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A COMPARATIVE STUDY AND PERFORMANCE ANALYSIS OF COMMONLY USED SIGNAL PROCESSING TECHNIQUES IN POWER QUALITY APPLICATIONS

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Abstract. It is quite important to identify the power quality problems that may occur in the process from generation to distribution of electricity. The voltage obtained from an ideal three-phase alternating current source is a continuous sinusoidal voltage with approximately the same amplitude and 120° phase difference between them. Current or voltage distortions that may occur in power systems such as harmonics and the voltage sag, swell, and interruption cause the low quality of the power. These power quality disturbances may cause the failure of the devices used by the consumer, an increase in maintenance costs and current or voltage unbalance. The causes and types of problems must be well known to improve power quality. Especially if the type of power quality disturbances is classified correctly, the effects of disturbances under load can be identified, the source of the disturbances can be analyzed and thus appropriate solution methods can be developed. It is obtained that the increasing system reliability, reducing line losses, and increasing energy efficiency thanks to improving the power quality. Power quality problems are generally described as waveform distortions in a current and voltage. Sinusoidal distortions in voltage and current waveforms in the electric grid create harmonics. In this study, the purification of harmonics is provided by using signal processing techniques commonly used in different applications in the literature. The optimum signal processing technique to be used in solving power quality problems is determined It is presented comparatively simulation results of signal processing techniques that Fourier Transform (FT), Short-Time Fourier Transform (STFT) and Wavelet Transform (WT). the. The analysis results show that WT is superior to other used transform techniques for signal processing. The signals can be analyzed locally by obtaining low-frequency information in long-time intervals and high-frequency information in a short time interval thanks to the WT.

Keywords: signal processing, power quality, wavelet transform, short-time fourier transform, fourier transform.

INTRODUCTION

The demand for energy is increasing with the rapid development of technology day by day. The number of electronic devices used in homes and industry is also increasing rapidly. As a result of the increase in the use of non-linear loads, disturbance in power quality has occurred. The critical loads may be adversely affected by power quality problems. Many signal processing techniques are widely used to analyze power quality problems. Generally, the purpose of signal processing is to improve signal components in noise measurements or to transform the measured data sets so that new features are visible. The rapid development of signal processing techniques has made it possible to analyze the performance of a system and the quality of its signals. Signal processing tools used for the analysis of a system are tools that work in the time domain or frequency domain. Signal processing in power systems allows the analysis of voltage and current signals that are impossible to detect using conventional measurement devices. These techniques reveal new ways to define new concepts of electric power in non-stationary regimes. In signal processing techniques, new control algorithms are used to increase system efficiency. Researchers have used different signal processing techniques in different areas to improve the quality of the signal analysis.

The acoustic emission (AE) signals from the rolling contact fatigue (RCF) tests were analyzed. The wavelet packet transform method is proposed to extract a single effective signal in the rail contact fatigue test. The application of the wavelet packet transform to acoustic emission signals has been shown to be an effective and powerful numerical method for analyzing these signals and filtering their noise (Bianchi et al., 2015). An empirical WT based on the data-driven adaptive Fourier spectrum segment method is presented for mechanical fault detection. One of the main purposes of the paper is that the description of the mechanical failure property can be obtained by separating the signal in several empirical modes with physical meanings (Pan et al., 2016). A review about analyzing by WT method in rotating machine fault diagnosis is presented. The WT method has been used to extract natural modulation information by separating the signal into mono components. The proposed method has been applied to successfully identify the failure characteristic of the generator bearing on the wind turbine in the wind farm (Chen et al., 2016). A new approach using WT is proposed for arc error analysis in DA systems. The basic feasibility of the WT application is presented. The results showed that the WT method is extraordinarily effective in detecting the moment the signal changes (Wang & Balog, 2015).

