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Harmonic Measurement Algorithm of Power System Integrating Wavelet Transform and Deep Learning

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Abstract

INTRODUCTION: The problem of low accuracy in harmonic measurement is a significant challenge in power systems. Traditional methods often exhibit higher measurement errors, leading to unreliable detection of harmonics. To address this, the author proposes a new approach that integrates wavelet transform and deep learning techniques for enhanced harmonic measurement accuracy.

OBJECTIVES: The primary goal of this study is to develop a more accurate harmonic measurement algorithm by combining full phase fast Fourier transform (FFT) and adaptive neural networks. The research aims to automatically detect power system harmonics with minimal error and improve upon the limitations of traditional methods.

METHODS: The study implemented a harmonic measurement method using full phase FFT integrated with an adaptive neural network. This approach calculates harmonic amplitudes based on the fundamental component and its amplitude, while determining the precise start and end times of harmonics. The system also incorporates mean filtering for automatic detection of harmonics. The effectiveness of the proposed method was evaluated through experiments that compared it to traditional harmonic measurement techniques.

RESULTS: Experimental results demonstrated that the proposed method achieved an average measurement error of 0.02V, with a maximum error of 0.03V, both of which are below the acceptable error limit. In contrast, traditional methods exhibited significantly higher average errors of 3.31V and a maximum error of 5.17V. The new method consistently showed higher accuracy in harmonic detection compared to conventional approaches.

CONCLUSION: The study concludes that the proposed harmonic measurement algorithm significantly improves accuracy compared to traditional methods. With its lower measurement error and effective automatic detection capabilities, the method proves to be highly suitable for harmonic measurement in power systems.

Keywords: Harmonic measurement, Power systems, Wavelet transform, Deep learning, Adaptive neural network

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1. Introduction

As society progresses, the widespread use of electrical devices in everyday life has led to a significant rise in harmonic levels within the power grid. This increase in harmonics degrades the quality of grid operation, poses risks to the grid's safety, stability, and economic efficiency, and has a substantial impact on the surrounding electrical environment. Consequently, harmonics have become a major public safety concern for modern power grids [1]. Accurate and prompt measurement of harmonics in the power grid has thus become crucial for addressing the issue of harmonic pollution caused by power electronic devices and other sources of harmonics. The primary task in solving harmonic problems is to accurately measure the components, amplitude, phase, and other information of harmonics. Since the end of the last century, due to the inherent nonlinearity, randomness, distribution, non stationarity, and complexity of influencing factors of harmonics in the power grid, although a lot of research has been done in harmonic measurement technology, it is still difficult to accurately measure harmonic information [2]. With the development of the power system, research on harmonic measurement has gradually deepened, mainly resulting in harmonic measurement methods based on frequency domain theory and time domain theory. In the early stages of development, the principle of analog filtering was mainly used to measure harmonic information, namely the frequency domain theoretical measurement method. This measurement method mainly uses a structurally simple filtering circuit with high output impedance, low measurement cost, and easy control of quality factor [3]. However, due to the significant impact of circuit component parameters on the center frequency of the filter, when the component parameters change due to external environmental factors, the measurement effect significantly deteriorates, making it difficult to obtain ideal phase frequency and amplitude frequency characteristics. Especially when the grid frequency changes, the measurement error is greater and the real-time performance is worse. Therefore, this method is no longer preferred. With the increasing requirements for harmonic measurement in power systems, harmonic measurement methods are constantly being updated [4].

Deep learning models, particularly Convolutional Neural Networks (CNN) and Long Short-Term Memory Networks (LSTM), have shown remarkable effectiveness in managing intricate nonlinear and high-dimensional data. Combining wavelet transform with deep learning can fully leverage the advantages of both: using wavelet transform for time-frequency feature extraction, and then achieving high-precision harmonic feature recognition and classification through deep learning models. This fusion method can not only improve the accuracy of harmonic measurement, but also enhance the robustness and real-time performance of the algorithm. The author aims to explore the harmonic measurement algorithm that combines wavelet transform and deep learning, and analyse its potential application in power system harmonic detection. Through in-depth research and experimental verification of existing technologies, we hope to propose a more efficient and accurate harmonic measurement method, providing strong support for the safe and stable operation of power systems [5-6].

