Research Summary of Power Quality Disturbance Detection and Classification Recognition Method Based on Transform Domain

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Abstract—**With the diversification of power connection forms and increasing types of loads, the power quality of the power system is deteriorating. Various indicators of power quality are essential for the normal operation of the power grid, especially the increasing harmonic pollution caused by various nonlinear loads. Therefore, power quality disturbance detection and classification recognition is the key to improve power quality. This article combines the current domestic and foreign power quality related standards, summarizes the feature extraction of electric energy quality disturbance based on transform domain, meanwhile recognize and classify the extracted feature vectors.**

Keywords- Transform domain; Power quality; Wavelet transform; Extreme learning machine; Short-time Fourier transform

I. INTRODUCTION

With the widespread use of power electronic devices in the electric wire netting and the generation of new energy. The power quality problem is becoming more and more serious, which has a serious impact on the power system and social economy[1]. To enhance power quality, the electric energy quality disturbance signal must be analyzed quickly and efficiently. Accurately identifying the characteristics of electric energy quality interference signals is the prerequisite for improving and enhancing power quality[2-4].

II. ANALYSIS METHOD OF POWER QUALITY DISTURBANCE IN TRANSFORM DOMAIN

There are many methods for analyzing power quality disturbances in the transform domain, and the most broadly applied. In the last few years, the most commonly used methods at home and abroad are the Fast Fourier transform (FFT), Short-time Fourier transform (STFT) , Wavelet transform(WT), S-transform, Hilbert transform(HHT) and so on[5-6].

A. Fast Fourier Transform(FFT)

The essence of Fourier transform is to convert time signal to frequency signal for analysis. If $f(t)$ is a function of t, And meet the Dirichlet conditions:(1) Having a finite number of extreme points;(2) Absolutely integrable;(3) Has a limited number of discontinuities. Then the Fourier transform of $f(t)$ is $F(w)$:

$$F(w) = \int_{-\infty}^{+\infty} f(t)e^{-i\omega t}dt \tag{1}$$

In this way, the time signal can be converted into a frequency spectrum for analysis[6]. In power quality disturbance analysis, the Fourier transform is a broad and classic methods. Especially for stationary signals, it has a good analysis effect. However, due to the principle of transformation is to integrate the entire time period, the time information is lost. Therefore, the time-domain and frequency-domain information cannot be expressed simultaneously in the signal analysis[5].

B. Short-time Fourier Transform(STFT)

Because the detection of disturbance semaphore by Fourier transform is global. In order to enable it to analyze local information, the disturbance signal is introduced into a time window concept, and then Fourier transform——STFT. For a time signal $f(t)$,its STFT is $S(t,s)$:

$$S(t,f) = \int_{-\infty}^{+\infty} f(\tau)g(\tau - t)d\tau \tag{2}$$

Where f is frequency,50HZ; $g(\tau - t)$ is Time window function. The window function intercepts the disturbance signal, and then performs spectrum analysis to obtain a local spectrum analysis. Overcoming the limitation that the Fourier transform can only analyze the global[6]. However,

2473-3636/20/$31.00 ©2020 IEEE
DOI 10.1109/DCABES50732.2020.00022

when the STFT window is selected， the frequency resolution on the time-frequency plane are fixed. The low frequency component window is too narrow to cover a long enough signal segment. For high frequency components, the window is too wide to reflect the signal transformation in time.

When detecting complex disturbances, due to the fixed time domain and frequency resolution, it is not possible to take into account both steady-state disturbances and transient disturbances.

C. Wavelet Transform(WT)

WT is a multi-resolution time-frequency analysis method. If $\varphi(t) \in L^2(R)$,its FFT is $\psi(w)$ To meet the condition:

$$C_\varphi = \int \frac{|\varphi(w)|^2}{w} d\omega < \infty \tag{3}$$

The above formula is called admissible condition of wavelet function.

The wavelets used in the wavelet transformation are all based on the basic wavelet through scaling and position translation[7].

