Proceedings of the 5th International Conference on Signal Processing and Machine Learning
DOI: 10.54254/2755-2721/121/2025.19841

Power Grid Stability Analysis Based on Convolutional Neural Networks

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Abstract: Power grid stability is key to reliable operation. The rise of renewables and growing loads demand better methods to ensure power supply quality. To address these issues, this paper proposes a method for power grid stability analysis based on Convolutional Neural Networks (CNN). First, the original grid data is preprocessed, and classification features are one-hot encoded. Then, a deep learning model based on CNN is designed and trained. Finally, the effectiveness of the proposed method is verified through case analysis. The case study compares fully connected neural networks with CNN, and the results show that CNN outperforms fully connected networks in accuracy, precision, recall, and F1 score.

Keywords: Grid stability, Convolutional neural network, Binary cross-entropy loss.

1. Introduction

1.1. Literature Review

Power grid stability has long been a critical focus in the field of power systems engineering. Traditional methods for stability analysis often rely on physical modeling and simulation techniques, such as time-domain simulations and small-signal stability analysis. These approaches, while effective in specific scenarios, face challenges in adapting to the growing complexity of modern power systems driven by the integration of renewable energy and increasing demand. For example, studies on microgrid stability and DC power systems emphasize the importance of adaptive and real-time methods in ensuring operational reliability.

Recent advancements in artificial intelligence (AI) have introduced data-driven approaches to address these challenges. Machine learning models, particularly neural networks, have demonstrated significant potential in processing large-scale power grid data to extract features, predict instabilities, and optimize control strategies. Research by Qiao et al. highlights the integration of explainable AI techniques to improve decision-making in power system operations. Additionally, CNNs and deep learning frameworks are increasingly recognized for their ability to handle high-dimensional data and temporal correlations, as shown in work focused on the stability of distributed and renewable-heavy power systems.

The use of CNNs specifically for grid stability analysis offers several advantages over traditional AI methods. Their capability to automatically extract spatial and temporal features makes them ideal for applications involving sequential data, such as time-series voltage and frequency measurements. This aligns with the findings of Li et al., who implemented convolutional architectures to enhance

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transient stability assessments in renewable energy systems. However, challenges such as overfitting and generalization to unseen conditions remain areas of active research.

In summary, the literature underscores the transformative potential of AI, and particularly CNNs, in modernizing power grid stability analysis. This study builds upon this foundation by proposing a CNN-based framework that combines high accuracy with practical applicability, addressing existing gaps in scalability and adaptability.

1.2. Backgrounds

Power grid stability analysis is essential for ensuring the safe, reliable, and efficient operation of power systems[1-4]. It evaluates the system's ability to recover after disturbances, preventing issues like voltage collapse and frequency instability, thereby ensuring continuous and high-quality power supply[5,6]. With the large-scale integration of renewable energy and the growing demand for electricity, power grid stability faces new challenges[7-10]. Any disruption to grid stability could lead to power outages for a large number of users, or even the collapse of the entire system, with severe consequences. Therefore, analyzing and predicting grid stability is vital for maintaining societal and economic stability.

Grid stability analysis mainly covers dynamic stability, transient stability, frequency stability, and voltage stability. In recent years, with the continuous advancement of Artificial Intelligence (AI), AI technologies have been widely applied across various fields. In the power system, AI has shown advantages in addressing uncertainties and complex systems, especially under the backdrop of high proportions of renewable energy and power market reforms. AI provides new approaches for addressing these emerging challenges[11-13].

Compared to traditional grid stability analysis methods[14,15], AI-based approaches can process and analyze large amounts of data, offering real-time and accurate predictions that optimize control strategies and improve the efficiency of power system operations . Based on this background, this paper proposes a Convolutional Neural Networks (CNN)-based approach for grid stability analysis. First, data is preprocessed to ensure completeness. Then, a CNN model is designed to extract data features. Finally, the experimental results are analyzed based on metrics such as accuracy, precision, and F1 score. The accuracy of CNN on the test set reaches 99.1%, and the F1 score is 98.6, demonstrating its advantage in handling complex grid data.

2. CNN-Based Power Grid Stability Analysis Methods

2.1. Data Preprocessing

The accuracy of power grid stability analysis largely depends on the quality and handling of the data. Raw data often contains noise, missing values, or inconsistencies, which may affect the reliability of the analysis results. Therefore, data preprocessing becomes a crucial step in grid stability analysis. In this study, we first preprocess the grid dataset to ensure data cleanliness and applicability.

