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Research on Harmonic Source Prediction Problem under New Power System

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Abstract: ***With the development of new power systems, the impact of harmonics on power systems has received increasing attention. Accurate prediction of harmonic sources is crucial to the stable operation of power systems. This paper uses an improved Temporal Convolutional Network and combines the characteristics of the power system to predict the composite harmonic sources under the new power system. First, the generation mechanism of harmonics in the power system and its impact on the system are introduced. Then, the principles and applications of the TCN model are introduced in detail. Then, a harmonic source prediction method based on the improved TCN model was proposed, and the effectiveness of the method was verified through simulation experiments.***

Keywords: New power system**,** Complex harmonic source, Prediction, TCN

1. Introduction

In new power systems, harmonics are a common problem, which may be caused by nonlinear loads, and power electronic equipment [1]. Harmonics can cause voltage distortion, equipment damage, and other problems, seriously affecting the stability and reliability of the power system [2]. Therefore, accurate prediction of harmonic sources is crucial to the operation and management of power systems. Traditional harmonic source prediction methods usually rely on empirical or statistical models, but these methods are often difficult to adapt to complex power system changes. Therefore, it is of great significance to use deep learning methods to predict harmonic sources [3].

In the field of harmonic source prediction, traditional methods mainly include methods based on statistics and empirical models. Among them, the autoregressive integrated moving average model (ARIMA) is one of the most common statistical methods, which is suitable for time series data with linear trends and seasonality. However, ARIMA models require manual selection of model parameters and perform poorly when dealing with nonlinear and complex time series data. On the other hand, methods based on empirical models usually build models based on historical data and domain knowledge, such as neural networks, support vector machines, etc. Although these methods can achieve good prediction results in some cases, they usually require a large amount of feature engineering and parameter tuning and are difficult to adapt to complex power system environments.

Power harmonic prediction is an important research direction in the field of power systems. With the proliferation of nonlinear devices in power systems, harmonic issues are becoming increasingly severe. Accurate harmonic prediction is of great significance for ensuring the high-quality operation of the power grid. Traditional harmonic prediction methods often fall short of meeting actual requirements due to their limited nonlinear mapping capabilities and generalization capabilities for unknown time series data. Therefore, researchers have proposed various new harmonic prediction methods based on deep learning, big data analysis, and Internet of Things technology.

In 2019, Liu Qibin and colleagues proposed a power harmonic monitoring data prediction method based on a Long Short-Term Memory network (LSTM) [4]. This method mainly comprises four steps: preprocessing of harmonic monitoring data, training of the prediction model through fitting, application of the prediction model, and evaluation of the model's prediction effectiveness. Experimental results demonstrate that this approach yields favorable outcomes in the prediction analysis of harmonic monitoring data across various time scales.

In 2020, Liu Haitao and others designed a nonlinear harmonic load prediction method based on big data analysis technology [5]. First, the current research progress of nonlinear harmonic load forecasting is analyzed, and then the historical data of nonlinear harmonic load are collected, big data analysis technology is introduced for modeling and learning, and the parameters of the nonlinear harmonic load forecasting model are optimized. Experimental results show that the nonlinear harmonic load prediction accuracy of this method exceeds 95%, and the deviation is significantly smaller than other current nonlinear harmonic load prediction methods.

In 2021, Yongle et al. proposed a nonlinear load harmonic prediction method based on the Power Distribution Internet of Things architecture [6]. This method first integrates the characteristics of edge computing technology and Power Distribution Internet of Things technology and then establishes a nonlinear load harmonic prediction model based on dynamic time warping and long short-term memory network (DTW-LSTM) in the cloud computing center. The simulation results show that the MAE evaluation index of this method in the experimental group is less than 5%, and it has good generalization ability.

In 2023, Liu et al. proposed a nuclear extreme learning machine (KELM) model power harmonic prediction method based on gray relational analysis (GRA), variational mode decomposition (VMD), and Harris Hawk optimization (HHO) [7]. This method first uses the GRA method to construct similar day sets, then uses the VMD method to decompose the harmonic data of similar day sets, and finally superimposes the prediction results of each subsequence and conducts a numerical evaluation. Experimental results show that compared with traditional prediction methods, the prediction error of this method is reduced by at least 39%.

Indeed, a common issue across the above literature is the lack of consideration for the prediction of harmonic sources in emerging power systems and the absence of analysis regarding the coupling of multiple harmonic sources. The existing research appears to focus on traditional power systems or specific types of harmonic sources without addressing the complexities introduced by modern power systems.

The emergence of new power system architectures, such as smart grids or renewable energy integration, brings unique challenges related to harmonic generation and propagation. These systems often involve distributed generation, power electronic converters, and varying load profiles, leading to nonlinear behaviors and complex interactions among different harmonic sources.

