

# A Real-Time Fault Detection and Remediation in Power Grids Using Hybrid Deep Learning Models

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**Abstract:** The smart grid is a power grid that includes digital communication technology, composed by a computer-based control, which makes it possible to regulate, through new automation systems, the electricity demand and supply in a much more intelligent manner. In the past, power system studies were mostly based on commercial software package proprietary in combination with mathematical models that were established using a combination of data analysis, control theory, and statistical methods. With continued expansion of power grids and the need for more efficient and sustainable power systems, there has been increased emphasis on the application of artificial intelligence. As power system challenges and demands for increased efficiency and reliability have been on the rise, AI has been thought to solve these challenges. In this regard, real-time data are collected from the consumer side, besides internal and external grid fluctuations occurring during a three-year timeline. In particular, this study will leverage next-generation machine learning hybrid models at end-user sites for power grid fault detection and prediction. Hybrid models using convolutional neural networks (CNN) have been proposed in this study, including CNN-RNN and CNN-LSTM. These methods are employed to investigate how these models can identify and diagnose faults automatically in real-time, resulting in quicker and more efficient fault detection and removal with less losses. Through the application of AI technology, the modern power grids can be strengthened, optimized, and made more sustainable, eventually making the world greener and cleaner future energy.

**Keywords:** Smart Grid, Artificial Intelligence, Deep Learning, Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks

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## Introduction

The increasing need for reliable, efficient, and sustainable electricity requires changes to the traditional power system. We need a smart grid that can meet the complex demands of the future. Smart grids use advanced sensors, communication tools, and computing devices to monitor and manage the flow of electricity in real-time. This helps improve grid stability and performance [1]. However, smart grids face several challenges, including load forecasting, fault diagnosis, cybersecurity threats, and maintaining stability during fluctuations in demand and supply [2].

Recent developments in artificial intelligence (AI) and deep learning (DL) show promise in addressing these challenges. Deep learning models are good candidates for predictive analytics and real-time grid

optimization because they can extract nonlinear patterns from large datasets. This type of neural network learns representations from data using multiple features that are organized hierarchically, along with time-based dynamics. This makes deep learning appealing for smart grid applications [3] [4]. Load forecasting is one of the most popular uses of deep learning in smart grids. Accurate load prediction is crucial for managing demand, distributing resources, and planning infrastructure. Convolutional Neural Networks (CNNs) have proven successful in uncovering spatial relationships in electricity consumption data. Meanwhile, Recurrent Neural Networks (RNNs), including Long Short-Term Memory (LSTM) networks, excel at managing temporal dependencies [5]. Hybrid networks that combine CNNs and LSTMs achieve higher accuracy by leveraging both spatial and temporal characteristics simultaneously. When it comes to finding and classifying faults, another key area is fault diagnosis. Early detection of grid failure can significantly reduce power outages and maintenance costs. DNN models trained on historical fault records can effectively spot anomalies and identify fault types, helping to keep the system safe and reliable [6].

In this paper, we introduce an ensemble deep learning framework that combines common and advanced technologies, specifically CNN and LSTM, to improve smart grid performance. We benchmark this framework using smart grid datasets and provide experimental results for load forecasting and fault detection. We also conduct a comparative study with traditional machine learning models to show the advantages of deep learning methods. When it comes to identifying and classifying faults, fault diagnosis is another important area. Early detection of grid failure can significantly reduce power failures and maintenance costs. The DNN models that learned from historical fault records can effectively spot anomalies and identify types of faults, which helps keep the system safe and reliable.

The rest of the paper is organized as follows: Section II presents recent literature that uses deep learning methods in smart grids. In Section III, we explain our methodology, which includes system architecture and model training. Section IV contains experimental results and a discussion. Section V wraps up the paper and outlines brief future work.

