TELKOMNIKA Indonesian Journal of Electrical Engineering
Vol.12, No.5, May 2014, pp. 3662 ~ 3670
DOI: http://dx.doi.org/10.11591/telkomnika.v12i5.4206

An Effective Approach of AC Signal Detection in DC Power System Based on Wavelet Neural Network

Zhongyuan Zhang[1], Wei Zheng[2], Chao Ma[2], Yuchen Zhang*[3], Shuaibing Li[4]
[1]Gansu Electric Power Corporation, No. 8 of Beibing He Road, Cheng-guan District, 730030, Lanzhou, China, +86-0931-4956106
[2]Gansu Electric Power Research Institute, No. 648 of Xi-jin East Road, Qi-li He District, 730050, Lanzhou, China, +86-0931-4956106
[3]Gansu Ruite Electric Power Science & Technology Co., Ltd, District of Lanzhou High-tech Development, 730010, Lanzhou, China, +86-0931-4956106
[4]School of Automation & Electrical Engineering, Lanzhou Jiao Tong University, Anning West Road,730070 Lanzhou, China, +86-0931-4956106
*Corresponding author, e-mail: zyc9818@163.com

Abstract

This paper develops and experimentally demonstrates an AC signal detection method in DC power system with a combination of a novel detection circuit and the wavelet neural network method. Aims at dealing with the travelling wave and fault signal cannot be detected accurately with the uncertainty of signal velocity when AC signal injected. In which, the injected AC signal in DC power system is detected via the current transformers and the voltage transformers distributed in different current loops. The acquired signal is taken as original fault signal while the sub-band energy function of wavelet packet decomposition is used as secondary characteristic and the minimum distance is used as the criterion in WNN method. Simulations are carried out to demonstrate the correctness and validity of the proposed method and which gives a good consistency with experimental test. Results show that the AC signals can be detected and located in DC power system accurately with the proposed method applied.

Keywords*: AC signal, wavelet neural network (WNN), DC power system, fault detection*

1. Introduction

In power system and substations of large enterprises and plants, the DC power system is essential to the operation, monitoring and protection of substations. The normal operation of electrical equipment in substation or power grid would be affected once a severe fault occurred like AC signal injection, DC grounding etc. [1, 2]. Of all these power failures, the AC signal mixed faults own the largest proportion, which result in the outage of a whole plant and generator tripping out [3-5]. Thus, relevant technical measures are developed in order to prevent the AC signals inject into DC power system and its insulation system, is of a great significance for the safety and stability of DC power system.

Currently, the fault detection in DC power system mainly focused on DC power supply like uninterruptible power supply system (UPS) and high voltage direct current (HVDC) system. To the former, there are three different practical implementations for fault detection:

(1) The balancing bridge method. In [6], a balancing bridge model is suggested to detect the isolation fault in DC power system, in which the voltage and current various in shunt resistance results in an unbalance of the bridge, and the output signal can be detected. But this method cannot classify the fault categories.

(2) The unbalanced bridge method is used for grounding fault detection in positive and negative electrodes of DC power system, the faults can be detected when the voltage drops of isolation resistances is equal [7], but also has the same shortage with the method introduced above.

(3) AC signal injection is used for an ungrounded battery system, and uses an AC signal source to impose an AC voltage to ground on the ungrounded battery string. The fact that an AC current signal is used for detection purposes makes this an attractive option for larger battery systems, i.e. an AC current CT is used for detection and the detection level is

Received August 24, 2013; Revised December 16, 2013; Accepted January 4, 2014

independent of the DC battery power level. The success of such a detection method has not been verified to date [8, 9].

Other studies are about HVDC fault detection with utilizations of filtering techniques, wavelet transformation, neural network based method and the combination of the wavelet and neural network named wavelet neural network (WNN) method. The traveling wave and the change rate of voltage or current are used in HVDC system mainly concentrated in fault location [10-12]. Generally, there is no effectively method for the detection of mixed AC signals in DC power system. The current protection approach is to avoid laying the AC and DC cables side by side, battery cables wear on the metal sleeves and other protective measures.

