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Characterization of power quality disturbances using hybrid technique of linear Kalman filter and fuzzy-expert system

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ABSTRACT

This paper presents a hybrid technique for characterizing power quality (PQ) disturbances. The hybrid technique is based on Kalman filter for extracting three parameters (amplitude, slope of amplitude, harmonic indication) from the captured distorted waveform. Discrete wavelet transform (DWT) is used to help Kalman filter to give a good performance; the captured distorted waveform is passed through the DWT to determine the noise inside it and the covariance of this noise is fed together with the captured voltage waveform to the Kalman filter. The three parameters are the inputs to fuzzy-expert system that uses some rules on these inputs to characterize the PQ events in the captured waveform. This hybrid technique can classify two simultaneous PQ events such as sag and harmonic or swell and harmonic. Several simulation and experimental data are used to validate the proposed technique. The results depict that the proposed technique has the ability to accurately identify and characterize PQ disturbances.

1. Introduction

Power quality (PQ) disturbances such as voltage sags, swells, interruptions, flicker and harmonic distortion may lead to mal-operation or failure of any sensitive electric facilities such as computer based processor or automatic system. The critical aspect of PQ studies is the ability to perform PQ data analysis and classification. The important step in understanding and hence improving the quality of electric power is to extract sufficient information about the events that cause the PQ issues.

A number of papers based on different techniques for detection and classification of power quality phenomena have been published over the past years. Some survey studies can be found in [1–3].

Traditionally, Fourier transform permits mapping signals from time domain to frequency domain by decomposing the signals into several frequency components [4]. This technique is critical where the time information of transients is totally lost. In order to overcome this limitation, the short-time Fourier transform (STFT) technique is adopted in [5]. But STFT is well suited for stationary signal where frequency does not vary with time. For non-stationary signal STFT does not recognize the signal dynamics property due to the limitation of fixed window width.

To overcome the drawback of STFT, the wavelet transform (WT) provides the time-scale analysis of the non-stationary signal. It decomposes the signal into time scale representation rather than time-frequency representation. The wavelet transform has been explored extensively in various studies as an alternative to the STFT [6–14].

The S-transform [15–20] is an extension to the idea of wavelet transform and is based on a moving and scalable localization Gaussian window and has characteristics superior to either of the transform. The S-transform is fully convertible from time domain to two dimension frequency translation domain and then familiar Fourier frequency domain.

Using the change in magnitude of the fundamental component of supply voltage, Kalman filter can be employed to detect and to analyze voltage event [21–24]. The results of Kalman filter depend on the model of the system used and the suitable selection of the filter parameters. If the selection of the Kalman filter parameters is not suitable, the rate of convergence of the results will be slow or the results will diverge.

Hybrid technique for detecting and characterizing various types of power quality disturbances, including harmonics distortion is proposed in this paper. First, the captured voltage waveform is passed through discrete wavelet transform (DWT) to identify its noise. The covariance of this noise together with the captured voltage waveform is fed to the Kalman filter to enhance and speed

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up its rate of convergence. After that the outputs of Kalman filter, amplitude of fundamental frequency component and amplitudes of harmonic components of the captured voltage waveform, are used to prepare the inputs of fuzzy-expert system. Second, the amplitude of fundamental component and its rate of change with time (slope) are passed through a fuzzy expert system that identifies the class to which the disturbance waveform belongs. Although the power system disturbances fall into five categories like outage, sag, normal, swell and surge, the harmonic distortion can be present in each of them. The characterization of distorted waveform can be made by defining a third input to fuzzy system. This input is used to indicate the harmonics present in the distorted waveform or not. Several digital simulation results using MATLAB and experimental results are presented to satisfy and ensure the capability of the proposed technique for characterizing the disturbances successfully.

2. The proposed technique

The proposed technique is shown in Fig. 1. The two stages are performed with each new voltage sample: (i) evaluating a new value of the amplitude and slope using Kalman filter with the help of DWT and (ii) characterizing the disturbance using fuzzy-expert system according to the evaluated values.

2.1. Wavelet transform

The continuous wavelet transform (WT) of a signal $x\ (t)$ is defined as [25]:

$$X_{a,b} = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} x(t)\psi\left(\frac{t-b}{a}\right) dt \tag{1}$$

$$\psi_{a,b}(t) = \frac{1}{\sqrt{|a|}}\psi\left(\frac{t-b}{a}\right) \tag{2}$$

where $\psi\ (t)$ is the mother wavelet, a and b are the time shift and scale, respectively.

