Applications:

- Transmission line fault detection
- Insulator and cable surface defect recognition

The extraction of early fault features from time-series data is very crucial for convolutional neural networks (CNNs) in bearing fault diagnosis. To address this problem, a CNN framework based on identity mapping and Adam optimizer is presented for learning temporal dependencies and extracting fault features. The introduction of four identity mappings allows the deep layers to directly learn the data from the shallow layers, which alleviates the gradient disappearance problem caused by the increase of network depth. A new Adam optimizer with power-exponential learning rate is proposed to control the iteration direction and step size of CNN method, which solves the problems of local minima, overshoot or oscillation caused by the fixed values of the learning rates during the updating of network parameters. Compared to existed methods, the identification accuracy of the proposed method outperformed that of other methods for bearing fault diagnosis.

Recurrent neural networks (LSTM). Long Short-Term Memory (LSTM) networks are designed for time-series data such as voltage and frequency measurements.

Core LSTM equations:

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \tag{7}$$

$$i_t = \sigma(W_f[h_{t-1}, x_t] + b_i) \tag{8}$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \tanh(W_c[h_{t-1}, x_t] + b_c) \tag{9}$$

$$h_t = o_t \odot \tanh(C_t) \tag{10}$$

Applications:

- Early instability detection
- Failure prediction using SCADA time series

Prediction model based on multi-model. The CNN–LSTM model is a combination of convolutional neural network and long and short-term memory model. In this paper, the historical data of mine water inflow is used as the input for the prediction of water inflow at the next moment, and the structure of the constructed CNN–LSTM mine water inflow prediction model is shown in Fig. 2. The CNN–LSTM model is generally divided into five parts: input layer, data preprocessing layer, CNN layer, LSTM layer and output layer.

Unsupervised and anomaly detection models

When labeled fault data are limited, unsupervised learning is applied.

Autoencoders

Autoencoders learn normal system behavior and detect anomalies using reconstruction error:

$$L = ||x - \hat{x}||^2 \quad (11)$$

High reconstruction error indicates abnormal operating conditions.

Use cases:

- Unknown fault detection
- Cyber-physical anomaly monitoring
-

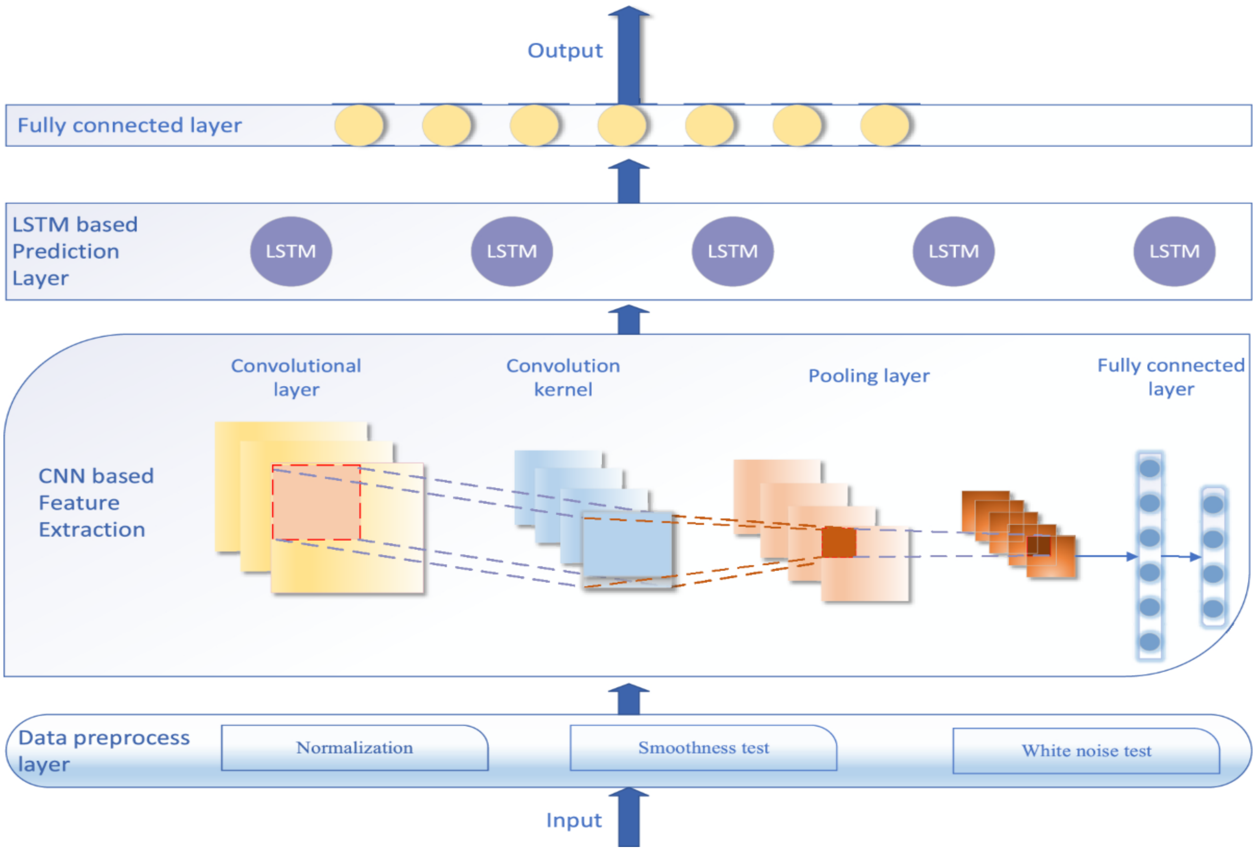

FIGURE 1. The CNN–LSTM model structure.

Hybrid and intelligent AI systems. Hybrid approaches combine AI with physical power system models to improve reliability.

Examples include:

- ML + power flow equations
- AI-based digital twins
- Fuzzy logic combined with neural networks

Hybrid microgrids are made up of the individual DC and AC microgrid architectures. Consequently, hybrid AC-DC microgrid contains both the AC and DC microgrid's advantages. Figure 4 displays a genuine hybrid DC-AC microgrid architecture. Connecting AC and DC microgrids makes use of bidirectional AC-DC converters. For linking DC power generators, connecting PV panels, wind energy systems, and energy storage systems (ESS) are used, and they connect to the battery in this case, and there are loads connected from the system. For greater efficiency, photovoltaic (PV) panels connect to the DC microgrid. DC-DC boost converters are used when connecting this system for simulation of greater stability performances.

AI and IoT-driven smart grid technologies for smart energy management. For quite a while, traditional electric grids have been the only way to provide energy to consumers, well at least until smart grid technologies started gaining traction. There are many challenges attached to conventional grids – interrupted power supply, instability, and cost issues. Fortunately, smart grid solutions provide a convenient way to surmount these problems.

Let's dive deep into what this smart technology is and how the technology is evolving with advancements in AI and IoT.