This paper presents the AC signal detection method and a novel acquisition circuit in DC power system, firstly. And then gives an online fault detection approach with WNN applied on the bases of a theoretic analysis of regular isolation detection method and wavelet transformation combines with regular analog signal acquisition method. Finally, simulations and experiments are used to verify the correctness of the proposed method.

2. Implementation of Signal Acquisition

There are three patterns of AC signal injects into DC power system, the first way is AC power source injects between DC positive electrode and ground, the second way is AC power source injects between DC negative electrode and ground and the last way is AC power source injects between the positive bus and negative bus. In this paper, we use AC source with maximum amplitude 220V (RMS) as test signal, the signal detection structure can be seen in Figure 1.

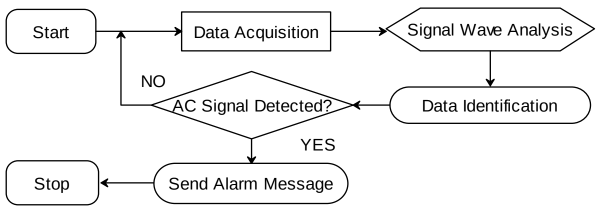


Figure 1. Flow Diagram of AC Signal Detection in DC Power System

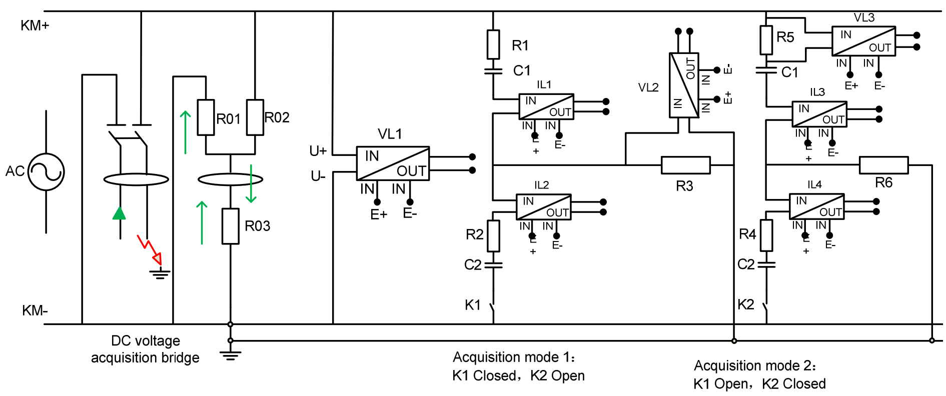


Figure 2. Schematic Diagram of AC Signal Detection in Positive and Negative Electrodes

The Figure 2 presents two patterns for AC signal acquisition, the first pattern uses R1, C1, R2, IL1, IL2 and VL2 as part of AC signal acquisition circuit. Once an AC signal mixed in either positive or negative electrode of DC power system, it would make up a circle circuit with R1, C1, R2, C2 and R3. If the output of IL1 equals to IL2 and the voltage drop in R3 is zero, we can point out that the AC signal is mixed between positive electrode and ground. In the second pattern, R4, C3, R5, C4, R6, IL3, IL4, VL3 and VL4 are used to make up another circle circuit. The location of AC signal mixed can be decided between negative electrode and ground or between positive bus and negative bus by making an analysis in voltage drops of R4 and R5. Where IL* and VL* respectively stand for the current sensor and the voltage sensor.

3. WNN Based Fault Analysis

3.1. Wavelet Transform Theory

Wavelet function is constructed through a series of basic transformation with a mother wavelet function. Let $\varphi(t)$ be a square integrable function, that is $\varphi(t) \in L^2(\mathbf{R})$. If its Fourier transform $\Psi(\omega)$ can satisfy the following compatibility condition:

$$\int_R \frac{|\Psi(\omega)|^2}{\omega} d\omega < \infty \tag{1}$$

Then $\varphi(t)$ is called a basic wavelet or mother wavelet function. We make translation and scale for wavelet function, the translation factor τ, and the scale factor (also known as the expansion factor) *a*, so that we get function:

$$\varphi_{a,\tau}(t) = a^{1/2}\Psi\left(\frac{t-\tau}{a}\right) \quad a > 0, \tau \in \mathbf{R} \tag{2}$$

As the translation factor *b* and the scale factor *a* are continuous variables, their value can be positive or negative; so $\Psi_{a,\tau}(\omega)$ is called continuous wavelet function (also called the mother wavelet function).