It is aimed to reveal the advantages of the WT method compared to the FT method in detecting rotor failure of induction motors (da Costa et al., 2015). FT fault detection was carried out by examining two sideband components visible around the supply frequency component. Satisfactory results have been obtained with this approach. The results revealed that the WT method can be considered as a complement of the traditional FT method to the unstable states. The current approaches and methods in the rapidly growing FT-based optical communication field are classified under a common framework. It has been observed that the nonlinear FT is more effective in the analysis of nonlinear spectra and signals than conventional Fourier processes in the field of optics (Turitsyn et al., 2017). Image processing analysis is presented for color image development that processes three color components simultaneously. The image enhancement procedure is supported by the two-dimensional discrete quaternion FT and the new multi-frequency band α-rooting concept (Grigoryan et al. 2015). An accurate and effective method has been proposed for parameter estimation by fractional FT. The algorithm has progressed iteratively by repeatedly rotating the parameter estimates of the most dominant signal component (Zhao et al., 2016). Multichannel random Discrete Fractional FT with random weighting coefficients and partial transform kernel functions is proposed. Then, the kernel functions selected according to a selection scheme are selected using random phase-only masks (Kang et al. 2015). A new method of data stored in images encoded using modern signal processing and discrete FT has been proposed (Liao et al. 2017). Time frequency techniques are used to define and solve the vibration problem occurring in the rotor. Three signal processing tools, STFT, Continuous Wavelet Transform (CWT) and Hilbert Huang Transform, were compared to evaluate the detection performance. The results revealed that when using CWT, the resolution of the main wavelength needs to be adjusted appropriately to detect errors (Chandra & Sekhar, 2016). A new identification method based on STFT and neural networks is presented to improve the recognition rate of radar emitters with complex signal systems in an electromagnetic environment. STFT radar emitter has obtained the time-frequency distribution of pulse-pulsed modulated signals with the proposed method (Wang X. et al., 2017). It combines the time-frequency distribution concepts with the non-negative matrix factorization method, and a new method of time-frequency distribution matrix factorization is proposed to improve the identification of motor bearing failure. The time-frequency distribution of a vibration signal was first performed to describe localized errors by STFT (Gao et al., 2015).

STFT and a definition method based on neural networks are examined for the diagnosis of induction motors. The vibration signals of different fault motors are collected. The raw signal was pre-processed using STFT to obtain the corresponding time-frequency map (Wang et al., 2017). The extracted properties of the signals were analyzed to recognize arm movements. STFT and WT based on Euclidean distance are applied to reordered signals. The STFT resulted in a signal representation along the time-frequency-amplitude axes. This means it gives information about the frequencies found in the signal and when they occurred. It is obtained that critical information at both the analysis and synthesis of the original signal thanks to the WT. (Veer & Agarwal, 2015).

The signal processing techniques used in different applications and analyzes in the last five years have been examined with a literature review. It was determined that the most used signal processing techniques in the literature are WT, FT, discrete-time FT and STFT. In this study, the efficiency of the signal processing techniques commonly used in the literature in solving power quality problems is revealed. The efficiency of four effective signal processing techniques in reducing sinusoidal wave distortion has been determined by performance analysis results.

COMMON SIGNAL PROCESSING METHODS AND ANALYSIS RESULTS IN POWER QUALITY PROBLEMS

A. FOURIER TRANSFORM

One of the most used techniques in signal processing in the field of power quality is the FT method. This method is a transformation that enables the separation of a noiseless or noise irregularly changing signal into the frequency values it contains. With Fourier analysis, a signal in the time domain is

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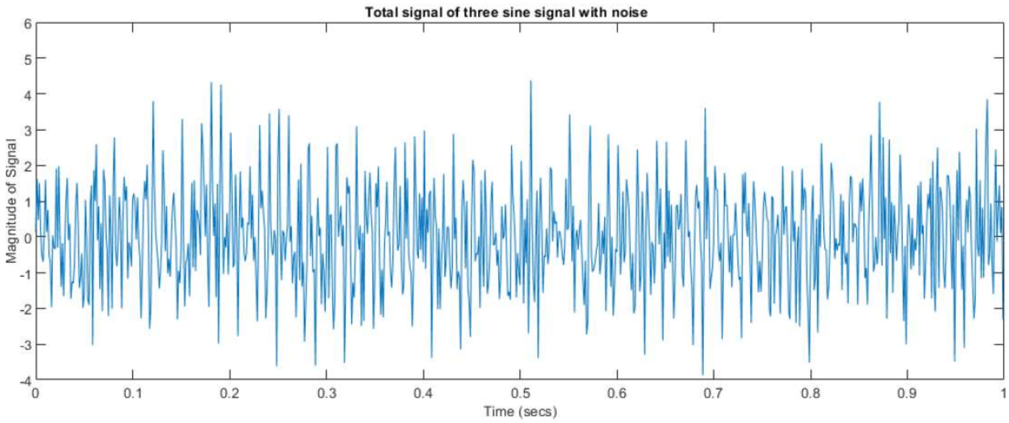
transferred to the frequency domain and the frequency information of the signal, which frequency values are not known, is reached. However, different frequency values obtained by the FT method do not give information about which frequency values in which time interval. As a result of this situation, it is a very effective conversion method in the conversion of signals that do not change with time. Continuous-time FT is shown in Equation (1). On the other hand, discrete-time FT is as shown in Equation (2). FT is a very effective method for determining harmonics occurring in signals. In this way, it becomes easier to determine the filter to be designed to eliminate harmonics.