First, missing or abnormal values are identified and handled. For missing values, statistical methods such as mean or median filling are applied to ensure data completeness. For abnormal values, we identify them using descriptive statistical analysis and replace or remove them using the three-sigma rule, ensuring the accuracy and consistency of the model input data. Additionally, to improve the generalization ability of the model, we performed one-hot encoding on classification features and removed unnecessary original feature columns. The dataset was then divided into training, validation, and test sets to train and validate the model. Stratified sampling based on different states of grid stability ensured that each data subset represented the entire dataset's distribution.

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2.2. CNN-Based Grid Stability Analysis Framework

2.2.1. Model Input and Output

In this study, the model is designed to process multidimensional operational feature data from the power grid system. Each row in the dataset corresponds to a specific moment in time, capturing the grid's operational state. The input features include key parameters such as time constants, power levels, and admittance, which collectively describe the electrical characteristics and behavior of the grid under varying conditions. To transform this data into a format suitable for binary classification, the 'stabf' column, which indicates the stability state, is one-hot encoded. This transformation ensures that the output is clearly delineated into two categories: "stable" and "unstable". By removing the original stability state label column, the model is provided with these two variables as independent labels, enabling it to predict whether the grid is in a stable or unstable state at any given time. The ultimate output of the model is a binary classification, where a value of 0 represents an unstable state, and 1 indicates stability. This classification serves as a vital tool for grid operators to predict and mitigate potential stability issues in real-time, ensuring the grid's continuous, reliable operation.

2.2.2. Data-Driven Static Voltage Stability Assessment

Data-driven static voltage stability assessment is grounded in leveraging large volumes of historical operational data to extract insights into the behavior of power grids under different conditions. In this study, deep learning models, particularly those capable of capturing complex temporal and spatial relationships in the data, are employed to learn these operational patterns directly from historical grid data. This allows the model to automatically identify critical indicators of static voltage stability without the need for manual feature extraction or expert intervention. By training on diverse datasets representing a wide range of operating conditions, the model gains the ability to predict static voltage stability with high accuracy for new, unseen data inputs. This data-driven approach helps mitigate the risk of overfitting that often arises when models are trained on limited datasets, thus enhancing the model's generalization ability. Consequently, the model not only provides real-time stability predictions but also contributes to a proactive approach in grid management, helping to prevent voltage instability before it occurs.

2.3. Neural Networks

Power grid stability analysis is a complex task due to the high dimensionality and dynamic nature of grid data. Traditional methods often struggle with these challenges, requiring substantial domain knowledge and extensive manual intervention. To address these limitations, this study explores the use of Convolutional Neural Networks (CNNs) as a tool for efficiently processing and analyzing power grid data. CNNs, which have demonstrated remarkable success in various domains such as image recognition and speech processing, are particularly suited for capturing spatial and temporal patterns within complex datasets. By leveraging their ability to automatically extract hierarchical features, this study seeks to enhance the accuracy and predictive capacity of power grid stability models. The ultimate goal is to improve the early detection of potential stability issues and provide more reliable forecasting tools for grid operators, ensuring a more robust and resilient power infrastructure.

2.3.1. CNNs for Feature Extraction

Power grid systems typically generate vast amounts of time-series data, which often exhibit intricate temporal correlations. These correlations can include fluctuations in voltage, frequency, and current,

DOI: 10.54254/2755-2721/121/2025.19841

which evolve over time due to various disturbances or operational changes. CNNs are particularly adept at identifying local patterns within this type of data due to their unique architecture, which involves multiple layers of convolutions that capture both spatial and temporal dependencies. The convolutional filters act as feature extractors, enabling the model to automatically learn the relevant patterns from raw grid data without the need for extensive manual feature engineering. This ability to learn directly from the data significantly reduces the reliance on human expertise for preprocessing and allows the model to discover complex relationships within the data, which might be difficult to detect using traditional methods. Additionally, CNNs offer an efficient way to handle high-dimensional data by using shared weights across different time steps, further improving computational efficiency and reducing the risk of overfitting. This approach not only streamlines the process of feature extraction but also enhances the overall robustness and accuracy of the power grid stability prediction models.