## **Literature Review**

The rise of deep learning has significantly improved smart grid optimization, allowing for better precision and real-time decision-making. This paper discusses fifteen recent journal articles that explore the relationship between deep learning and smart grid systems. In [7], D. Kim et al. introduced a deep learning framework for load forecasting in smart grid systems. Their model outperformed traditional statistical methods in short-term and day-ahead predictions, showing its usefulness in real grid control. Building on this, K.Zhao et al. [8] developed a hybrid CNN-LSTM model for joint spatial and temporal embedding. In this model, spatial analysis responds to convolutional layers, while LSTM units encode temporal patterns. Compared to other models, this method showed much lower RMSE and MAPE, proving that hybrid learning is a viable approach for predicting electricity demand.

Huang et al. [9] created a fault diagnosis system using a CNN-LSTM model, which improved both accuracy and calculation speed. The combination of feature extraction and sequence modeling allowed for early detection of transient faults, reducing system vulnerability. Luo et al. [10] elaborated on deep learning's role in smart grid security. Their study highlighted how deep neural networks can detect cyber threats and emphasized the need for explainable models to gain the trust of operators.

A.Sharma et al. [11] focused on anomaly detection with unsupervised deep autoencoders. Their model showed strong detection performance in noisy and sparse environments, suggesting that autoencoders work well in realistic grid conditions. The also confirmed the effectiveness of CNN-LSTM architectures for multi-horizon load forecasting of time-series due to their adaptability to seasonal and characteristic changes.

In [12], J.Peng applied a long short-term memory (LSTM) network for near real-time load forecasting. These models consistently achieved high accuracy in the short term and needed minimal retraining, making them useful for demand-side management. For example, Zhang et al. [13] tackled Energy Theft Detection, a significant issue for utility providers. Their deep learning classifier reduced investigation efforts by spotting subtle data anomalies, which helped prevent false positives. Abedin et al. [14] examined various deep learning fault detection methods and found that hybrid models outperformed single-architecture methods. They advocated for more flexible learning strategies that adjust to changing grid conditions. This aligns with recommendations focusing on lifelong learning methods for grid resilience.

### System Architecture

The proposed system architecture consists of four main modules: Data Acquisition, Pre-processing, CNN-LSTM Model, and Decision Module.

