Detection and Localization of Power Quality Disturbances Based on Wavelet Network

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Abstract: - Power quality (PQ) is becoming prevalent and of critical importance for power industry recently. The fast expansion in use of power electronics devices led to a wide diffusion of nonlinear, time-variant loads in the power distribution network, which cause massive serious power quality problems. The quantitative detection of two distortions of voltage waveform, i.e., voltage sag and voltage swell, is conducted and on this base a novel approach based on wavelet transform (WT) to detect and locate the PQ disturbances is proposed. The signal containing noise is de-noised by wavelet transform to obtain a signal with higher signal-to-noise ratio (SNR), and then is input to the wavelet network; the synthesized method of recursive orthogonal least squares algorithm (ROLSA) and improved Givens transform is used to fulfill the network structure; the fundamental component of the signal is estimated to extract the mixed information using wavelet network, and then the disturbance is acquired by subtracting the fundamental component; the principle of singularity detection using WT modulus maxima is presented and a dyadic wavelet transform approach for the detection and localization of the power quality disturbance is proposed. The simulation results demonstrate that the proposed method is effective.

Key-Words: - Power quality disturbance, wavelet transform, signal de-noise, singularity detection, disturbance localization, power system

1 Introduction

Power quality (PQ) issues have emerged, after the worldwide energy market deregulation, as an exponentially demanding attention research field for electric utilities and endusers. The electrical energy market has observed a growth in the number of independent power producers with poorly controlled synchronization, an increase in competition, a somehow related reluctance to exchange information, besides new system interconnections and customers necessities. Power quality issues and the resulting problems are the consequences of the increasing use of solid state switching devices, nonlinear and power electronically switched loads, unbalanced power systems, lighting controls, computer and data processing equipment, as well as industrial plant rectifiers and inverters. These electronic-type loads cause quasistatic harmonic dynamic voltage distortions, inrush, pulse-type current phenomenon with excessive harmonics, and high distortion. A power quality problem usually involves a variation in the electric service voltage or current, such as voltage dips and fluctuations, momentary interruptions, harmonics and oscillatory transients causing failure, or maloperation of the power service equipment.

Hence, to improve power quality, it is required to know the sources of power system disturbances and find ways to mitigate them. To monitor electrical power quality disturbance, new and powerful tools for the analysis and operation of power systems, as well as for PQ diagnosis are currently available. The new tools of interest are those of artificial intelligence (AI) and wavelet transform[1]-[3] (WT).

The use of AI techniques in electric power has received extensive attention from researchers in the electric power area and the literature on these applications has become rather huge in volume. Areas of electric power where the use of AI has been researched include: alarm processing, systems diagnosis, protection, system security, system restoration, system control, operational aid devices, generation scheduling, power system planning, power system stability, power system analysis, load forecasting, and fault diagnosis and location. Wavelet analysis is based on the decomposition of a signal according to time-scale, rather than frequency, using basis functions with adaptable scaling properties which are known as multi-resolution analysis. The wavelet function is localized in time and frequency yielding wavelet coefficients at different scales. This gives the wavelet transform much grater compact support for analysis of signals with localized transient components arising in power quality disturbances manifested in voltage, current, or frequency deviations.

In this paper, the power quality disturbance signal is de-noised by WT to obtain higher signal-to-noise ratio (SNR) firstly; the synthesized method of recursive orthogonal least squares algorithm (ROLSA) and improved Givens transform is used to fulfill the wavelet network structure; the fundamental component of the signal is estimated by the wavelet network and then the disturbance is acquired by subtracting the fundamental component; the principle of singularity detection using WT modulus maxima is presented in detection and localization of the power quality disturbance. The simulation results show that the proposed method has good performance in calculation speed and accuracy.

2 Wavelet Network structure and training algorithm

2.1 Wavelet transform and signal denoising

The wavelet analysis block transforms the distorted signal into different time-frequency scales. The wavelet transform (WT) uses the wavelet function φ and scaling function ϕ to perform simultaneously the multiresolution analysis (MRA) decomposition and reconstruction of the measured signal. The wavelet function φ will generate the detailed version (high-frequency components) of the decomposed signal and the scaling function ϕ will generate the approximated version (low-frequency components) of the decomposed signal. The wavelet transform is a well-suited tool for analyzing high-frequency transients in the presence of low-frequency components such as nonstationary and nonperiodic wideband signals.

The first main characteristic in WT is the MRA technique that can decompose the original signal into several other signals with different levels (scales) of resolution. From these decomposed signals, the original time-domain signal can be recovered without losing any information.