The basic wavelet function $\varphi(t)$ can be expanded and translated to obtain the function $\varphi_{a,\tau}(t)$:

$$\varphi_{a,\tau}(t) = \frac{1}{\sqrt{a}} \varphi\left(\frac{t-\tau}{a}\right) \tag{4}$$

In the formula: a——Scaling factor;

τ——Translation factor

$\varphi_{a,\tau}(t)$ is a set of wavelet function sequences evolved from the mother wavelet function $\varphi(t)$ through mathematical operations. The window area of the wavelet basis function is fixed and does not change with the changes of parameters a and τ. At any scale and at any point in time, the window area remains unchanged, and time and scale resolution are mutually constrained.

If $f(t) \in L^2(R)$, its CWT is $WT_f(a,\tau)$:

$$\begin{aligned} WT_f(a,\tau) &= \langle f(t), \varphi_{a,\tau}(t) \rangle \\ &= \frac{1}{a} \int f(t) \varphi^*\left(\frac{t-\tau}{a}\right) dt \end{aligned} \tag{5}$$

In the formula:

$\varphi^*(t)$——Conjugation of $\varphi(t)$;

$WT_f(a,\tau)$—Wavelet transform coefficient

The wavelet transform overcomes the shortcomings of the fixed time-frequency resolution caused by the fixed time-frequency of the short-time Fourier transformation. The low frequency and high frequency in the signal are selected with different wide and narrow time windows. The narrow time window will get extremely high value in time resolution, but it can not get high frequency resolution. But the wide time window is the opposite[8]. Different wavelet basis analysis will get different results. The choice of wavelet basis is also not clearly specified. It can only be obtained by experience and continuous trial and error to obtain a suitable wavelet basis function.

D. S- transform

The S-transform is based on the Fourier transformation and the wavelet transform[9]. The S- transform of the signal $f(t)$ can be regarded as the wavelet transform of $f(t)$ and times a phase coefficient. The WT of $f(t)$ is $W(\tau,s)$:

$$W(\tau,s) = \int_{-\infty}^{+\infty} f(t) w(\tau - t, s) dt \tag{6}$$

In the formula:

τ——translation factor;

S——scale factor;

$w(t,s)$——Wavelet basis function

its expression is as follows:

$$w(\tau,s) = \frac{|s|}{\sqrt{2\pi}} e^{-\frac{t^2 s^2}{2}} e^{-i2\pi st} \tag{7}$$

Further multiply the wavelet transform result $W(\tau,s)$ in (7) by a phase factor to obtain:

$$S(\tau,s) = e^{-i2\pi st} w(\tau,s) \tag{8}$$

Let $s = f$, bring into the formula (6), (7) and (8), we can get the one-dimensional continuous S transform of the signal $f(t)$:

$$S(\tau,f) = \int_{-\infty}^{+\infty} f(t) \cdot \frac{|f|}{\sqrt{2\pi}} e^{-\frac{(t-\tau)^2 f^2}{2}} e^{-i2\pi ft} dt \tag{9}$$

In the formula:

τ——the center position of the Gaussian window function;

f——frequency

The consequence of the S-transform is a intricate matrix，which contains signal time and frequency domain information. Overcoming the shortcomings of fixed window width. And compared with wavelet transform, S-transform has better frequency domain analysis ability and anti-interference ability.

III. CLASSIFICATION AND RECOGNITION OF DISTURBANCE

SIGNALS

After the electric energy quality disturbance signal is processed by STFT，WT and S transform, this information that can clearly represent the main characteristics of the disturbance signal is extracted. The next step is to build a classification and identification model depended on the extracted feature vectors. Currently commonly used recognition methods are Back Propagation Neural Networks, ELM, SVM, Deep Learning , Expert System and many more.

A. Back Propagation Neural Networks(BPNN)

BPNN is a neural network with three or more layers of neurons.