2.3.2. CNN Architecture and Components

The CNN model employed in this study starts with one-dimensional convolutional layers designed to process sequential data like time series. The convolutional layers use sliding filters (kernels) to scan through the data, capturing local temporal features such as sudden dips or spikes that might indicate instability in the grid. Each convolution operation produces feature maps, highlighting key patterns or trends in the input sequence.

To enhance the model's non-linear representation and learning capability, the ReLU (Rectified Linear Unit) activation function is applied after each convolution layer. ReLU introduces non-linearity by mapping negative values to zero while keeping positive values unchanged, thereby preventing vanishing gradient issues and improving computational efficiency.

After feature extraction, max-pooling layers are incorporated to reduce the spatial dimensions of the feature maps. Max-pooling effectively selects the most prominent feature within a defined window, ensuring robustness against noise and small variations in the data. This step also helps reduce the computational cost, making the model more efficient for large-scale grid data.

In the final stages, a Flatten layer is used to transform the multi-dimensional feature maps into a one-dimensional vector. This vector serves as the input to the fully connected layer, which performs the final classification task. For binary classification tasks, such as determining whether the grid is stable or unstable, a Sigmoid activation function is employed in the output layer. The Sigmoid function maps the output to a value between 0 and 1, making it suitable for probabilistic interpretations of the stability status.

2.3.3. Advantages of CNN-Based Analysis

The CNN architecture proposed in this study offers several distinct advantages over traditional methods, making it a highly effective tool for power grid stability analysis. First, one of the key strengths of CNNs lies in their ability to automatically extract and prioritize features from raw input data, significantly reducing the need for domain-specific expertise. In traditional approaches, feature extraction often requires deep knowledge of the underlying physical processes, which can be time-consuming and prone to human error. In contrast, CNNs are capable of learning these important features directly from the data, leading to more generalizable models that can be applied across different grids and operational scenarios.

Second, the hierarchical structure of CNNs is particularly advantageous when dealing with complex datasets such as time-series data from power grids. The network's layered architecture enables it to capture patterns at multiple scales, from fine-grained, localized features to more global, system-wide interactions. This is critical for understanding the multi-scale and dynamic relationships

DOI: 10.54254/2755-2721/121/2025.19841

inherent in power grid systems, where small, localized disturbances can escalate into broader instability events if not detected and mitigated early. By capturing both fine-grained and global features, CNNs provide a more holistic view of the system's stability, enhancing the model's predictive capabilities.

Finally, the robustness introduced by pooling layers and non-linear activation functions is another significant advantage of the CNN approach. Pooling layers help reduce the dimensionality of the data while retaining essential information, effectively filtering out noise and minor variations in the input data. This capability ensures that the model remains resilient to fluctuations or irregularities in the data, which are common in real-world power grid operations. Non-linear activation functions, such as ReLU (Rectified Linear Unit), further contribute to the model's ability to learn complex, non-linear relationships between the features, making it more adaptable to diverse operational conditions.

By integrating these powerful design elements, the CNN model provides a robust and efficient framework for tackling the challenges of power grid stability analysis. It not only enables the identification of critical temporal patterns within the grid's operational data but also facilitates the early prediction of instability events, allowing grid operators to take proactive measures. This predictive capability can lead to significant improvements in grid reliability and efficiency, helping to prevent costly outages and ensuring the stability of power systems in the long term.

2.3.4. Binary Cross-Entropy Loss

During CNN training, binary cross-entropy loss (BCELoss): is adopted as the loss function. The loss function is defined as BCELoss:

$$BCELoss(y, \hat{y}) = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)] \tag{1}$$

where y is the true label, $\hat{y}$ is the predicted value, and N is the sample size.

By training the CNN model, it can automatically learn useful features for grid stability analysis from the original time-series data without manual feature engineering. This automatic feature extraction capability makes CNNs perform excellently when handling complex and high-dimensional grid data.

3. Case Study

3.1. Dataset and Preprocessing

In this section, we evaluate the performance of the proposed Convolutional Neural Network (CNN) model for grid stability prediction using actual power system datasets. To ensure the reliability of the results, we use a fully connected neural network (FNN) as a comparison.

The selected power system dataset contains 12 features related to the operational status and stability indicators of the grid. These features include 12 variables, such as time constants (tau1-4), power (p1-4), and admittance (g1-4).After one-hot encoding and feature engineering, the dataset includes labels for system stability (stable) and instability (unstable). The total number of samples is 10,000, of which approximately 60% represent stable samples, and 40% represent unstable samples.