The recursive mathematical representation of the MRA is as follows:

$$V_j = W_{j+1} \oplus V_{j+1} = W_{j+1} \oplus W_{j+2} \cdots \oplus W_{j+n} \oplus V_n$$
(1)

where V_{j+1} represents approximated version of the given signal at scale $j+1$; V_{j+1} represents detailed version that displays all transient phenomena of the given signal at scale $j+1$; $\oplus$ denotes a summation of two decomposed signals; n is the decomposition level.

Before the WT is performed, the wavelet function $\varphi(t)$ and scaling function $\phi(t)$ must be defined. The wavelet function serving as a highpass filter can generate the detailed version of the distorted signal, while the scaling function can generate the approximated version of the distorted signal. In general, the discrete $\varphi(t)$ and $\phi(t)$ can be defined as follows:

$$\phi_{j,n}[t] = 2^{\frac{j}{2}} \sum_n c_{j,n} \phi[2^j t - n] \tag{2}$$

$$\varphi_{j,n}[t] = 2^{\frac{j}{2}} \sum_n d_{j,n} \varphi[2^j t - n] \tag{3}$$

where $c_{j,n}$ is the scaling coefficient at scale j, and $d_{j,n}$ is the wavelet coefficient at scale j.

Simultaneously, the two functions must be orthonormal and satisfy the properties as follows:

$$\langle \phi \cdot \phi \rangle = \frac{1}{2^j}, \langle \varphi \cdot \varphi \rangle = \frac{1}{2^j}, \ \langle \phi \cdot \varphi \rangle = 0 \tag{4}$$

Assuming the original signal $x_j[t]$ at scale j is sampled at constant time intervals, thus $x_j[t] = (v_0, v_1, ..., v_{N-1})$, the sampling number is $N = 2^J$. J is an integer number. For $x_j[t]$, its DWT mathematical recursive equation is presented as follows:

$$DWT(x_j[t]) = \sum_k x_j[t] \phi_{j,k}[t]$$

$$= 2^{\frac{j+1}{2}} \left(\sum_n u_{j+1,n} \phi[2^{j+1} - n] + \sum_n \omega_{j+1,n} \varphi[2^{j+1} - n] \right)$$

$$0 \le n \le \frac{N}{2^j} - 1 \tag{5}$$

where

$$u_{j+1,n} = \sum_k c_{j,k} v_{j,k+2n} \ , \ \omega_{j+1,n} = \sum_k d_{j,k} v_{j,k+2n} \ , ,$$

$$0 \le k \le \frac{N}{2^j} - 1, \ p = \frac{N}{2^j} \tag{6}$$

where $u_{j+1,n}$ is the approximated version at scale $j+1$, $\omega_{j+1,n}$ is the detailed version at scale $j+1$, and j is the translation coefficient.

According to the orthonormal wavelet functions and (5), the signal $x_j(t)$ can be reconstructed from both u_{j+1} and ω_{j+1} coefficients using the inverse discrete wavelet transform (IDWT) .

Usually the high-frequency part includes noise component. In particular, the disturbance signal contains many kinds of noise. Sometimes, the disturbance signals are submerged by noise, so it is difficult to analyze directly. It is essential to denoise before analyzing. There are two key problems that need to be solved in practice use of denoising. One is the determination of the threshold; another is the determination of the decomposition level. In this paper, a novel method based on the soft threshold rule is brought forward to achieve a higher SNR. It is especially suitable for the detection of weak signal under noise background. The signal de-noising algorithm is summarized as follows:

B1)Compute noise intensity $\sigma = \left(\sum_{i=1}^{M_N} \left| d_{i,N} \right| / M_N \right) / 0.6745$, where M_N is the length of N level wavelet decomposition coefficient, $d_{i,N}$ is the N level high-frequency coefficient;

B2)Compute the soft threshold $T_{thr} = \sigma \sqrt{2 \ln(M_N)}$;If $\left| d_{i,N} \right| \geq T_{thr}$ then reserve the coefficient; otherwise set $d_{i,N} = 0$;

B3) The denoised disturbance signal can be obtained by reconstructing the wavelet decomposition coefficient.

2.2 Wavelet network training algorithm

Simplified table is the result of simplifying condition attribute, and the classification function remains to be. And simplified decision table contains less complicated condition attributes. We know a simplified condition is necessary in making decisions. The algorithm has 2 steps, i.e. attribute reduction and attribute value reduction as follows.