The structure of the three-layer Back Propagation Neural Networks is shown in Figure 1:

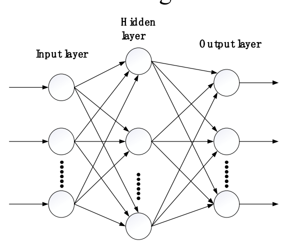

Figure1. Diagrammatic drawing of BP neural network structure

Input experimental samples to the network, and the sample information is processed from the input layer layer by layer, and finally the output result is obtained. If the required result accuracy is not obtained in the output layer, the error is returned along the original path. By modifying the weight of the neuron, the error meets the requirement. The trained network can use the disturbance signal to identify the power quality. The workflow block diagram is displayed in Figure 2:

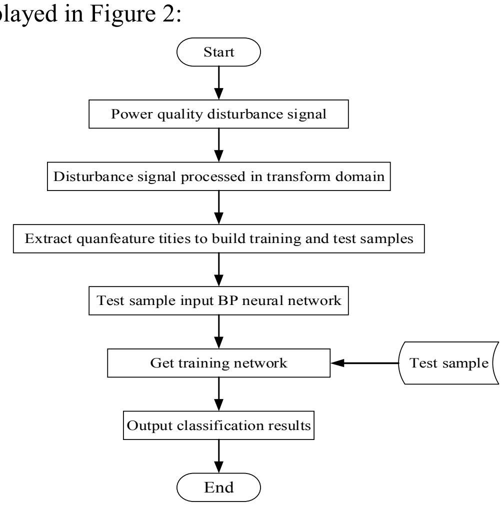

Figure 2. Flow chart of classification and recognition of BP

The advantages of BP neural network: (1) can realize any nonlinear and complex mapping relationship;(2) the network has self-learning ability;(3) particularly suitable for solving the problems of internal complex mechanisms.

The disadvantages of BP neural network: (1) tardy convergence speed; (2) lengthy practice time;(3) BP algorithm can make the weights converge to a certain value, but the internal algorithm is simple to produce local minimums, the convergence result is not guaranteed Global minimum;(4) New samples need to be retrained, and there is no memory of previous weights and thresholds.

B. Extreme Learning Machine (ELM)

The basic idea is to first randomly initialize the hidden layer weights and offsets, input the training set and calculate the hidden layer output, and then directly obtain the output layer weights according to the training label. The extreme learning machine improves the BP neural network to continuously adjust the weights by error feedback, but is directly obtained by the generalized inverse matrix, and the training time is greatly reduced.

ELM as a single hidden layer feedforward neural network makes up of three layers.

A single hidden layer neural network, for N arbitrary samples(X_i, t_i).

$$X_i = [x_{i1}, x_{i2}, \ldots \ldots, x_{in}]^T \in R^n,$$

$$T_i = [t_{i1}, t_{i2}, \ldots \ldots, t_{im}]^T \in R^m;$$

Its network model as shown in Figure 3:

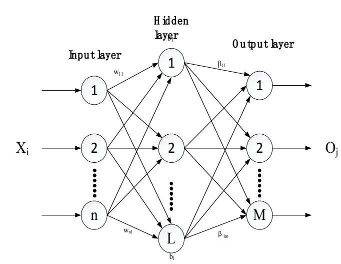

Figure 3. ELM network model diagram

In the figure above, for a three-layer network with L hidden neurons, the mathematical expression is:

$$\sum_{i=1}^{L} \beta_i \cdot g(w_i \times X_i + b_i) = O_j \, , j = 1,2, \ldots, n; \qquad (10)$$

In the formula:

$g(x)$——Activation function;

$W_i = [w_{i1}, w_{i2}, \ldots \ldots, w_{in}]^T$——Input weight;

β_i——Output weight;

b_i——Hidden layer neuron bias;

O_j—— Output;

$W_i \times X_i$—— Inner product

For testing a single layer network, it is necessary to get $\widehat{W}_i$, $\hat{b}_i$ and $\hat{\beta}_i$.

$$|H(\widehat{W}_i, \hat{b}_i)\hat{\beta}_i - T|_2 = \min_{w,b,\beta} |H(W_i b_i)\beta_i - T|_2 \quad (11)$$