2. Literature Review

In recent years, with the development of society, the field of power grid has also developed rapidly. When measuring harmonic energy in the power system, the phase difference and angle difference between the voltage divider circuit and the transformer affect the accuracy of the measurement results. How to accurately measure electrical energy has become one of the urgent problems to be solved both domestically and internationally. Kandezy, R.S. et al. introduced a novel approach for estimating harmonic distortion using convolution-based metrics, offering a more appropriate solution for real-time applications. The proposed technique features a sampling window with low sensitivity to deviations in fundamental frequency and signal stationarity, effectively preventing aliasing and spectral leakage. Additionally, it eliminates the impact of the fence effect on the estimation of harmonic distortion levels [7]. Ahmadi Horojayi, F. et al. introduced a novel harmonic state estimation (HSE) method designed specifically for low observability distribution systems. This method relies solely on the harmonic synchronous phasor data from a limited number of harmonic phasor measurement units (H-PMUs) located on the distribution feeder. The proposed HSE approach presents an innovative and practical use for H-PMUs, a new type of smart grid sensor that addresses a significant and challenging issue in power distribution system monitoring [8]. Du, L. et al. introduced a highly accurate method for measuring harmonic voltage that utilizes the dielectric equivalent model (DEM) of capacitive devices and their response current. By employing the DEM, they established the voltage-current transfer function for capacitive devices and reconstructed the harmonic voltage based on the response current. The study took into account the dielectric relaxation properties of capacitive devices, which differ from those of pure capacitor models. The authors evaluated the fitting performance of various equivalent capacitance models and enhanced the traditional pure capacitor model into a DEM, making it better suited for harmonic voltage reconstruction [9].

In order to solve the problems in error correction mentioned above, the author proposes a power system harmonic measurement algorithm that combines wavelet transform and deep learning.

3. Method

3.1. Automatic measurement of harmonics in power systems

Input the harmonic signal extracted from the fundamental component into the processing center of the power system for automatic processing, and obtain the automatic measurement results of the power system harmonics. After filtering, the harmonic signal will be transmitted to the processing center through the network channel. The transmission of the harmonic signal adopts the GPRS network, which has many transmission advantages, as shown in Figure 1.

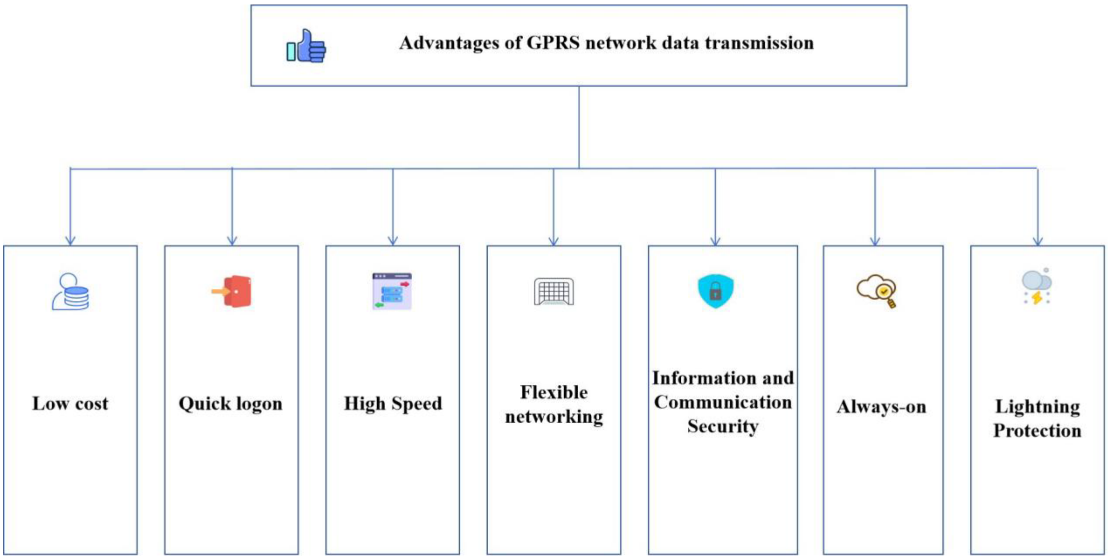

Figure 1. Advantages of GPRS network data transmission

Using GPRS network to complete the transmission of harmonic signals in the power system, the signals are transmitted to the processing center for measurement and processing. The processing center uses Fourier transform to automatically analyze and process these transmitted harmonic signals in the power system, and finally forms automatic harmonic measurement results, which are sent to the display or client for power workers to view.