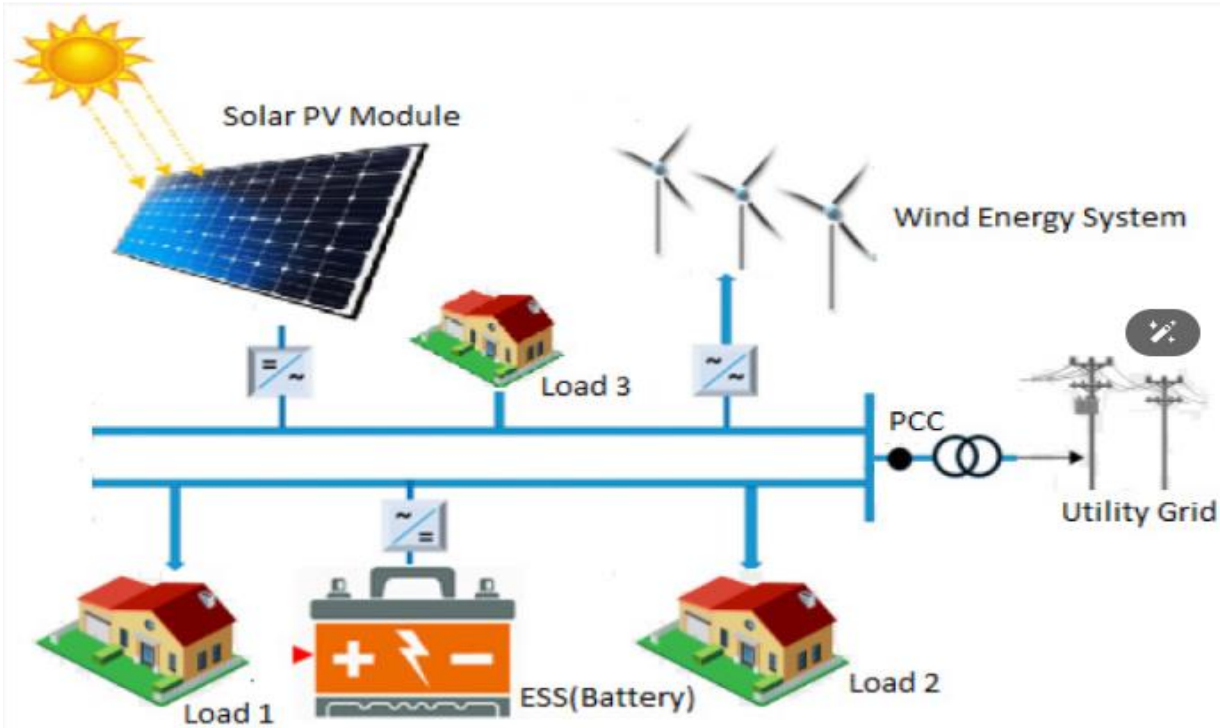

FIGURE 2. Hybrid DC/AC microgrid System.