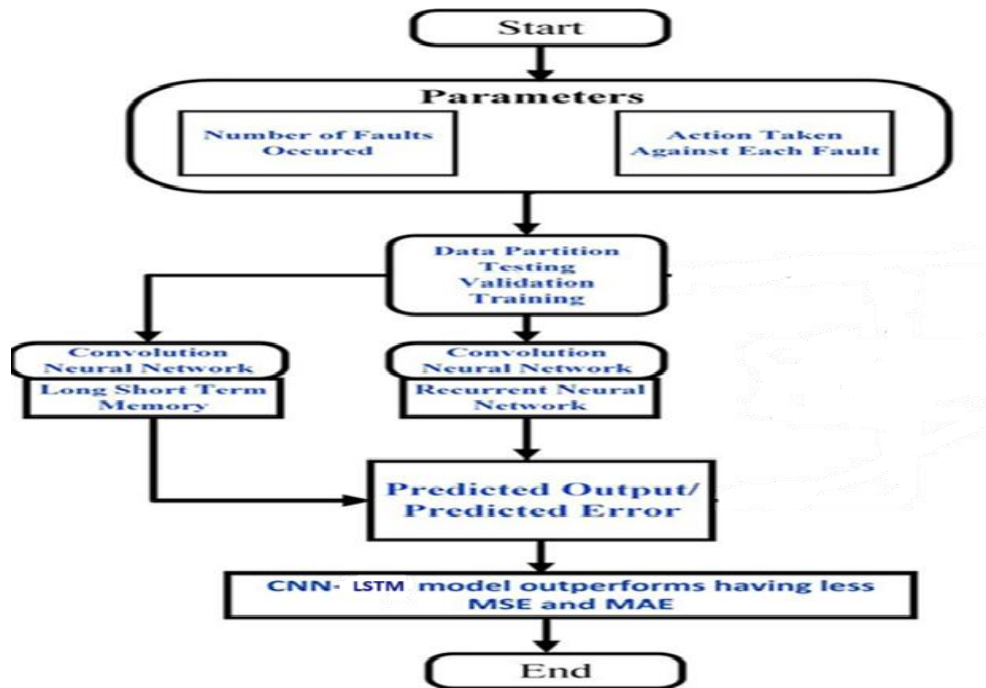


Figure 1: Proposed Strategy for Fault prediction and Elimination

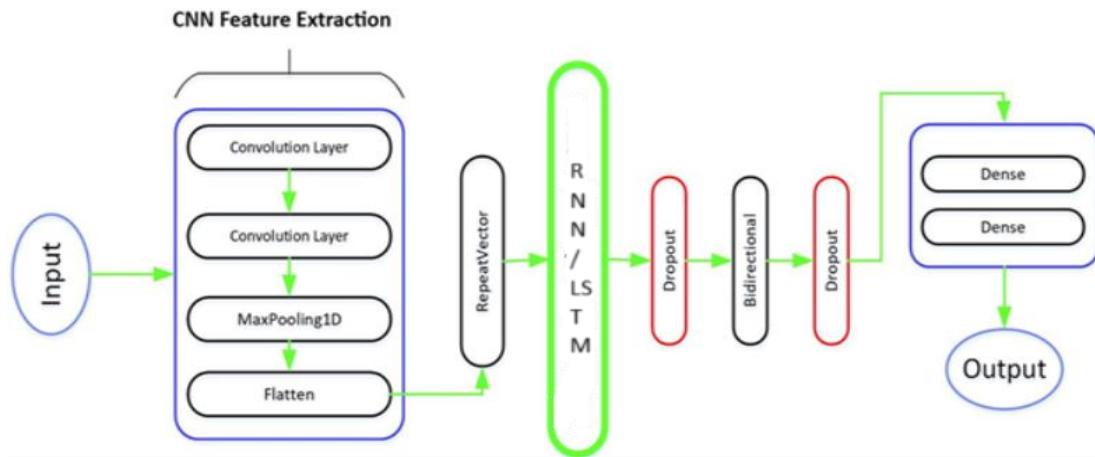


Figure 2. Proposed General framework for hybrid models

Each module plays a vital role in the deep learning process, starting with the Data acquisition layer that is responsible for gathering information from various real-time smart meter sensors. The collected dataset includes voltage, current, load demand, and historical fault records. The data that is collected is sent to the preprocessing layer that cleans the raw data of the various irrelevant information and converts it to a form from which information can be extracted. The convolution layer receives this data and produces a range of feature outputs obtained by dot product matrix. A non-linear activation function is applied to each data of the layer outputs to introduce non-linearities to generate complex patterns. The non-linear data is down sampled in the pooling layer using the max pooling layer. The output of the convolutional layers is first transformed into a vector and then fed into one or more fully connected layers.

## Result and Conclusion

Table. Comparison table

Hybrid Models for Prediction	Accuracy (%)	Mean Absolute Loss (MAE) Loss	Loss	Root Mean Square Error (RMSE) Loss
CNN-RNN	92.85	0.21	0.19	0.10
CNN-LSTM	93.05	0.17	0.15	0.07
RNN [1]	89.21	0.45	0.28	0.47
LSTM [1]	91.69	0.42	0.22	0.40

The results indicate that CNN-LSTM achieved the highest accuracy of 93.05% and the lowest MAE and RMSE losses of 0.17 and 0.07, respectively. The research concludes that machine learning hybrid models, such as CNN-RNN and CNN-LSTM, can effectively detect and eliminate faults in grid stations, facilitating the integration of renewable energy sources and improving power grid efficiency and reliability. This research has proved that deep learning algorithms, especially hybrid CNN-LSTM architecture, can play an important role in improving the performance of smart grid systems. By leveraging the spatial feature

extraction ability of Convolutional Neural Networks (CNNs) and the temporal learning capability of Long Short-Term Memory (LSTM) networks, the proposed structure was capable to handle critical issues that are inherent in load forecasting and fault detection.

In the future, explainable AI methods will be investigated with the goal of improving model interpretability, as well as transfer and continual learning to ensure that the model is adaptive to changing grid conditions. Such directions are harmonized with the upcoming smart grid infrastructure resiliency, sustainability, and efficiency targets.

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