3.2. Harmonic Measurement Based on All Phase Fast Fourier Transform and BP Neural Network

3.2.1. Harmonic phase angle measurement

The all-phase fast Fourier transform has phase invariance. Using this property to perform full phase fast Fourier transform spectral analysis on the sampled values of power grid voltage signals, high-precision harmonic phase values can be obtained [10]. The steps are as follows:

(1) Collect power grid signals and obtain $2^N - 1$sampling values.

(2) Perform full phase fast Fourier transform spectral analysis on the sampled data to obtain amplitude and phase spectra.

(3) The amplitude spectrum obtained by the all-phase fast Fourier transform is affected by the fence effect and cannot obtain accurate harmonic signal amplitude. However, peak spectral lines appear near the corresponding frequency of the harmonic in the amplitude spectrum. By reading the phase value corresponding to this peak spectral line, the accurate harmonic phase can be obtained [11].

3.2.2. Harmonic amplitude measurement based on BP neural network

Select the BP neural network as the method for measuring harmonic amplitude. The process for determining harmonic amplitude using the BP neural network involves the following steps:

3.2.3. Constructing a BP neural network structure for harmonic measurement

The traditional BP neural network harmonic measurement network consists of an input layer, a hidden layer, and an output layer. The network constructed by the author only contains one hidden layer. Due to the fact that the output layer of traditional BP neural networks shares the same hidden layer among neurons, there is a significant impact on each other, resulting in low accuracy in measuring harmonic amplitude. Therefore, the author adopts an improved BP neural network structure, with unchanged input and output layer settings, only making each neuron in the output layer correspond to a hidden layer, solving the problem of mutual influence among the measured harmonics and improving the accuracy of harmonic measurement [12].

Determine the learning algorithm of BP neural network for harmonic measurement

Assuming the voltage signal in the power grid is a periodic non sinusoidal signal $A(t)$, sample $A(t)$ at equal time intervals within one cycle. Sample data $X = [x_1, x_2, \cdots, x_{20}]$ as input to the neural network. The output of the hidden layer is O_3, O_4. The output layer corresponds to the amplitudes of the third and fifth harmonics for Y_3, Y_5. Due to the fact that each harmonic has the same learning algorithm, only the third harmonic will be used as an example to introduce its learning algorithm. The outputs of the hidden layer and output layer of the third harmonic are:

$$\begin{cases} O_3(j) = f_2\left(\sum_i W_{ij} x(i) + \theta_2(j)\right), & i = 1,2,\cdots,20; j = 1,2,\cdots,9 \\ Y_3 = f_3\left(\sum_i W_{jk} O_3(j) + \theta_3\right), & k = 1 \end{cases} \tag{1}$$

In the formula, f_2, f_3 represent the neural excitation functions of the hidden layer and output layer, respectively. W_i, W_{jk} represent the connection weights from the input layer to the hidden layer and from the hidden layer to the output layer, respectively; i. J and k are the neuron labels of the input layer, hidden layer, and output layer, respectively [13-14].

The performance indicator formula for correcting weights is:

$$E = \frac{1}{2}(d_3 - Y_3)^2 \tag{2}$$

In the formula, d_3 represents the expected output value of the third harmonic.