Wavelet transform calculates the inner product between the signal $x(t)$ with mother wavelet function:

$$f_x(a,\tau) = \frac{1}{\sqrt{a}}\int_{-\infty}^{+\infty} x(t)\varphi^*(\frac{t-\tau}{a})dt \tag{3}$$

Equivalent expression in time domain is given as:

$$f_x(a,b) = \frac{\sqrt{a}}{2\pi}\int_{-\infty}^{+\infty} X(\omega)\Psi^*(a\omega)e^{j\omega t}d\omega \tag{4}$$

Where $a > 0, \tau \in \mathbf{R}$, $X(\omega)$ and $\Psi(\omega)$ are the Fourier transform of $x(t)$ and $\varphi(t)$, respectively.

3.2. The Theoretical Analysis of WNN

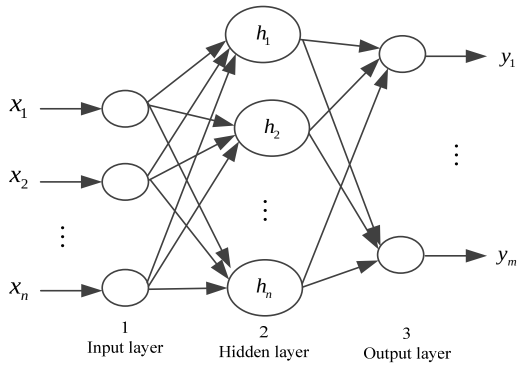


Figure 3. Topology of Wavelet Neural Network

The WNN is a variety of two techniques and inherits the advantages of the neural network and wavelet transformation. The WNN topology is based on BP network; the transfer function of hidden layer nodes is the mother wavelet function; and the network signal is prior to transmission while error is backpropagation in the training process. The network topology is shown in Figure 1. In Figure 1, $x_1, x_2, ..., x_n$ is the input vector; $y_1, y_2, ..., y_l$ is the predicted output; w_{ij} and w_{kj} are the weights connecting every layer; and h_j is mother wavelet function [16].

For the input signal sequence $x = (x_1, x_2, ..., x_n)$, the output of the hidden layer is calculated as:

$$h(j) = h_j \left[\frac{\sum_{i=1}^{n} w_{ij} x_i - b_j}{a_j} \right], \quad j = 1, 2, ..., m, \tag{5}$$

Where $h(j)$ is output value for the node *j* in the hidden layer; h_j is the mother wavelet function; w_{ij} is weight connecting the input layer and hidden layer; b_j is the shift factor, and a_j is the stretch factor for h_j.
The output of the output layer is calculated as:

$$y(k) = \sum_{i=1}^{m} w_{ik} h(i), \quad k = 1, 2, ..., l, \tag{6}$$

Where $h(i)$ is the output value for node *i* in the hidden layer; w_{ik} is weight connecting the hidden layer and output layer; *l* and *m* are the number of nodes for output layer and the hidden layer, respectively.

For WNN, the updating weight algorithm is similar to BP network; the gradient method is used to update mother wavelet function parameters and connection weights between the layers, making the prediction output closer and closer to the desired output. The weights of WNN and the parameters of wavelet function are updated as follows.

(1) Calculating the prediction error of WNN.

$$e = \sum_{k=1}^{m} yn(k) - y(k), \tag{7}$$

Where, $y(k)$ is the predicted output value, $yn(k)$ is the expected output value for the network.

(2) Updating the weights of WNN and the parameters of wavelet function according to the prediction error *e.*

$$w_{n,k}^{(i+1)} = w_{n,k}^{(i)} + \Delta w_{n,k}^{(i+1)}, a_k^{(i+1)} = a_k^{(i)} + \Delta a_k^{(i+1)}, b_k^{(i+1)} = b_k^{(i)} + \Delta b_k^{(i+1)}, \tag{8}$$

Where $\Delta w_{n,k}^{(i+1)}$, $\Delta a_k^{(i+1)}$ and $\Delta b_k^{(i+1)}$ are calculated by the network prediction error.