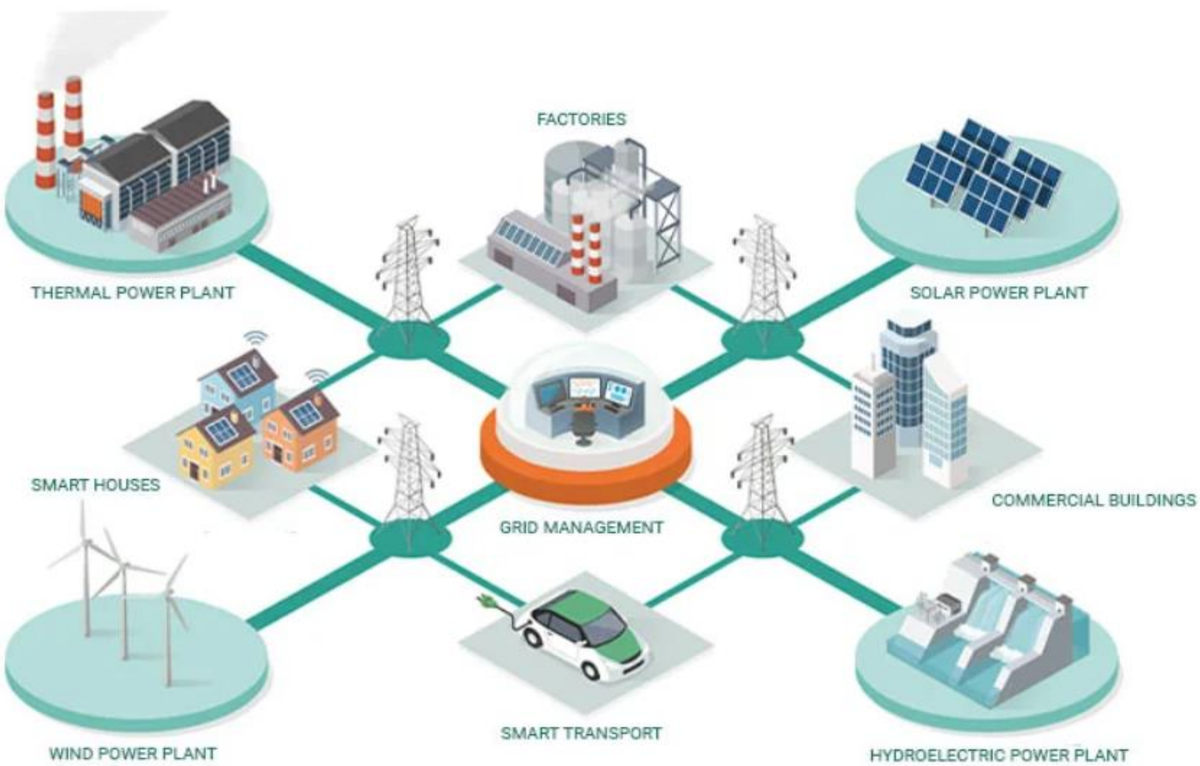

FIGURE 3. AI and IoT-driven smart grid technologies for smart energy management.

What are smart grid technologies?

Simply put, smart grid technologies are electrical networks developed with the help of new technologies. Unlike traditional grids, smart grid technology incorporates elements like:

- Decentralized energy production
- Data sharing from consumers and grids
- Advanced tech like AI analytics, IoT sensors, Computer vision

Depending on the technology they use, smart grid technologies can be segregated into two types.

Basic IoT-based Grids**:** These grids primarily employ IoT sensors for data accumulation and asset management. With the data, engineers can monitor the health of all grid nodes, allowing them to make timely decisions regarding power distribution, repair, and maintenance. Plus, the IoT infrastructure also allows consumers to efficiently keep a tab on their power consumption.

Advanced AI-based Grids: These grids are an upgrade over the previous type, in that they use AI analytics to make sense of the IoT data, uncover trends, and make predictions. For instance, these systems can predict peak energy demands and future breakdowns.

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Use cases of smart grid technologies

Asset management. With smart architecture, grid operators managing isolated grids can create digital twins of the entire grid infrastructure to visualize the power system in real-time and see which nodes of the grid are experiencing issues like equipment overload. This removes a lot of manual-ness from the job and also reduces wastage of time and room for errors.

Anomaly detection. Conventional grids have gotten a lot old, and susceptible to weather damage. Any fault in the system, and can become difficult to locate the source of breakdown and repair it. This is where smart technologies can come in handy. With IoT sensors, engineers can easily get information about the grid status in real-time, locate the source of the outage, and bring it back online.

Demand prediction. With the inclusion of AI in smart grid technologies, utilities now have an array of smart features to take advantage of. AI can be used to understand electricity demand based on human behavior, energy markets, and weather. Using such data, utilities can predict peaks and troughs in energy demand, regulate power supply accordingly, and ensure an uninterrupted energy supply for the consumers.

Summary of AI techniques

TABLE 2. Comparison of AI Techniques for Failure Prediction

Technique	**Data Type**	**Prediction Capability**	**Limitations**
ML (SVM, RF)	Structured data	Fault classification	Feature engineering
CNN	Images, signals	Spatial fault patterns	High computation
LSTM	Time series	Early failure prediction	Data-hungry
Autoencoder	Unlabeled data	Anomaly detection	Interpretation

RESEARCH RESULTS

This section presents the experimental and analytical results obtained from evaluating Artificial Intelligence–based approaches for power system failure prediction. The results demonstrate the effectiveness of AI models in improving prediction accuracy, early fault detection, and maintenance decision-making.