Additionally, the coupling effects between multiple harmonic sources can significantly impact the overall harmonic distortion in the power system. Neglecting this aspect can result in inaccurate predictions and ineffective mitigation strategies. Therefore, future research should address the prediction of harmonic sources in the context of modern power systems and consider the coupling effects between multiple sources to provide more comprehensive and effective solutions for harmonic mitigation and management.

With the development of deep learning technology, more and more studies have begun to explore the use of deep learning models to solve harmonic source prediction problems. Among them, recurrent neural networks (RNN) and their variant long short-term memory network (LSTM) are widely used in time series prediction tasks. These models can capture complex patterns and regularities in the data by learning long-term dependencies in time series data. However, traditional RNN and LSTM models are prone to gradient disappearance or gradient explosion problems during training, and the computational cost is high when processing long sequence data.

To overcome the limitations of traditional RNN and LSTM models, a new time series prediction model-TCN model has emerged in recent years. The TCN model is based on a convolutional neural network (CNN), which learns the characteristics of time series data through a series of convolutional layers and residual connections and uses multi-scale convolution kernels to capture information at different time scales. Compared with traditional RNN and LSTM models, the TCN model has advantages in training speed and prediction performance and is especially suitable for processing long sequence data and capturing long-term dependencies.

Although the TCN model has achieved remarkable results in speech recognition, natural language processing, and other fields, it has been relatively rarely used in the field of power systems. At present, the research on the TCN model in the field of harmonic source prediction is still in its preliminary stage, and its effectiveness and applicability in power systems need to be further explored and verified. Therefore, this article will try to use the TCN model to solve the problem of harmonic source prediction under new power systems and explore its application prospects in the field of power systems.

The main contribution of this paper is to propose a harmonic source prediction method based on the TCN model and verify its effectiveness through experiments. First, applying the TCN model to the harmonic source prediction problem is a new attempt, which can make full use of the deep learning model to learn the characteristics of time series data. Secondly, through experimental verification, we will evaluate and analyze the performance of the TCN model on harmonic source prediction problems, thereby providing new ideas and methods for harmonic source prediction in power systems.

In the subsequent chapters, we will begin by elucidating the generation mechanism and ramifications of harmonic issues in power systems. Subsequently, we will delve into the principles and applications of the Temporal Convolutional Network (TCN) model in detail. Following this, we propose a harmonic source prediction method based on the TCN model, substantiating its efficacy through verification and analysis via experimental results. Lastly, the article will conclude with a summary and a glance towards future research directions.

2. Harmonic data feature analysis

Harmonic source data feature analysis is one of the key steps in the harmonic source prediction problem. Through the analysis and feature extraction of historical data, we can better understand the generation rules of harmonic sources and provide a basis for establishing accurate prediction models. For different types of harmonic sources, their harmonic data characteristics will be different. The following are possible characteristics for different types of harmonic sources such as wind farms, rolling mills, and rail transit:

The wind farm is a renewable energy generation system with unstable wind speed and power output characteristics, which may lead to harmonic fluctuations in the power grid. The power electronics of wind turbines (such as converters) often introduce harmonics, and the frequency may be different from the grid frequency, such as 50Hz or 60Hz. Both the harmonic content and the harmonic waveform may change with the wind speed and the operating status of the wind farm, especially under low wind speed or high load conditions, the harmonic content is large. Rolling mills are common equipment in the metal processing industry and usually involve bulk electric motors and power electronic equipment, which may introduce high-frequency harmonics and voltage waveform distortion. The periodic working process of the rolling mill may cause periodic changes in harmonics, and the harmonic spectrum may contain multiple frequency components. The operating status and load conditions of the rolling mill equipment may affect the generation of harmonic sources. For example, changes in the rotation speed and load force of the roll may cause changes in harmonics. Rail transit systems include subways, trams, etc., involving an array electric of motors and traction equipment, which may introduce harmonics and voltage waveform distortion. The starting and braking process of the train and changes in the train running speed may cause changes in the harmonic source, and the harmonic waveform and amplitude may change accordingly. The working periodicity and frequent start and stop processes of rail transit systems may affect power system harmonics, especially during high load periods.

For different types of harmonic sources, harmonic data characteristics need to be analyzed based on their specific working principles and operating characteristics to better understand their harmonic generation mechanisms and impact levels.