A nonlinear optimization algorithm, such as gradient descent, conjugate gradients or Broyden-Fletcher-Goldfarb-Shanno (BFGS), could be applied to training a wavelet network. However, an advantage of the wavelet network architecture is that it can be trained in stages using linear optimization algorithms, which allows for faster training and improved convergence compared with nonlinear alternatives.

Orthogonal decomposition is well known to be a numerically robust method for solving the least squares problem and can be applied to computing the output layer weights in a wavelet network[4], [5]. It was recently demonstrated that a recursive version can maintain the robust property while requiring less computer memory than a batch version.

In this paper, the recursive orthogonal least squares (ROLS) algorithm is developed for determining the weighting W , in a wavelet network. Also, the form of the ROLS algorithm used here determines the full weighting matrix at each iteration $W(t)$. The weighting W matrix is computed to minimize the error, $e(t) = y(t) - \hat{y}(t)$ where $y(t)$ is the target network output. The algorithm is therefore developed below.

Considering for a set of N input-output training data, we have

$$Y = \hat{Y} + E = \Phi W + E \tag{7}$$

where Y is the desired output matrix; $\hat{Y}$ is the wavelet network output matrix; Φ is the hidden layer output matrix; E is the error matrix and

$Y^T = [y(1), y(2), ..., y(N)]$,

$\hat{Y}^T = [\hat{y}(1), \hat{y}(2), ..., \hat{y}(N)]$,

$\Phi^T = [\Phi(1), \Phi(2), ..., \Phi(N)]$,

$E^T = [e(1), e(2), ..., e(N)]$.

Now a multiple-input single-output (MISO) least squares problem can be formulated to solve W such that the following cost function is minimized:

$$J(W) = \|E\|_F = \|Y - \Phi W\|_F \tag{8}$$

where $\|*\|_F$ is the Frobenius norm defined as

$$\|A\|_F^2 = trace(A^T A) \tag{9}$$

To obtain a recursive algorithm, we need to solve an optimal $W(t)$ at each iteration t that minimizes

$$J(t) = \|E(t)\|_F = \left\| \begin{bmatrix} Y(t-1) \\ y^T(t) \end{bmatrix} - \begin{bmatrix} \Phi(t-1) \\ \Phi^T(t) \end{bmatrix} W(t) \right\|_F$$

(10)

Because the sizes of matrices Φ and Y increase with new data, the manipulation of Φ and Y will be more difficult when the number of data becomes large. However, Φ and $\hat{Y}$ can be manipulated much more easily as their sizes are constant and small. Following a similar procedure to that described above, apply an orthogonal decomposition

$$\Phi(t-1) = Q(t-1) \begin{bmatrix} R(t-1) \\ 0 \end{bmatrix} \tag{11}$$

$$Q^T(t-1) Y(t-1) = \begin{bmatrix} \hat{Y}(t-1) \\ \tilde{Y}(t-1) \end{bmatrix} \tag{12}$$

Equation (10) is then transformed to

$$J(t) = \left\| \begin{bmatrix} \hat{Y}(t-1) \\ y^T(t) \\ \tilde{Y}(t-1) \end{bmatrix} - \begin{bmatrix} R(t-1) \\ \Phi^T(t) \\ 0 \end{bmatrix} W(t) \right\|_F \qquad (13)$$

To find an update for $R(t-1)$ and $\hat{Y}(t-1)$, compute another orthogonal decomposition as follows:

$$\begin{bmatrix} R(t-1) \\ \cdots \\ \Phi^T(t) \end{bmatrix} = Q_1(t) \begin{bmatrix} R(t) \\ \cdots \\ 0 \end{bmatrix}$$

$$\begin{bmatrix} \hat{Y}(t) \\ \cdots \\ \tilde{y}^T(t) \end{bmatrix} = Q_1^T(t) \begin{bmatrix} Y(t-1) \\ \cdots \\ y^T(t) \end{bmatrix} \qquad (14)$$

The final cost function is then

$$J(t) = \left\| \begin{bmatrix} Y(t) - R(t)W(t) \\ \tilde{y}^T(t) \\ \tilde{Y}(t-1) \end{bmatrix} \right\|_F \qquad (15)$$

Hence, the optimal $W(t)$ in (15) can be solved from

$$R(t)W(t) = \hat{Y}(t) \qquad (16)$$

The residual at iteration t can be computed from the recursive equation

$$\left\| \tilde{Y}(t) \right\|_F^2 = \left\| \begin{bmatrix} \tilde{y}^T(t) \\ \tilde{Y}(t-1) \end{bmatrix} \right\|_F^2 = \left\| \tilde{y}^T(t) \right\|_F^2 + \left\| \tilde{Y}(t-1) \right\|_F^2$$

(17)

Therefore, $\left\| \tilde{y}^T(t) \right\|_F^2$ is an increment to the squared residual at each iteration t. Recall $R(t)$ that is an upper triangular matrix and therefore $R(t)$ can be easily solved from (11) by backward substitution.