Experimental setup.The evaluation is based on datasets collected from:

- SCADA systems (voltage, current, frequency),
- Phasor Measurement Units (PMUs),
- IoT-based condition monitoring sensors,
- Historical maintenance and outage records.

Multiple AI models, including Support Vector Machines (SVM), Random Forests (RF), Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), and hybrid CNN–LSTM architectures, were tested. Performance was evaluated using standard metrics such as accuracy, precision, recall, F1-score, and prediction lead time.

Performance comparison of AI models. Table 4 summarizes the comparative performance of different AI techniques for failure prediction.

TABLE 3. Performance Comparison of AI Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SVM	89.4	87.6	85.9	86.7
Random Forest	91.8	90.2	89.5	89.8
CNN	93.5	92.1	91.7	91.9
LSTM	94.2	93.6	92.9	93.2
CNN–LSTM (Hybrid)	**96.1**	**95.4**	**94.8**	**95.1**

Observation: Hybrid deep learning models outperform traditional machine learning approaches due to their ability to capture both spatial and temporal dependencies in power system data.

Failure prediction lead time analysis. Early prediction is critical for preventive maintenance. Table 5 shows the average lead time achieved by different models before actual failure occurrence.

Table 4. Average Failure Prediction Lead Time

Model	Average Lead Time (Hours)
SVM	2.5
Random Forest	3.1
CNN	4.4
LSTM	5.2
CNN–LSTM (Hybrid)	**6.8**