3. Harmonic source prediction method based on TCN model

3.1 Harmonic source prediction problem

The harmonic source prediction problem refers to predicting the generation and level of harmonics in the future power system based on historical data and system status. Harmonic sources refer to sources that cause periodic changes in voltage or current in power systems, usually caused by nonlinear loads, power electronic equipment, etc. The purpose of harmonic source prediction is to promptly identify possible harmonic problems and take appropriate control measures to ensure the safe and stable operation of the power system. The key to the harmonic source prediction problem is to establish an accurate prediction model that can learn the generation rules of harmonic sources from historical data and predict future harmonic levels accordingly. Generally, the harmonic source prediction problem can be divided into the following aspects:

1) Data collection and processing: First, historical data related to harmonics need to be collected, including voltage, current waveforms, load conditions, power electronic equipment status, and other information. The data is then preprocessed, including noise removal, data normalization, etc., to improve the accuracy and stability of the prediction model.
2) Feature extraction and selection: Extract harmonic-related features from historical data and perform feature selection to reduce data dimensions and improve the generalization ability of the model. These features can include spectrum analysis, time domain features, frequency domain features, etc., which can reflect the generation mechanism and changing rules of harmonic sources.
3) Model establishment and training: Select an appropriate prediction model and use historical data to train the model. Commonly used prediction models include statistical models (such as ARIMA), machine learning models (such as neural networks, and support vector machines), and deep learning models (such as recurrent neural networks, and convolutional neural networks), etc. During the training process, it is necessary to consider the generalization ability of the model, over-fitting problems, and the selection of hyperparameters.
4) Model evaluation and optimization: evaluate the model through cross-validation, loss function, and other methods, and optimize the model based on the evaluation results. Evaluation indicators usually include prediction accuracy, mean square error, mean absolute error, etc., which can objectively reflect the prediction ability of the model.
5) Prediction and application: Use the trained model to predict future harmonic sources and take corresponding control measures based on the prediction results. These measures can include adjusting load distribution, optimizing power system operation strategies, improving power electronic equipment design, etc., to reduce the impact of harmonics on the power system and ensure the safe and stable operation of the system.

In the power system, the lack of clear label data makes it difficult for existing personnel to accurately identify and classify the collected power system data. The application of deep learning models provides new possibilities to address this challenge. However, due to the lack of real label data, the training and application of existing deep learning models for harmonic source identification in the power system are limited. Although simulation software can simulate harmonic distortion and coupling relationships in the power system, the simulation process still requires a significant amount of time and effort, hindering research progress.

3.2 TCN modeling

The TCN model typically comprises multiple convolutional layers, with each layer potentially containing multiple convolutional kernels. These layers are interconnected via residual connections, forming a deep neural network structure. Within each convolutional layer, different dilation rates can be employed to capture information at various temporal scales. Finally, the outputs of the convolutional layers are transformed into the final prediction through global pooling layers or fully connected layers.

The TCN model learns features from time-series data through convolutional operations, where each convolutional kernel performs a sliding convolution operation on the input data to capture information at different time scales. Residual connections effectively alleviate the vanishing or exploding gradient problem, thereby enhancing the training efficiency and stability of the model. Dilation convolution layers increase the receptive field by increasing the dilation rate, enabling the model to capture dependencies over longer time spans, thereby improving prediction performance.

The main components of the TCN model include one-dimensional convolutional layers, residual connections, dilation convolutions, pooling layers, and output layers. One-dimensional convolutional layers are used to extract features from time-series data. These convolutional layers extract local features over time by using sliding windows, capturing information at different temporal scales. Residual connections add the output of the convolutional layers to their input, constructing residual blocks. These connections effectively alleviate the vanishing or exploding gradient problem and improve the training efficiency and stability of the model. Dilation convolution layers introduce dilation rates in the convolutional layers, allowing convolution kernels to have a larger receptive field over the time dimension. These layers can capture dependencies over longer time spans, thereby enhancing the prediction performance of the model. Pooling layers reduce feature dimensionality and extract the most important features. These layers reduce computational complexity and parameter count by down-sampling feature maps using operations such as max pooling or average pooling. Finally, the output layer transforms the output of the convolutional layers into the final prediction. Typically, fully connected layers or global pooling layers are used to map features to the final predicted values.

This paper proposes a harmonic source prediction method based on an improved TCN model. The architecture of the improved TCN model is illustrated in Figure 1. The input layer consists of time-frequency current data from two harmonic sources, where the temporal features represent a sequence with a single time step, and the frequency features represent the Fourier-transformed harmonic features. The output layer predicts the composite harmonic data from these two sources, which also include both temporal and frequency domain features. Notably, the residual layer incorporates three residual modules with different dilation factors, enabling a gradual expansion of the receptive field and an increase in the sequence length for feature extraction.