The formulas for adjusting weights between the input layer and the hidden layer, as well as between the hidden layer and the output layer, during the training phase are as follows:

$$\begin{cases} W_{ij}(t+1) = W_{ij}(t) + \alpha\left(W_{ij}(t) - W_{ij}(t-1)\right) + \eta\delta_k^3 x(i) \\ \delta_j^2 = O(j)(1 - O(j))\sum\delta_k^3 W_{jk}^3 \\ \theta_j^2(t+1) = \theta_j^2(t) + \eta\delta_j^2 \end{cases} \tag{3}$$

$$\begin{cases} W_{jk}(t+1) = W_{jk}(t) + \alpha\left(W_{jk}(t) - W_{jk}(t-1)\right) + \eta\delta_k^3 O(j) \\ \delta_k^3 = Y_3(d_3 - Y_3)(1 - Y_3) \\ \theta_k^3(t+1) = \theta_k^3(t) + \eta\delta_k^3 \end{cases} \tag{4}$$

Select training samples for harmonic measurement neural network

In actual measurement, the focus is on measuring the lower order harmonics among odd harmonics. Before harmonic measurement, the process of selecting training samples is illustrated by filtering out the fundamental and higher-order harmonics, and selecting harmonic currents composed of third and fifth harmonics as an example. Harmonic voltage can be expressed as:

$$A(t) = A_3 \sin(3\omega t + \varphi_3) + A_5 \sin(5\omega t + \varphi_5) \tag{5}$$

Under the determined harmonic phase conditions, the amplitude of the fundamental wave is normalized to 1. Based on the amplitude of the fundamental wave, the amplitude of the harmonic wave is normalized. When selecting training samples, the increment of the harmonic wave amplitude each time is the amplitude of the fundamental wave. Therefore, A3 and A5 each have 26 values that can be taken as (0-0.5) [15]. Therefore, a total of 676 sets of training sample inputs can be obtained, and the corresponding 676 sets of expected outputs are:

$$D = \{(0.0,0.0), (0.02,0.0), (0.0,0.02), \cdots, (0.5,0.5)\} \tag{6}$$

After selecting the learning samples, train the neural network according to the training process of the BP neural network [16]. After the training is completed, obtain the weights of each connection in the neural network to fix the structure and connection weights of the BP neural network, and complete the memory of harmonic wave amplitude values. Afterwards, only the power grid signal needs to be collected as the input of the BP neural network under the same phase condition, and the amplitude of each harmonic contained in the signal can be obtained from the network output.

3.2.4. Harmonic Measurement Simulation

This simulation only verifies the amplitude of the third and fifth harmonics of the BP neural network under a certain phase condition. Under the condition that the phase of the third harmonic is 30 ° and the phase of the fifth harmonic is 60 °, a training sample selection method was used to obtain 676 sets of training samples for offline training of the harmonic measurement BP neural network. The simulation program flow is shown in Figure 2.

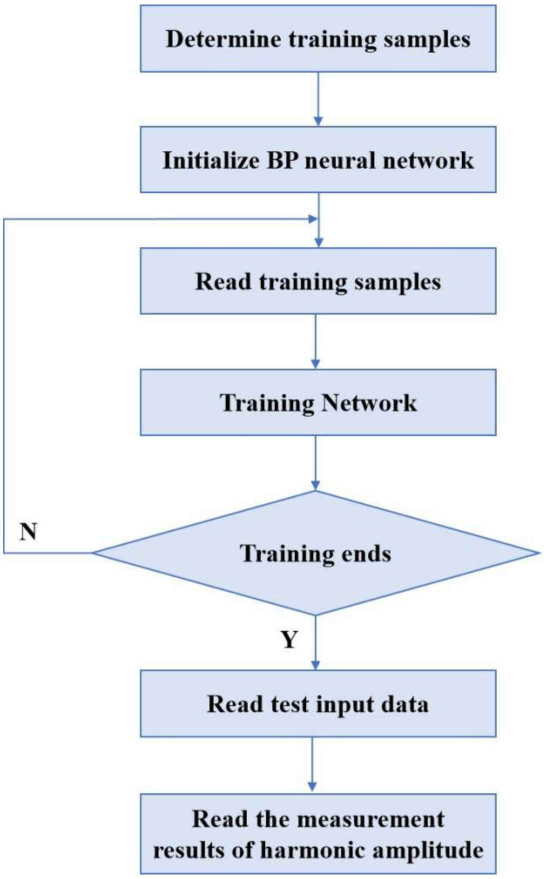

Figure 2. Simulation program flowchart

After training, select multiple sets of untrained samples with the same phase of 30 ° and 60 ° to simulate and verify the accuracy of harmonic amplitude measurement. Experimental results show that the BP neural network method for measuring harmonic amplitude outperforms interpolation FFT in terms of accuracy. Furthermore, increasing the number of training samples can further enhance the precision of harmonic amplitude measurements in neural networks [17].