3.2. Model Design

- For the FNN model, we designed a five-layer fully connected network with the structure: (12, 512, 128, 32, 1). The activation function in the middle layers is ReLU, and the output layer uses Sigmoid to compress the output values between 0 and 1, suitable for binary classification (stable/unstable) .

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- For the CNN model, we added two 1D convolutional and pooling layers on top of the FNN. The channels were expanded from 1 to 16, and from 16 to 32, with the convolution kernel size set to 2, and the pooling windows set to 2 and 4, respectively. Finally, the features were flattened and passed through fully connected layers to produce two neurons, and the activation function was Sigmoid.

The BCELoss was chosen as the loss function, and stochastic gradient descent (SGD) was used as the optimizer.

3.3. Model Performance Evaluation

During data processing and modeling, key metrics used to evaluate the model performance include accuracy, precision, recall, and F1 score:

Accuracy measures the proportion of correctly predicted samples among all samples:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{2}$$

where TP is true positives, TN is true negatives, FP is false positives, and FN is false negatives .

Precision is the proportion of true positives among the samples predicted as positive:

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

Recall measures the proportion of true positives among all actual positive samples:

$$Recall = \frac{TP}{TP + FN} \tag{4}$$

F1 score is the harmonic mean of precision and recall, reflecting the model's overall performance on imbalanced data:

$$F1\ Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{5}$$

To test the generalization ability of the model, the dataset was randomly split into 70% for training, 15% for validation, and 15% for testing. The model was trained for 2000 epochs with a batch size of 32 and a learning rate of 0.01.

During the training process, the loss and performance metrics on both the training and validation sets were recorded. As the number of training epochs increased, the loss gradually decreased, and the accuracy on both the training and validation sets improved and eventually converged.

To further verify the model's effectiveness, we compared the FNN and CNN models. The results show that the CNN model better extracted features through convolution operations, improving the accuracy of stability predictions. On the validation set, the CNN model outperformed the FNN.

3.4. Result

The evaluation results on the test set are shown in the following table:

Table 1: Results of the performance index evaluation

Metric	FNN Model	CNN Model
Accuracy	98.5%	99.1%
Precision	98.2%	98.8%
Recall	97.8%	98.5%
F1 Score	98.0	98.6
Loss	0.0035	0.0028

The CNN model achieved a slightly higher accuracy than the FNN model, reaching 99.1% on the test set, compared to 98.5% for the FNN. This indicates that CNNs have an advantage in feature extraction and can better capture hidden patterns in the data.

In terms of precision and recall, the CNN model also outperformed the FNN. Particularly for recall, the CNN achieved 98.5%, significantly higher than the FNN's 97.8%. This means that the CNN is more robust in correctly identifying stable states, especially in complex test scenarios.

The F1 score, which balances precision and recall, also favored the CNN, with a score of 98.6 compared to 98.0 for the FNN. This improvement in F1 score indicates that the CNN model can better balance precision and recall, avoiding biased predictions.

The final loss value of the CNN model was 0.0028, significantly better than the FNN's 0.0035, indicating that the CNN model not only performed better in classification but also converged more effectively during optimization.

4. Conclusion

This paper proposes a method for power grid stability analysis based on Convolutional Neural Networks (CNN), demonstrating excellent feature extraction and generalization capabilities. The method first uses one-hot encoding to preprocess classification labels, ensuring data completeness and consistency. Next, the dataset is split into training, validation, and test sets to guarantee the model's generalization ability.

Then, the CNN model is designed and trained. The input features include time constants, power, and admittance. The model first applies 1D convolution layers to extract local features, with two convolution layers (kernel size of 2, with channels 16 and 32) and max-pooling operations to gradually reduce feature dimensions. The output layer uses a Sigmoid activation function to perform binary classification for stability.

After 2000 training epochs, the experimental results show that the CNN model outperforms the FNN in power grid stability analysis, achieving an accuracy of 99.1% and an F1 score of 98.6. This significantly enhances the model's effectiveness in grid stability prediction, verifying the practical application value of this method.

In the future, it could be expanded to similar power systems and combined with real-time data for online prediction, facilitating intelligent management and real-time decision-making, thus laying the foundation for monitoring and decision support.

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