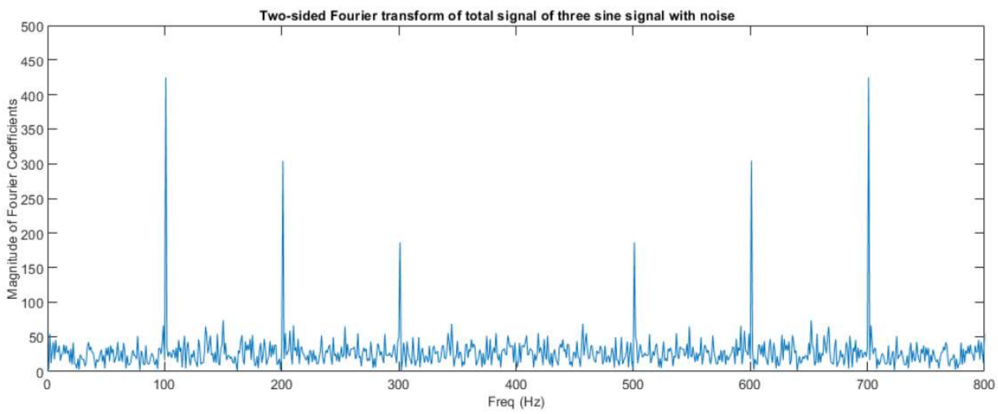
$$f(\omega) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{+\infty} f(x) e^{-j\omega x} dx \tag{1}$$

$$X(e^{j\Omega}) = \sum_{n=-\infty}^{\infty} x[n] e^{-j\Omega} \tag{2}$$

MATLAB software was used to compare the performance of signal processing techniques. First of all, current signals with three different frequency values were collected and the noise was added to the resulting signal. The frequency values are chosen randomly. And then the FT is applied to the resulting signal. In the following sections, STFT and CWT applications were also carried out on this signal. As seen in Figure 1, as a result of Fourier analysis, it is seen that the noise signal has 100 Hz, 200 Hz and 300 Hz frequency values. However, there is no information about the time interval in which these frequency values are available.



(a)



(b)

Figure 1. (a) **Total signal of three sine signal with noise** (b) **Fourier Transform of total signal**

A. SHORT-TIME FOURIER TRANSFORM

The STFT is a type of FT used to find the frequency and phase of the local parts of a time varying sinusoidal signal. In the analysis of transient states occurring in power quality signals, the FT cannot give the desired information. At this point, the harmonic information in the transient state of the signal is obtained by STFT. The advantage of the STFT technique is that it can provide the desired harmonic information in a defined time window and as a natural result of this, the harmonic content of the signal in any desired time interval. However, the disadvantage of this conversion method is that it only gives information about frequency components in the relevant time interval. Analyzing a continuous-time signal with this transformation method is as in Equation (3), (4) and (5).

$$KZFD\{s(t)\} \equiv \Upsilon(b,\omega) = \int_{-\infty}^{+\infty} s(t).\phi_{b,\,\omega}(t)\,dt \tag{3}$$

$$\phi_{b,\,\omega}(t) \equiv \phi(t-b).e^{-j\omega t} \tag{4}$$

$$\Upsilon(b,\omega) = \int_{-\infty}^{+\infty} s(t).\phi(t-b).e^{-j\omega t}\,dt \tag{5}$$

Where $\phi(t)$ is the window function. $s(t)$ is the signal to be transformed. b is the magnitude of the shift value in the analyzed signal. Discrete-time STFT of $\Upsilon(n,\omega)$ is shown in Equation (6).

$$KZFD\{s[k]\} \equiv \Upsilon(n,\omega) = \sum_{k=0}^{N-1} s[k].\phi\,[k-n].e^{-j\omega k} \tag{6}$$

Where ω is equal to $2\pi n / N$. N is the length of $s[k]$; $n = 1,.., N$; and $\phi[k-n]$ is a selected window that slides over the analyzed signal. This technique has some disadvantages such as low resolution for non-periodic signals. It is divided into equal-sized window sizes on the sampled signal. When this sampled signal has a high-frequency value within the window size, it will give low-resolution frequency information as a result of the transformation. In Figure 2, information about frequency and time information is obtained as a result of the STFT of our noise current signal to be analyzed. However, no information about the magnitude of our signal is available at these frequency and time values.