3.3. Harmonic measurement based on full phase fast Fourier transform and adaptive neural network

3.3.1. Measurement steps

The specific steps of the harmonic measurement method based on full phase fast Fourier transform and adaptive neural network are as follows:

(1) Collect training samples. Set sampling frequency and sampling time, collect power grid voltage signals, provide analysis data for full phase fast Fourier transform, and provide training samples for adaptive artificial neural networks.

(2) Determine the initial phase of harmonics. Sample the power grid signal data through full phase fast Fourier transform analysis, identify peak spectral lines in the amplitude spectrum of the analysis results, and obtain high-precision phases of each harmonic from the phase values corresponding to the peak spectral lines.

(3) Initialize the harmonic amplitude measurement neural network. Use the harmonic phase measurement results to set the phase values of each harmonic in the reference input vector of the neural network.

(4) Calculate the error by reading a training sample once, calculate the neuron output $Y(t_i)$ based on the sampling time, subtract it from the current grid signal sampling value $V(t_i)$, and then calculate the error function $e(t_i)$ and performance indicator J_i.

(5) Adjust the weights of the neural network based on the error.

Using the Least Mean Square Error (LMS) method as the learning algorithm for the adaptive neural network for harmonic amplitude measurement, the weight adjustment formula, that is the harmonic amplitude adjustment formula, is:

$$\omega_m(i+1) = \omega_m(i) + \Delta\omega_m(i) \tag{7}$$

$$\Delta\omega_m(i) = -\eta \frac{\partial J_i}{\partial \omega_m} = \eta \sin(2\pi m f_0 t_i + \varphi_m) e(i) \tag{8}$$

In the equation, η is the learning factor.

In order to improve the convergence speed of neural networks, a momentum term is added to the weight adjustment formula [18]. The new weight increment formula is:

$$\Delta\omega_m(i) = -\eta \frac{\partial J_i}{\partial \omega_m} = \eta \sin(2\pi m f_0 t_i + \varphi_m) e(i) + \lambda \Delta\omega_m(i-1) \tag{9}$$

In the equation, λ is the momentum factor.

(6) Check if the current iteration index i matches the total number of training samples N. If it does, then verify whether the maximum number of training iterations has been reached. If the maximum number has been reached, conclude the training process and move on to the subsequent step. If it does not meet the requirements, it is necessary to calculate J and determine whether J meets the performance indicators. If it meets the standards, proceed to the next step. If it does not meet the standards, return to step (4) and execute it again. If not, return to step (4) to continue execution.

(7) Training is over. Obtain the amplitude of each harmonic based on the obtained neural network weights.

3.3.2. Harmonic Measurement Simulation

Let the current signal of the power grid be:

$$A(t) = \sum_{m=1}^{7} A_m \sin(2\pi m f_0 t_i + \varphi_m) \tag{10}$$

In the formula: Fundamental frequency $f_0 = 50\text{Hz}$, sampling frequency 1kHz; Neural network learning rate $\eta = 0.05$; Momentum factor $\lambda = 0.5$; Error criterion $\varepsilon = 10^{-26}$. The flowchart of the simulation program is shown in Figure 3.