With the development of gradient descent algorithm. the problem of minimizing the loss function is solved. For the application of the algorithm,it needs to adjust all arguments during the iteration process[10]. For ELM, once the W_i and b_i are randomly selected, the H is uniquely determined. It can be converted to solving linear equations $H\beta = T$. Then the β can be obtained:

$$\hat{\beta} = H^{+}T \quad (12)$$

In the formula:

H^{+}——generalized inverse matrix of matrix H

The most prominent advantage of ELM is that the training speed is very fast. It can complete the training of samples in a few seconds. At the same time, under the condition of maintaining high speed, it performs better than the traditional gradient descent-based algorithm in many cases. Moreover, traditional gradient-based descent algorithms will face the problem of local minimization.

IV. Power Quality Control Methods

At present, there are several common methods of power quality control at home and abroad.

A. PID control

PID is the most widely used regulator control method. When the structure and parameters of the controlled object cannot be fully grasped, it is most convenient to apply PID technology. But the response is overshoot.

B. Space vector control

Conventional vector control methods generally use DSP for processing. It has good steady-state and transient performance. It can also use simplified algorithms to shorten real-time calculation time.

C. Fuzzy logic control

As a new intelligent control method, fuzzy control does not need to establish an accurate mathematical model of the system. It mimics human language and thinking to process and express fuzzy information, and fuzzy description of system characteristics to reduce the cost of acquiring dynamic and static characteristics of the system

V. Conclusion

With the rapid development of more and more high-precision instruments, the demand for power quality are getting increasingly high. Therefore, the detection and classification of electric energy quality interference is the key to improve and enhance electric energy quality. In this paper, by extracting the eigenvector of the electric energy quality interference signal in the transform domain, the principle of power vector disturbance signal extraction under FFT, SFTF, WT and S transforms is explained, and the strengths and weaknesses of a variety of ways and their use are summarized. Finally, the extracted feature vectors are classified and recognized by BP NN and ultimate learning machine.

References

[1] Mrutyunjaya Sahani,P.K. Dash,Debashisa Samal. A real-time power quality events recognition using variational mode decomposition and online-sequential extreme learning machine[J]. Measurement,2020,157.

[2] Panagiotis A. Karafotis,Vasileios A. Evangelopoulos,Pavlos S. Georgilakis. Evaluation of harmonic contribution to unbalance in power systems under non-stationary conditions using wavelet packet transform[J]. Electric Power Systems Research,2020,178.

[3] Wenjing Zhao,Liqun Shang,Jinfan Sun. Power quality disturbance classification based on time-frequency domain multi-feature and decision tree[J]. Protection and Control of Modern Power Systems,2019,4(4).

[4] Hui Liu,Fida Hussain,Yue Shen,Ruben Morales-Menendez,Muhammad Abubakar,Sheikh Junaid Yawar,Haris Jawad Arain. Signal Processing and Deep Learning Techniques for Power Quality Events Monitoring and Classification[J]. Electric Power Components and Systems,2019,47(14-15).

[5] Luciano Carli M. Andrade,Tejaswi Nanjundaswamy,Mário Oleskovicz,Ricardo A. S. Fernandes,Kenneth Rose. Advances in Classification and Compression of Power Quality Signals[J]. Journal of Control, Automation and Electrical Systems,2019,30(3).

[6] Ravinder Kumar,Hari Om Bansal. Hardware in the loop implementation of wavelet based strategy in shunt active power filter to mitigate power quality issues[J]. Electric Power Systems Research,2019,169.

[7] Prakash K. Ray,Asit Mohanty,Tapas Panigrahi. Power quality analysis in solar PV integrated microgrid using independent component analysis and support vector machine[J]. Optik,2019,180.

[8] Karthik Thirumala,Sushmita Pal,Trapti Jain,Amod C. Umarikar. A classification method for multiple power quality disturbances using EWT based adaptive filtering and multiclass SVM[J]. Neurocomputing,2019.

[9] Belkis Eristi,Ozal Yildirim,Huseyin Eristi,Yakup Demir. A new embedded power quality event classification system based on the wavelet transform[J]. International Transactions on Electrical Energy Systems,2018,28(9).