The DWT calculations are made for a chosen subset of scales and time shift. This scheme is conducted by using filters and computing the so-called *approximations and details.* The *approximations* (A) are the high-scale, low frequency components of the signal. The *details* (D) are the low-scale, high-frequency components. The DWT coefficients are computed using the equation:

$$X_{a,b} = X_{j,k} = \sum_{n\in Z} x[n]g_{j,k}[n] \tag{3}$$

where $a = 2j$, $b = \mathrm{k} \times 2j$, $j \in N$, $k \in N$. The wavelet filter g plays the role of ψ.

2.2. Linear Kalman filter

Kalman algorithm is applied in order to compute the amplitude of the waveform.

The Kalman filtering performs the following operations [26].

1) Vector modeling of the random processes under consideration.
2) Recursive processing of the noisy measured (input) data.

The random process to be estimated can be modeled in the following form:

$$x_{k+1} = \phi_K x_k + w_k \tag{4}$$

where x_k, x_{k+1} are the state vector at time instant k and $k+1$, respectively. Φ_k is the usual state transition matrix, w_k is assumed to be a white noise with known covariance structure.

It is assumed that the system signal under study (voltage signal) corresponds to a sinusoidal signal of fundamental frequency ω and different harmonic components and is expressed by the following equation:

$$Z_k = \sum_{i=1}^{n} A_i\ \sin(i\omega k\,\Delta T + \theta_i) \tag{5}$$

where n is the number of harmonics, A is the amplitude and ΔT is the sampling interval.

For the next time step $k+1$:

$$Z_{k+1} = \sum_{i=1}^{n} A_i\ \sin(i\omega(k+1)\,\Delta T + \theta_i) \tag{6}$$

Each frequency component requires two state variables. Thus, the total number of state variables is $2n$. These state variables are defined, at any time instant k, as follows:

$$\begin{array}{lll} \text{For 1st harmonic}: & x_1 = A_1\ \cos(\theta_1) & x_2 = A_1\ \sin(\theta_1 \\ \text{For 2nd harmonic}: & x_3 = A_2\ \cos(\theta_2) & x_4 = A_2\ \sin(\theta_2) \\ \cdots & \cdots & \cdots \\ \text{For } n\text{th harmonic}: & x_{2n-1} = A_n\ \cos(\theta_n) & x_{2n} = A_n\ \sin(\theta_n) \end{array} \tag{7}$$

The following relationship can be obtained:

$$x_{k+1} = \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_{2n-1} \\ x_{2n} \end{pmatrix}_{k+1} = \begin{bmatrix} 1 & 0 & \cdots & 0 & 0 \\ 0 & 1 & \cdots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & 1 & 0 \\ 0 & 0 & \cdots & 0 & 1 \end{bmatrix} \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_{2n-1} \\ x_{2n} \end{pmatrix}_k + w_k \tag{8}$$

Consequently, the measurement equation can be then expressed as:

$$z_k = H_k x_k + v_k = \begin{pmatrix} \sin(\omega k\ \ \Delta T) \\ \cos(\omega k\,\Delta T) \\ \vdots \\ \sin(n\omega k\,\Delta T) \\ \cos(n\omega k\,\Delta T) \end{pmatrix}^T \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_{2n-1} \\ x_{2n} \end{pmatrix}_k + v_k \tag{9}$$

where H is the matrix giving the ideal connection between the measurement and the state vector at time t_k and v_k is the measurement error, v_k is the details of the first level of DWT of the measurement signal.

The estimation of the process covariance, P^-, in the next time step $k+1$ can be obtained by the following equation:

$$P_{k+1}^- = \phi_k P_k \phi_k^T + Q_k \tag{10}$$

Q_k is the covariance matrix of w_k and is assumed to be equal to the identity matrix in this model [27].

The Kalman gain, K, can be computed as:

$$K_k = P_k^- H_k^T (H_k P_k^- H_k^T + R_k)^{-1} \tag{11}$$

R_k is the covariance matrix of v_k. The value of R_k is not assumed but it is considered the covariance of the details coefficients of the first level of DWT of the measurement signal.

$$E\left[v_k v_i^T\right] = \left\{ \begin{matrix} R_k, & i = k \\ 0, & i \neq k \end{matrix} \right\} \tag{12}$$

With this information the state estimation can be updated knowing the measured

$$\hat{x}_k = \hat{x}_k^- + K_k(z_k - H_k \hat{x}_k^-) \tag{13}$$

and the process covariance can be updated according to:

$$P_k = (I - K_k H_k) P_k^- \tag{14}$$