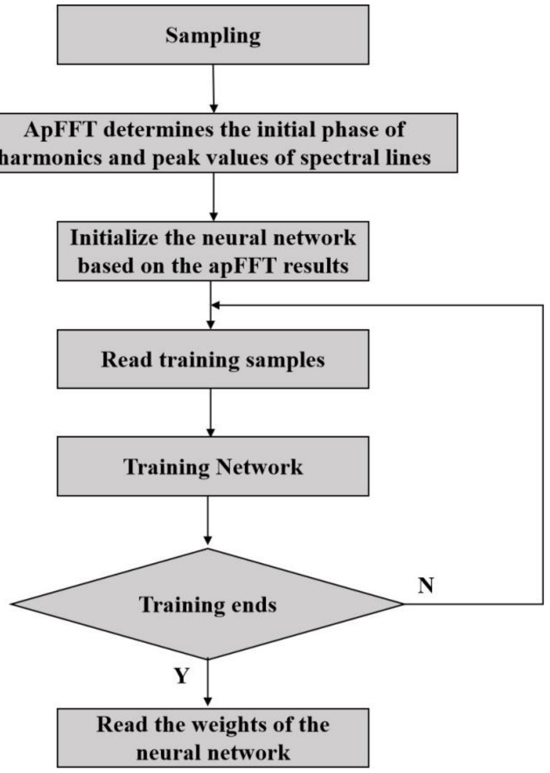

Figure 3. Simulation program flowchart

After analyzing 511 grid signal sampling points using apFFT, it can be seen that the harmonic phase measurement has high accuracy. Using apFFT analysis results to initialize the neural network, and taking 50 sets of training samples to train the neural network, it can be seen that the value of the performance index function can reach 10-12 under sufficient training times. After less than 10 training times, the fundamental and harmonic measurement values tend to stabilize. From the experimental data, it can be seen that the method adopted by the author greatly improves the measurement accuracy of harmonic amplitude [19].

3.4. Inter harmonic measurement based on full phase fast Fourier transform and enhanced adaptive neural network

3.4.1. Enhanced Adaptive Neural Network Interharmonic Measurement Model

In harmonic measurement, when the fundamental frequency is known, there's no need to measure the harmonic frequency since it is an integer multiple of the fundamental frequency. However, for interharmonic measurement, because the interharmonic frequency is not an integer multiple of the fundamental frequency, it cannot be determined based on the fundamental frequency alone. Therefore, in interharmonic measurement, the frequency of the interharmonic also needs to be included as a measurement item. For this purpose, the adaptive neural network structure applied to interharmonic measurement will be designed in the form shown in Figure 4.

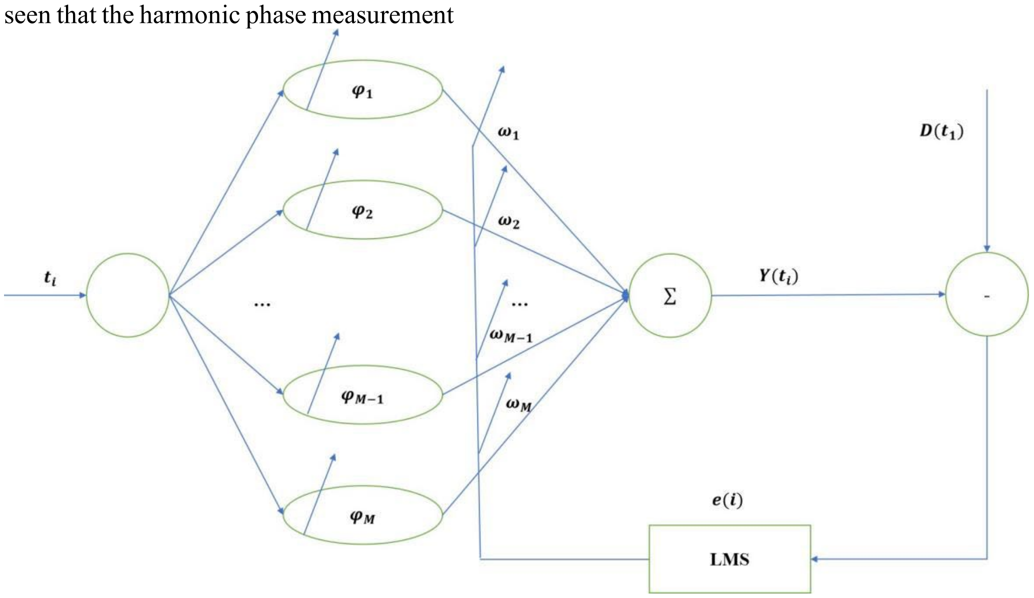

Figure 4. Adaptive neural network structure for interharmonic measurement

3.4.2. Harmonic measurement steps

The steps for measuring interharmonics based on full phase fast Fourier transform and enhanced adaptive neural network are as follows:

(1) Signal acquisition and apFFT analysis. After filtering out the measured fundamental and harmonic signals from the power grid signal, a signal composed of interharmonics is obtained. After sampling and analysis

using the apFFT algorithm, the amplitude spectrum and phase spectrum are obtained.