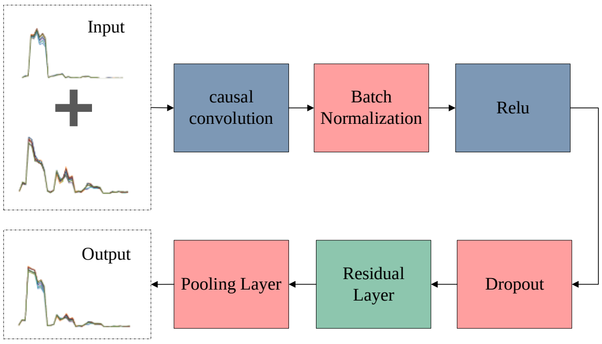

Figure 1: The architecture of the improved TCN model

3.3 Experimental Results and Analysis

This paper validates the effectiveness of the harmonic source prediction method based on the TCN model through simulation experiments using real power system data. The experimental results demonstrate that the proposed method accurately predicts the future levels of harmonic sources and exhibits high prediction accuracy and stability. Compared to traditional methods, the prediction method based on the TCN model shows improvements in both accuracy and efficiency.

The experimental data is divided into two parts: real single harmonic source data and simulated composite harmonic source data. Initially, the model is trained using partial real single harmonic source data and simulated composite harmonic source data, with the single data serving as input and the simulated composite harmonic source data serving as the output labels. Through iterative training, the model learns the coupling relationships between the two single harmonic source data, and finally, the trained model is used to predict the remaining real data to generate a large amount of composite harmonic source data. Compared to simulation software, using neural network models significantly improves data generation efficiency, saving time and labor costs and providing a data foundation for TTM model training.

Common evaluation metrics for regression problems include Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Squared Logarithmic Error (MSLE). RMSE measures the square root of the average squared differences between predicted and true values, being sensitive to large errors and providing a comprehensive assessment of overall model performance, but it shares the same unit as the original data and is less interpretable. MAE measures the average absolute differences between predicted and true values, being less sensitive to outliers and more interpretable, although it may not capture large errors well. MSLE measures the average logarithmic differences between predicted and true values, being more sensitive to larger errors and suitable for data with exponential growth trends. However, MSLE is not suitable for complex data distributions or data values that are zero. Given the broad applicability and complementary advantages of RMSE and MAE, this paper selects RMSE and MAE as the evaluation metrics for the model.

By designing ablation experiments on the improved TCN model containing Attention and the original TCN model, the role of the Attention mechanism in TCN is explored. Evaluate the performance difference between the TCN model containing Attention and the TCN model without Attention in sequence modeling tasks. Figure 2 is a comparison of the improved TCN model and the TCN model without the Attention mechanism in the time domain. From the figure, it can be found that around noon, the gap between the TCN model without the Attention mechanism and the label value is the largest, which is about twice that of the improved TCN model.

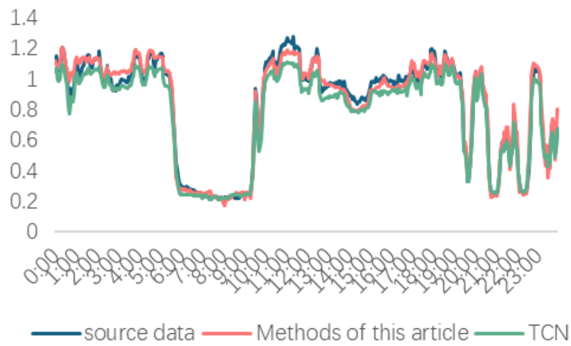

Figure 2: Results comparison chart

The above results show that in the harmonic source sequence modeling task, the TCN model introducing the Attention mechanism is more accurate and stable in the prediction of specific frequencies and periods than the original TCN model. It further verified the effectiveness and significant advantages of the Attention mechanism in sequence modeling when dealing with specific harmonic frequencies. Therefore, the improved TCN model integrated with the Attention mechanism can better adapt to the complex characteristics of the harmonic source sequence of the power system and improve the prediction performance of the model.

This paper conducts comparative experiments on CNN, TCN, and an improved TCN model incorporating the Attention mechanism, evaluating their performance in modeling harmonic source sequences in power systems. Table 1 presents the evaluation metrics for each model. From the table, it can be observed that among these three models, the improved TCN model has the smallest corresponding evaluation metrics, while the CNN model has the largest. Specifically, a smaller RMSE value indicates a better fitting of the model to the real data, and a smaller MAE value indicates a lower average prediction error concerning the real data. Therefore, based on the comparative experiments, it can be concluded that in the task of modeling harmonic source sequences in power systems, the improved TCN model exhibits the best predictive performance. Furthermore, the integration of the Attention mechanism enhances the overall performance of the TCN model, resulting in a reduction of 0.06 in RMSE and 0.026 in MAE.

Table 1: Evaluation index results

Model	*RMSE*	*MAE*
CNN	0.123	0.084
TCN	0.103	0.055
Methods of this article	0.043	0.029

4. Summary

This paper uses the TCN model and combines the characteristics of the power system to predict the harmonic sources under the new power system. Experimental results show that the prediction method based on the TCN model has high accuracy and stability. In the future, more complex model structures and algorithms can be further explored to improve the accuracy and efficiency of harmonic source prediction and provide more reliable support for the operation and management of power systems.

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Author Profile

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