3.3. Fault Detection with WNN
3.3.1. Feature Selection and Extraction

To the AC signal with a frequency of 50Hz, once injected into DC power system, the voltage and current can be detected as the AC signal contains harmonic with different orders. As is well known, the WNN is of significant effect in extraction of singular component. In this paper, we use the fundamental component i_0 of the injected AC signal current as the original signal for fault recognition.

The wavelet coefficients of sub bands is obtained by wavelet packet transform, and uses the function of the wavelet coefficient quadratic sum as the quadratic characteristic *E* of fault pattern recognition.

$$E = f(|d_m^{s,n}|^2) = k|d_l^{j,n}(i_0)|^2 \quad (9)$$

Where d_m is the average distance of each fault class, *l* and *m* stand for the output dimension of WNN, *s* and *j* stand for the dimension of fault eigenvector, and the proportional gain $k = 10^{10}$ [15].

3.3.2. WNN Architecture Design

This paper uses the loose WNN model as training Model as is shown in Figure 5. In which, back propagation (BP) network is selected for neural network, the excitation function of hidden layer uses tangent Sigmoid function, the excitation function of output layer uses a linear function and the network training function is adaptive learning rate algorithm. The network uses the wavelet energy function *E* of the bottom sub-band energy as input after a wavelet decomposition of the original fault signal.

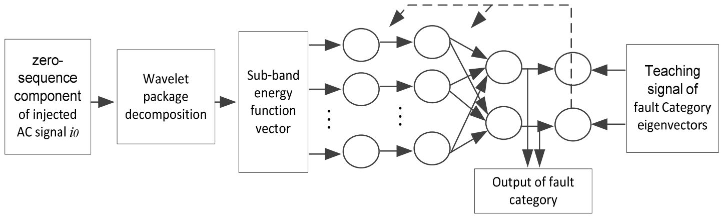


Figure 4. Structure of WNN for Fault Identification

The nodes of input layer are equal to vector dimensions of wavelet packet decomposition sub-band energy function of the original fault signal, in this paper, the number of layers are only one as using BP while the number of hidden neurons are 2*3+1=7 as there are three patterns of AC signal injects into DC power system. In this paper, as the fault classifier has three patterns, namely $c \le 3$ and training samples $\boldsymbol{X} \in T_j$, $j = 1, 2, 3$, the output *T* can be donated as:

$$T_1 = (0,0)^T, T_2 = (0,1)^T, T_3 = (1,1)^T$$

Where T_1 stands for the first way of AC signal injects into DC power system, namely AC signal injects between DC positive electrode and ground, T_2 is the second way of AC signal injects between DC negative electrode and ground and T_3 is AC signal injects between the positive bus and negative bus.

3.3.3. AC Signal Detection

The detail procedure for AC signal detection is: The training sample ***X*** is diffierence betten the fundamental component $\{i_{0N}^*\}_{k\in z}$ of AC signal injected into DC circuit and the the fundamental component $\{i_{0N}\}_{k\in z}$ of the parasitic AC signal inherented in DC circuit; the sub-band energy function uses the quadratic characteristic *E* mentioned in section A. The training sample ***X*** is decomposed into 3 layers by using orthogonal wavelet function, that is:

$$X = \sum_{k=0}^{2^n-1} \sum_{l\in \mathbf{z}} d_l^{3,n} 2^{3/2} u_n(2^3 t - 1) \quad (10)$$

Where $X = i_0^* - i_0$ is the or original signal, $2^{3/2}u_n$ is the *k* group of wavelet packet basis in the 3 layer of the space $V \in L^2(\mathbf{R})$ of ***X***, and $d_l^{3,n}$ is the wavelet bases coefficient corresponding to the *k* group of ***X***.

Set the sub-band energy function *E* discribed in (9) as the input of WNN, the *i* node output of the WNN can be written as:

$$y_i = w_{oi} + \sum_{j=1}^{m} w_{ji} o_j \tag{11}$$

Where o_j is the output of output layer.