The ROLS algorithm can be implemented efficiently using Givens rotations which avoids the need to explicitly compute the orthogonal matrices, and in the main algorithm update (14). Standard Givens rotations have been used in this research but equivalent implementations of the techniques can also be made using modified Givens rotations. The standard Givens rotation operates on two row vectors so as to zero the first nonzero element in the second row vector as follows:

$$\begin{bmatrix} 0, a_i, a_{i+1}, \ldots \\ 0, b_i, b_{i+1}, \ldots \end{bmatrix} \longrightarrow \begin{bmatrix} 0, a_i^{'}, a_{i+1}^{'}, \ldots \\ 0, b_i^{'}, b_{i+1}^{'}, \ldots \end{bmatrix} \qquad (18)$$

where $a_p^{'} = ca_p + sb_p, b_p^{'} = -sa_p + cb_p$, and $a_i^{'} = (a_i^2 + b_i^2)^2$, $c = a_i / a_i^{'}$, $s = b_i / b_i^{'}$, $p = i+1, i+2, \ldots$

Further more, the output matrices Φ rotation is

$$\begin{bmatrix} R_{i-1} & \vdots & \hat{Y}_{i-1} \\ & \vdots & \\ U_i & \vdots & y_i \end{bmatrix} \xrightarrow{Q^T(q)} \begin{bmatrix} R_i & \vdots & \hat{Y}_i \\ & \vdots & \\ 0 & \vdots & \tilde{y}_i \end{bmatrix} \qquad (19)$$

The ROLS algorithm and modified Givens rotation is summarized as follows:

B1) Initialize and set $i = 0$, $R_0 = aI$, $R(0) = aI$ where a is a small positive number, $\hat{Y}_0 = 0$ and set $\left\| \tilde{Y}_0 \right\|_2^2 = 0$, $R_{i-1} = R_0$, $\hat{Y}_{i-1} = \hat{Y}_0$, $\left\| \tilde{Y}_{i-1} \right\|_2^2 = \left\| \tilde{Y}_0 \right\|_2^2$.

B2) Select the training data X_i and Y_i , QR decomposition is applied using (19) when $q \geq 1$. Givens rotation is to achieve:

$$\begin{bmatrix} R_{i-1} \\ U_i \end{bmatrix} \longrightarrow \begin{bmatrix} R_i \\ 0 \end{bmatrix} \qquad (20)$$

R_i, Q_i^T, $\hat{Y}_i$, and $\tilde{y}_i$ are obtained.

B3) Compute $\left\| \tilde{Y}_i \right\|_2^2$ and set $R_{i-1} = R_i, \hat{Y}_{i-1} = \hat{Y}_i, \left\| \tilde{Y}_{i-1} \right\|_2^2 = \left\| \tilde{Y}_i \right\|_2^2$. If $i < N$ then let $i = i + 1$, and go to Step B2); otherwise $\hat{Y}(N) = R(N)U(N)$, stop the computation.

The wavelet network is trained off-line before combining with the DTC system. The design realizes the aim of wavelet network on-line identifying the stator resistance successfully by means of computer Matlab/Simulink simulation.

3 Simulation Results and analysis

3.1 Signal singularity detection principle

As mentioned in the introduction, a remarkable property of the wavelet transform is its ability to characterize the local regularity of functions. In mathematics, this local regularity is often measured with Lipschitz exponents. Let n be a positive integer and $n \leq \alpha \leq n+1$. A function $f(x)$ is said to be Lipschitz α at x_0, if and only if there exists two constants A and $h_0 > 0$, and a polynomial of order n, $P_n(x)$, such that for $h < h_0$,

$$\left| f(x_0 + h) - P_n(h) \right| \le A|h|^{\alpha} \quad (21)$$

The function $f(x)$ is uniformly Lipschitz a over the Interval $[a,b]$, if and only if there exists a constant A and for any $x_0 \in [a,b]$ there exists a polynomial of order n, $P_n(x)$, such that equation (21) is satisfied if $x_0 + h \in [a,b]$.

We call Lipschitz regularity of $f(x)$ and x_0, the superior bound of all values α such that $f(x)$ is Lipschitz α at x_0.

We say that a function is singular at x_0, if it is not Lipschitz 1 and x_0.