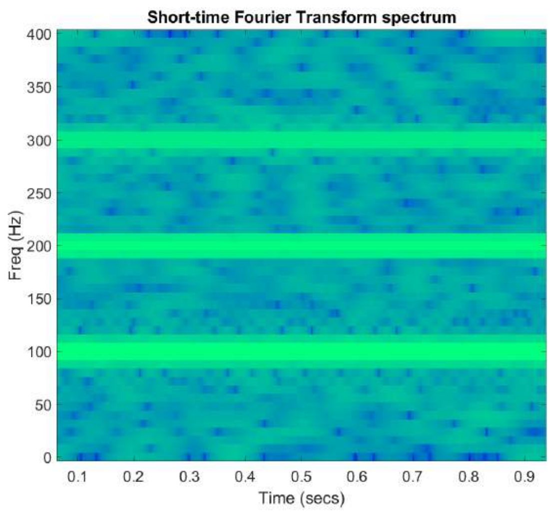


Figure 2. **Short-time Fourier Transform Spectrum**

A. WAVELET TRANSFORM

WT is one of the signal processing methods used to obtain better frequency or time resolution from the signal to be analyzed. WT is based on the decomposition of a signal to be analyzed into small waves to be obtained from a fixed wavelet function called "mother wavelet". The most important advantage of this transformation is that it allows different window widths. WT allows the use of long time intervals when high resolution is required at low frequencies and small intervals where high-frequency information is required. Thanks to this feature, it has a more effective structure than other signal processing techniques.

$$CWT(a,b) = \int_{-\infty}^{+\infty} s(t)\Psi^{*}_{a,b}(t)dt \tag{7}$$

$$\Psi_{a,b}(t) = \frac{1}{\sqrt{a}}\Psi\left(\frac{t-a}{b}\right) \tag{8}$$

In the equation, $s(t)$ is the time-dependent signal to be analyzed. $\Psi_{a,b}(t)$ is the mother wavelet and the symbol * means complex conjugate. a indicates the shift factor in time and b indicates the scale change. In this way, functions generated from the mother wavelet retain their shape while changing their position and size. As a result of the WT, the information about the magnitude and frequency values of the signal in which time interval can be reached.

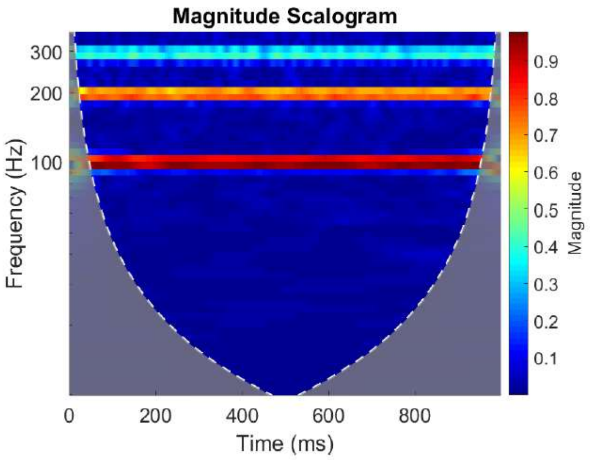


Figure 3. **Continuous-time wavelet transform analysis**

As a result of the CWT analysis, it is found that the noise signal has 100Hz, 200Hz and 300Hz frequency values as seen in Figure 3. However, thanks to the transformation, it can be observed which magnitude of the signal has these frequency values. As a result of the WT, reaching data about the magnitude of the signal, frequency and time information makes the WT superior to other transformation techniques.

CONCLUSIONS

The FT gives information about which frequencies the signal contains. However, it does not provide information about the time and magnitude of the signal as a result of this transformation. In other words, no change can be observed in the FT according to the time of the signal. STFT gives frequency information in an equal time interval. However, the selected time interval will be the same for each frequency value, which means low-resolution information for high-frequency values. WT gives information about which frequency value of the signal belongs to which magnitude signal and its time. WT allows the use of long time intervals when high-resolution information is required at low frequencies, and on the other hand, when high-frequency information is required, a small-time interval is used. Due to these properties, it has been presented that WT performs more effectively than other transformations in power quality signal analysis.

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