If ***Y*** is an n dimention output vector conrispoding to the original fault signal ***X***, the i_{th} state variable of fault category satisfies $t_i \in T_j \in T$. Where T_j stands for the j_{th} way of AC signal injection pattern, T is the space of fault pattern or AC signal injection pattern.

4. Simulations and Experiments Verification

4.1. Experiments of WNN

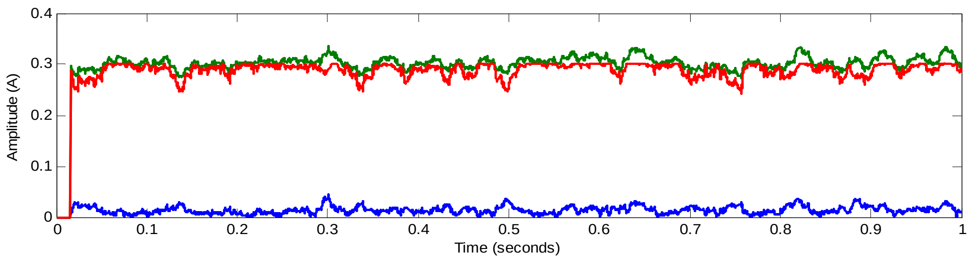


Figure 5. Fundamental Component of AC Signal

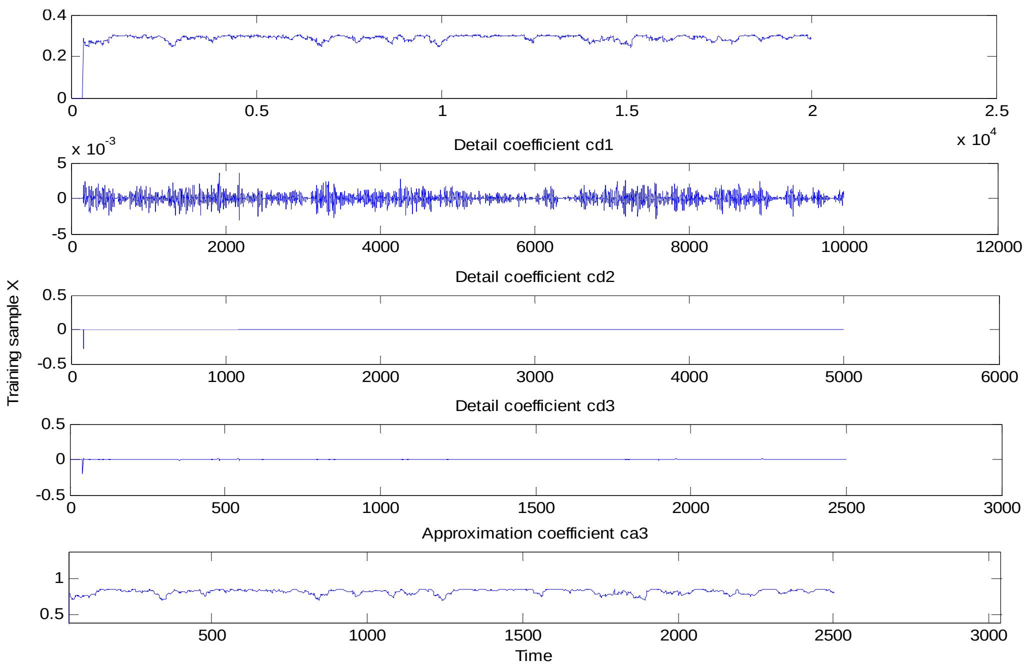


Figure 6. The 3 Layer Wavelet Deposition Results

As is mentioned above, the training sample ***X*** is differience betten the fundamental component of AC signal injected into DC circuit and the fundamental component of the parasitic AC signal inherented in DC circuit. Figure 5 shows the analyzed signal which is originally collected by using the fault detection circuit proposed in Figure 2 with between DC positive electrode and ground. The red line stands for the training sample ***X***, the blue line shows the fundamental component of the parasitic AC signal inherented in DC circuit and the green line stands for the fundamental component of AC signal injected into DC circuit. In this paper, we use 20001 sample data for the 3 layer wavelet deposition, and the decomposition results is shown in Figure 6.