3.2 Simulation results and analysis

Voltage sags are referred to the magnitude of voltage under 0.9 pu (in the range of 0.1—0.9 pu) lasting for 10ms — 1min, which is generally caused by the electric motor startup or switching operation of power equipments. Voltage sags cause the equipment operating abnormally. Fig. 1 shows the location results for a disturbed voltage curve with a sag lasting for 100ms and the falling magnitude by 10% and it's wavelet decomposition coefficient curve.

Voltage swells are referred to voltage magnitude beyond 10% of the rated value (in the range of 1.1—1.8pu) and lasting for 10ms—1min, generally caused by single phase short-circuit or tripping off, which usually make the equipments malfunction. Fig. 2 shows the detection results for a voltage curve with a swell lasting for 100ms and the rising magnitude by 10% and it's wavelet decomposition coefficient curve.

From Fig.1 and Fig.2, it can be seen that the modulus maxima of wavelet transform can correspond to the instantaneous discontinuity of the disturbance accurately and it is easy to determine the start point, recovery point and sustained time of the power quality disturbance. Suppose that the sample cycle is T_0, the start point is n_1 and the recovery point is n_2, the sustained time is can be obtained: $(n_2 - n_1)T_0$.

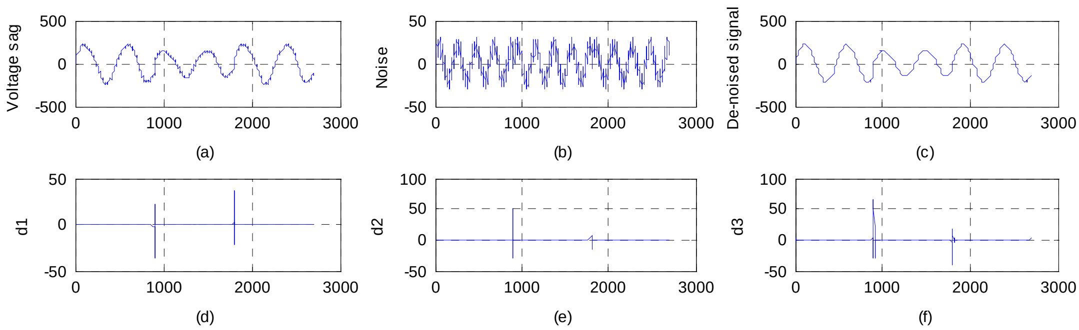

Fig.1 Curves of noise-riding voltage sag and calculation results using wavelet transform

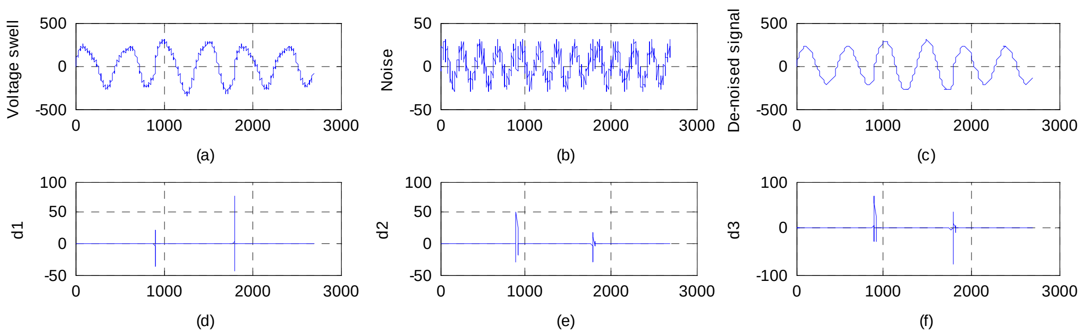

Fig.2 Curves of noise-riding voltage swell and calculation results using wavelet transform

4 Conclusions

This paper has presented a new technique which possesses the advantage of wavelet network to extract the power quality disturbance signal superimposing on the power frequency components. The synthesized method of recursive orthogonal least squares algorithm (ROLSA) and improved Givens transform is used to fulfill the wavelet network structure and estimate the power fundamental component. A novel soft threshold denoising method is put forward to improve the SNR, and the modulus combining polarities of wavelet transform coefficients has been developed for detection and localization of the power quality disturbance. The simulation results have shown that the satisfactory performance has been achieved under different disturbances and noise background.

Furthermore, the method enables an accurate classification of transient events to be performed, and characteristics are easily read from the time-frequency plane. This method will be extended to detect and characterize significant harmonic distortion and flicker levels. The whole method will then be used as a power quality analysis software tool in studies for utilities.

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