(2) Define and initialize the neural network structure. The number of neurons in the hidden layer corresponds to the number of interharmonics, which is determined by the number of peak spectral lines in the apFFT amplitude spectrum. Set the learning rate η and momentum factor λ for the interharmonic frequency and amplitude, respectively. Establish the maximum number of training iterations for the neural network, and then begin training the artificial neural network.

(3) Calculation error. Read one training sample, calculate the actual output $Y(i)$ of the neural network according to equation (11), and subtract it from the current sampling value $D(i)$ to calculate the error function $e(i)$ and performance indicator J_i.

$$Y(i)=\sum_{m=1}^{M} A_m \phi_m(t_i) \tag{11}$$

In the formula, M represents the number of interharmonics.

(4) Adjust the excitation function and neural network weights based on the error. LMS is also used as the learning algorithm for the neural network. In order to achieve inter harmonic frequency measurement, the angular frequency of the intermediate harmonics in the excitation function is also adjusted [20]. During the learning process, the formulas for adjusting the frequency and amplitude of interharmonics are as follows:

$$\omega_m(i+1)=\omega_m(i)+\Delta\omega_m(i) \tag{12}$$

$$\Delta\omega_m(i)=-\eta_{1m}\frac{\partial J_i}{\partial \omega_m}=\eta_{1m}e(i)A_m(i)t_i\cos(\omega_m t_i+\varphi_m) \tag{13}$$

$$A_m(i+1)=A_m(i)+\Delta A_m(i) \tag{14}$$

$$\Delta A_m(i)=-\eta_2\frac{\partial J_i}{\partial A_m}=\eta_2 e(i)\sin(\omega_m t_i+\varphi_m) \tag{15}$$

In the formula, $\eta_{1m}(m=1,2,\cdots,M)$ is the learning factor for adjusting the mth harmonic frequency; η_2 is a unified learning factor for adjusting the amplitude of harmonic waves.

Similarly, in order to improve the convergence speed of neural networks, momentum terms are added to the frequency and weight adjustment formulas. The new adjustment formula is:

$$\Delta\omega_m(i)=\eta_{1m}e(i)A_m(i)t_i\cos(\omega_m t_i+\varphi_m)+\lambda\Delta\omega_m(i-1) \tag{16}$$

$$\Delta A_m(i)=\eta_2 e(i)\sin(\omega_m t_i+\varphi_m)+\lambda\Delta A_m(i-1) \tag{17}$$

In the equation, λ is the momentum factor.

(5) Check if i equals the total number of training samples N. If it does, then verify whether the maximum number of training iterations has been reached. If the maximum iteration count has been reached, end the training process and move on to the next step. If it does not meet the requirements, it is necessary to calculate J and determine whether J meets the performance indicators. If it meets the standards, proceed to the next step. If it does not meet the standards, return to step (3) and execute it again. If not, return to step (3) to continue execution.

(6) Learning is over. After the learning is completed, the interharmonic frequency is obtained through the angular frequency of the excitation function, and the interharmonic amplitude is obtained through the neural network weights.

The principle of Fourier transform for automatic measurement of harmonics in power systems is as follows: The main characteristic of harmonics in power systems is spectral clipping value. When the power system operates stably and there is no periodic distortion in current and voltage, the sine and cosine signals of the three-phase current in the power system are relatively stable. The complex envelope of the short-time Fourier transform of the signal is a correct constant, and the spectral clipping value at the main frequency point in the instantaneous spectrum of reactive and active components is 1. When harmonics occur in the power system, periodic distortion occurs in the current and voltage, and the complex envelope of the short-time Fourier transform of the signal is an error constant. The spectral clipping value at the main frequency point in the instantaneous spectrum of the reactive and active components is -1. Therefore, the presence of harmonics in the power system can be determined based on the spectral clipping values at the main frequency points in the instantaneous spectra of reactive and active components, and the instantaneous spectral moments can be used to represent the instantaneous frequencies of reactive and active components. Using the power spectral density function, calculate the spectral clipping value at the main frequency point in the instantaneous spectrum of reactive and active components. The calculation formula is:

$$\kappa=\frac{B}{S_{2nF}}-2\left|\mathrm{mod}\frac{1}{2}\rho\right| \tag{18}$$

In the formula, k represents the spectral clipping value at the main frequency point in the instantaneous spectrum of reactive and active components; B represents the power spectral density function; ρ represents the degree of normalized energy distribution. Determine whether there are harmonics in the power system based on the calculated value using equation (18). If there are harmonics, calculate the amplitude of the harmonics based on the collected signal, and the calculation formula is:

$$\varepsilon=\frac{\varepsilon_0}{\mu}\times\tau \tag{19}$$

In the formula, ε represents the amplitude of harmonic waves in the power system; ε_0 represents the fundamental component value of the power system; μ represents the amplitude corresponding to the fundamental wave of the power system; τ represents the fundamental voltage of the power system. According to equation (19), calculate the harmonic amplitude and compare it with the signal sampling time series to draw the harmonic amplitude curve. The time at which the amplitude reaches its peak is identified as the beginning of the harmonic, while the time at which the amplitude hits its lowest point marks the end of the harmonic. From this, measure the start and end time of the power system harmonic, and then complete the power system harmonic measurement.

4. Results and Discussion

The experiment takes a certain power system as the experimental object. There are 16 power electronic devices in the power system, and harmonics often occur. Using this research method and traditional methods, the harmonics of the power system are automatically measured. In the experiment, the resampling frequency was set to 1.26kHz, and the sine signal sampling frequency was set to 2.32kHz. A total of 2.61GB of signal samples were collected in the experiment. According to the above measurement process, the signal was subjected to fundamental filtering and harmonic feature extraction operations, and a total of 0.26GB of fundamental components were filtered out. The fundamental frequency was 50Hz, and the specific measurement results are shown in Table 1.

Table 1. Harmonic Measurement Results of Power System

Index	**Fundamental Wave and harmonic amplitude /N**		**Occurrence time/s**		
	Fundamental wave	harmonic	starting time	End Time	duration
Theoretical	264.04	45.51	0.31	0.54	0.23
Measurement value	264.04	45.51	0.30	0.55	0.22

In order to compare the measurement accuracy of the two methods, a total of 19 harmonic automation measurements were conducted on the power system. Based on the measurement results and actual values of each measurement, the measurement errors of the two methods were calculated and used as the only indicator for this experiment. The data was recorded using a spreadsheet, as shown in Table 2.

Table 2. Comparison of Harmonic Measurement Errors in Power Systems between Two Methods/V

Measurement frequency/time	**Maximum error limit**	**Research Methods**	**traditional method**
1	0.1	0.03	2.52
3	0.1	0.02	3.04
5	0.1	0.01	4.51
7	0.1	0.01	3.53
11	0.1	0.01	5.17
19	0.1	0.01	4.52

By analyzing the data in the table above, the following conclusions can be drawn: the average measurement error of the studied method is 0.02V, and the highest measurement error is only 0.03V. The measurement error is less than the maximum error limit, and the error value is relatively small, close to zero, indicating that the measurement results of the studied method are basically consistent with harmonics in the power system. The average measurement error of traditional methods is 3.31V, and the maximum measurement error is 5.17V, which is not only greater than the studied method, but also exceeds the maximum error limit. Thus, the experimental results clearly show that the method under study outperforms traditional approaches in terms of measurement accuracy and is better suited for the automated measurement of harmonics in power systems.

5. Conclusion

The author proposes research on the integration of wavelet transform and deep learning for power system harmonic measurement algorithm. In response to the problem of low measurement accuracy of existing mature harmonic measurement algorithms, this study applies mean filtering technology to power system harmonic automation measurement, and studies a new power system harmonic automation measurement method. The feasibility and reliability of this method are verified through experiments, which can provide reliable data basis for power system harmonic control and guarantee stable, reliable and safe operation of the power system. Therefore, this study has good practical significance.

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