In practise, with different AC signal injection patterns, the resistance to ground is distinct, so, the definition of *T* is:

$$T_1 = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \; 100\text{k}\Omega \le R_g < 1\text{M}\Omega, \;\; T_2 = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \; R_g < 100\text{k}\Omega, \;\; T_3 = \begin{bmatrix} 1 \\ 1 \end{bmatrix} \; R_g \ge 1\text{M}\Omega \qquad (12)$$

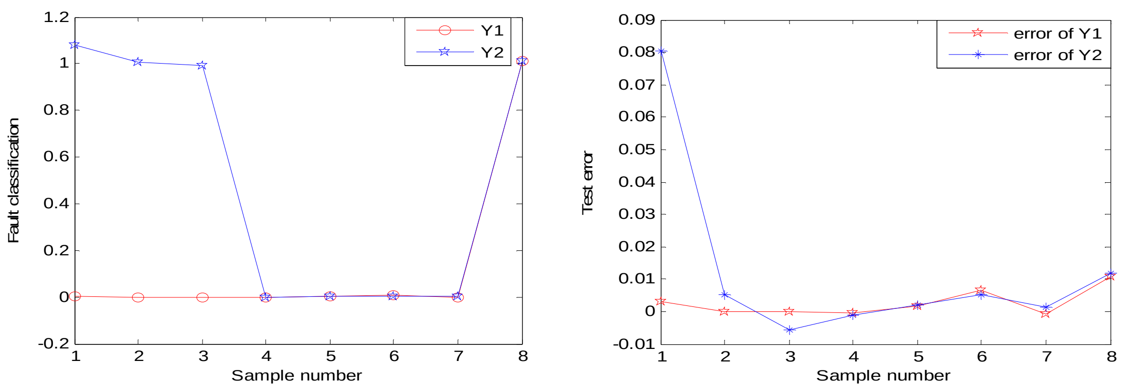
Where R_g stands for the resistance to ground of different AC signal injection patterns as is refered above.

Table 1. Fault Coverage Recognition Sample with AC Signal Injected

Fault resistance to ground	P	T	Fault resistance to ground	P'
$R_F = 15\Omega$	0.8577×10^9	$[0,1]^T$	$R_F = 20\Omega$	0.6005×10^9
$R_F = 50\Omega$	0.5623×10^9	$[0,1]^T$	$R_F = 70\Omega$	0.3992×10^9
$R_F = 100\Omega$	0.3846×10^9	$[0,1]^T$	$R_F = 200\Omega$	0.2157×10^9
$R_F = 500\Omega$	0.1025×10^{10}	$[0,0]^T$	$R_F = 600\Omega$	0.9522×10^9
$R_F = 10\text{k}\Omega$	0.2833×10^{10}	$[0,0]^T$	$R_F = 15\text{k}\Omega$	0.2074×10^{10}
$R_F = 20\text{k}\Omega$	0.7812×10^{10}	$[0,0]^T$	$R_F = 30\text{k}\Omega$	0.5237×10^{10}
$R_F = 75\text{k}\Omega$	0.1225×10^{11}	$[0,0]^T$	$R_F = 70\text{k}\Omega$	0.9041×10^{10}
$R_F = 90\text{k}\Omega$	0.1727×10^{12}	$[1,1]^T$	$R_F = 100\text{k}\Omega$	0.1041×10^{12}

Table 1 gives the input training samples *P*, the output samples *T* and the test samples of WNN P', where R_F is the fault resistance to ground and the input training sample is the lowest sub-band energy function value. In this paper, we select 15Ω, 50Ω, 100Ω and 500Ω as the low fault resistance values, and $10\text{k}\Omega$, $20\text{k}\Omega$, $75\text{k}\Omega$ and $90\text{k}\Omega$ as the high fault resistance values. For the training sample P', we select $150\text{k}\Omega$, $300\text{k}\Omega$, $700\text{k}\Omega$ and $1\text{M}\Omega$ as the high fault resistance values, and 20Ω, 70Ω, 200Ω and 600Ω as the low fault resistance values.

Figure 7(a) represents the test result of WNN, where “O” and “☆” is the output of WNN with trainning samples.