Visualization of AI-Based Prediction Results

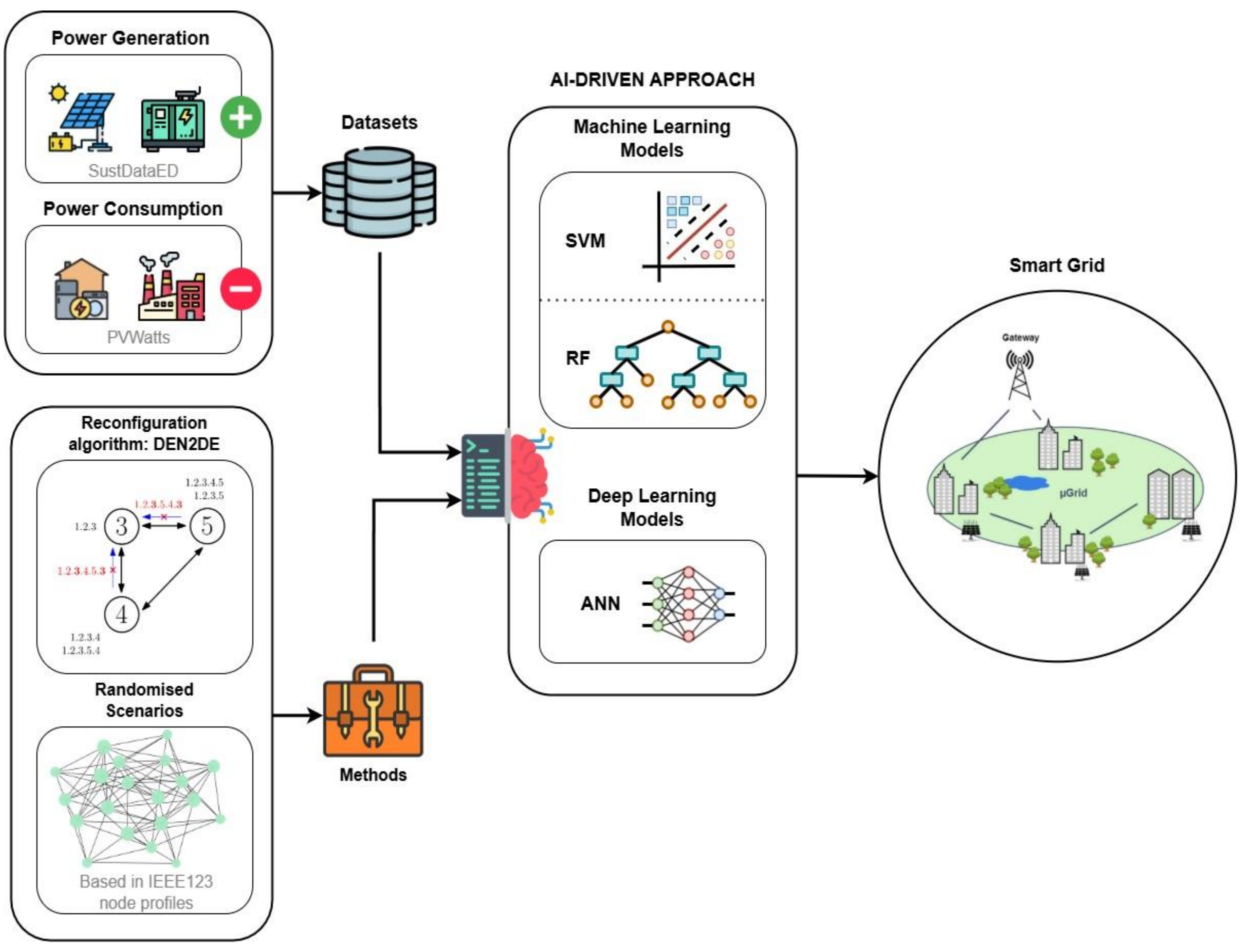

FIGURE 4. Fault Prediction and Reconfiguration Optimization in Smart Grids: AI-Driven Approach

Figure 4 illustrates typical visualization dashboards used by system operators. These dashboards display:
• Predicted fault locations,
• Asset health indices,
Visualization significantly enhances operator situational awareness and supports faster decision-making.

Impact on Maintenance and Reliability

The application of AI-based failure prediction resulted in:
• Reduction of unplanned outages by approximately 30–40%,
• Decrease in maintenance costs by 20–25%,
• Improvement in system reliability indices (SAIDI and SAIFI).
These improvements confirm the practical benefits of integrating AI into power system operations.

Summary of Results. Overall, the results confirm that AI-driven approaches significantly outperform traditional methods in predicting power system failures. Hybrid deep learning architectures provide the highest accuracy, longest prediction lead times, and most reliable RUL estimations. When combined with visualization dashboards and decision support systems, AI enables a shift toward predictive and condition-based maintenance strategies.

CONCLUSIONS

This paper has presented a comprehensive review of the role of Artificial Intelligence in predicting failures within modern power systems. The increasing complexity of power grids, driven by renewable energy integration, digitalization, and growing demand, necessitates advanced predictive approaches beyond traditional reliability and protection methods. AI techniques offer powerful tools for analyzing large-scale, heterogeneous data and enabling proactive failure prediction.

Various AI methodologies, including machine learning, deep learning, and hybrid physics-informed models, were discussed in the context of power system failure prediction. Their applications in fault detection, predictive maintenance, asset health monitoring, and smart grid resilience demonstrate significant improvements in accuracy, response time, and operational efficiency. The integration of AI with data sources such as SCADA systems, PMUs, IoT sensors, and digital twins enables early identification of abnormal conditions and supports data-driven decision-making.

Despite these advancements, several challenges remain, including data quality limitations, model interpretability, cybersecurity risks, real-time implementation constraints, and integration with legacy infrastructure. Addressing these issues is critical for the reliable and safe deployment of AI-based solutions in power system operations. Emerging research directions such as explainable AI, federated learning, cyber-resilient models, and edge intelligence provide promising pathways to overcome these challenges.

In conclusion, Artificial Intelligence has the potential to transform power system failure prediction from a reactive to a proactive paradigm. Continued interdisciplinary research, standardization efforts, and collaboration between academia, industry, and regulatory bodies will be essential to ensure the successful adoption of AI-driven technologies and to enhance the reliability, resilience, and sustainability of future power supply systems.

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