(a) Fault classification test of WNN (b) Absolute error of Fault classifer test

Figure 7. WNN Test Results with Different Types of Fault

The simulation output Y_1 and Y_2 of WNN are:

$$Y=\begin{bmatrix} Y_1 \\ Y_2 \end{bmatrix}=\begin{bmatrix} 0.0032 & -0.0000 & -0.0002 & -0.0005 & 0.0018 & 0.0065 & -0.0009 & 1.0108 \\ 1.0805 & 1.0052 & 0.9942 & -0.0010 & 0.0022 & 0.0051 & 0.0014 & 1.0117 \end{bmatrix}$$

And the simulation error E=T-Y is:

$$E=\begin{bmatrix} 0.0032 & 0.0000 & 0.0002 & 0.0005 & -0.0018 & -0.0065 & 0.0009 & 0.0108 \\ -0.0805 & -0.0052 & 0.0038 & 0.0010 & -0.0022 & -0.0051 & -0.0014 & -0.0117 \end{bmatrix}$$

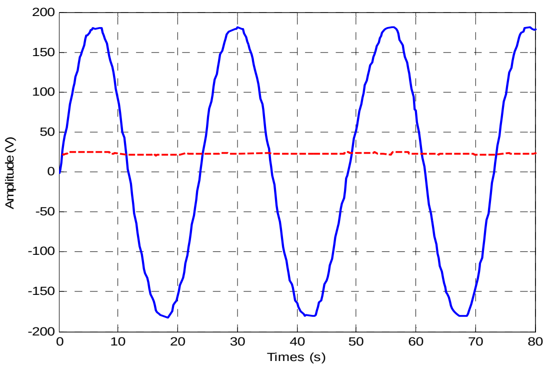
Which is shown in Figure 7(b), it can be seen that $|e_a| \le 0.0805$.

4.2. Circuit Simulation and Test

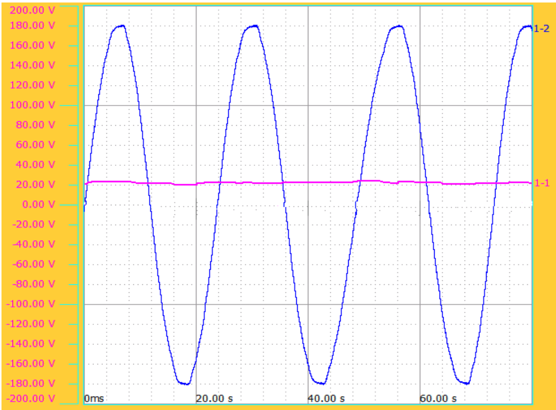
To verify the correctness of WNN method, an AC signal injection test is conducted, the results can be seen in Table 2. Figure 8(a) is the test circuit simulation result conducted in MATLAB/Simulink, where the AC signal is injected between positive bus and ground. Figure 8(b) shows the tested AC signal wave when injected into DC power system by using a HIOKI 8861-50 wave memory recorder.

Table 2. Test of AC Signal Injected into Positive Bus to Ground

AC voltage amplitude injected (RMS) (V)	10.4	100
Voltage between positive electrode and negative electrode DC (V)	24.5	24.5
Voltage between positive electrode AC (V)	10.4	100.2
Voltage between negative electrode AC (V)	10.4	100.2
Voltage on R4 (V)	3.4	32
Voltage on R5 (V)	3.4	31.8
Voltage on R6 (V)	7.0	66.8



(a) Simulation wave with 100V (RMS) AC signal injected



(b) Acquired wave with 100V (RMS) AC signal injected

Figure 8. Signal Waves of a 24V DC Power System with AC Signals Injected

From Figure 8 we can see that once a AC signal injected into DC power system, the developed AC signal detection device can detect the fault signals accurately, which realizes an acurrate detection of AC fault signal once injected into DC power systems.

5. Conclusion

This paper uses WNN as an effective approach to detect AC signals in DC power system, in which, the sub-band energy function of wavelet decomposition is used as eigenvector. The fault signal is accurately detected, classified and fully re-demonstrated with the premise of no additional hardware, and also realized synchronization and accuracy of AC signal detection, which is of great importance to the development of fault detection technology in DC power system.

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