NUCLEAR POWER PLANT MONITORING USING WAVELET ANALYSIS AND DATA VISUALIZATION

Aucyone Augusto da Silva
Instituto de Pesquisas Energeticas e Nucleares, CNEN/S.P.
Travessa R, 400 - caixa postal 11049
CEP:05508-900 - São Paulo / Brasil
e mail: dasilva@net.ipen.br

Belle R. Upadhyaya
The University of Tennessee
Nuclear Engineering Department
Knoxville, TN 37996-2300, USA

ABSTRACT

The purpose of this research is to develop a systematic approach for fault monitoring and diagnosis for nuclear power plant systems using discrete wavelet transform and short-time Fourier transform techniques during stationary and transient operating conditions. This research explored the significant improvements in the signal-to-noise ratio when the original signal was decomposed into different levels using the multiresolution analysis (MRA) technique. The MRA was combined with the standard digital signal processing techniques for diagnostics purposes. A data analysis and visualization system, that integrates several MATLAB™ signal processing tools, was developed and implemented with applications to a commercial pressurized water reactor. The problems to be investigated in nuclear power plant systems were concerned with the detection and characterization of transients in the data. The stationary or time-dependent characteristics of fuel channel vibration and the estimation of the frequency characteristics of the transient signals were analyzed using the multiresolution analysis. The reactor data analysis, in the time-frequency domain, also revealed the dominant frequencies triggering dips and spikes in the transmitter's output signals.

Key words: fault monitoring, fault diagnosis, wavelet transform, nuclear power plant monitoring, multiresolution analysis.

1. INTRODUCTION

The demand for monitoring and fault diagnosis of process dynamics and sensors in industrial systems has increased the efforts to develop new data analysis techniques. The main goal of this technological improvement is to obtain more detailed information contained in the measured data than had been previously possible. Standard digital signals processing techniques, such as time series statistics, correlation analysis and fast Fourier transform (FFT) have been used to detect faults in plant components. These techniques are not always effective in detecting short-term anomalies and in tracking nonstationary signals.

The early detection of anomalies in complex industrial systems is crucial for safety and economic operation. The challenge is to identify and characterize the causes of the anomalies during the incipient stage because the signals are sometimes weakened by noise background. New technologies are being developed for monitoring and fault diagnosis of plant systems. These technologies help to enhance decision making for maintenance and system reconfiguration.

Systems that operate in a stationary mode are usually analyzed with standard Fourier transform techniques. When a system is nonstationary or undergoes a transient, the Fourier technique does not provide proper information about the signals. The analysis of nonstationary signals should be performed using time-frequency (Short-Time Fourier Transform (STFT)) and time-scale (wavelet transform) techniques. The integration of STFT and wavelet transform provides a more powerful tool for signal monitoring than the standard FFT analysis.

2. WAVELET AND SHORT-TIME FOURIER TRANSFORMS

The wavelet transform is a method of analyzing a signal using basis functions which are localized in time and frequency (or scale).

The original idea of wavelets can be found in the Haar transform at the beginning of the century and they were not popular until the early eighties. Researchers from geophysics, theoretical physics and mathematics developed a solid mathematical foundation for wavelets. Since then, this topic has been investigated by many in different areas of applications, particularly in engineering. In 1989, Mallat and Meyer[1] discovered a close relationship between wavelet and multiresolution analysis structure, which leads to a simple way of calculating the so called "mother wavelet." Their work also established a connection between continuous-time wavelets and digital filter banks. Daubechies developed a systematic technique for generating finite-duration orthonormal wavelets with FIR (Finite Impulse Response) filter banks[2]. Those results triggered a great interest in the mathematics as well as signal processing communities. Due to the efficiency in representing nonstationary signals, such as speech and image/video, wavelet analysis has become one of the most active research areas.

The signals that usually surround us often require a detailed analysis in order to understand the phenomena that generate them. These signals could be originated by the seismic tremors, human speech, engine vibrations, medical images, financial data, music, and many others and they have to be encoded, compressed, reconstructed, described, simplified, distinguished, or located. Wavelet analysis is a tool and technique for accomplishing these tasks.

The Fourier analysis is essentially a mathematical technique to transform the signal from the time domain to a frequency domain. The Fourier analysis is very useful for many applications where the signals are stationary. In this case, we are not interested in the time information. The Fourier transform is not appropriate to analyze a signal that has a transitory characteristic such as drifts, abrupt changes and frequency trends.

To overcome this problem, Gabor (1946)[3] adapted the Fourier transform to analyze small sections of the signal at a time. This technique is known as Short-Time Fourier Transform or windowing technique[4]. Gabor's adaptation maps a signal into a two-dimensional function of time and frequency. The mathematical expression is given by

$$STFT(\tau, f) = \int_{-\infty}^{\infty} x(t)g(t-\tau)e^{-2\pi ft}\,dt \tag{1}$$

This equation maps the signal into a two-dimensional function in a time-frequency plane (τ , f) and the analysis depends on the chosen window g (t') (Figure 1). Once the window g (t') is chosen the STFT resolution is fixed over the entire time-frequency plane.

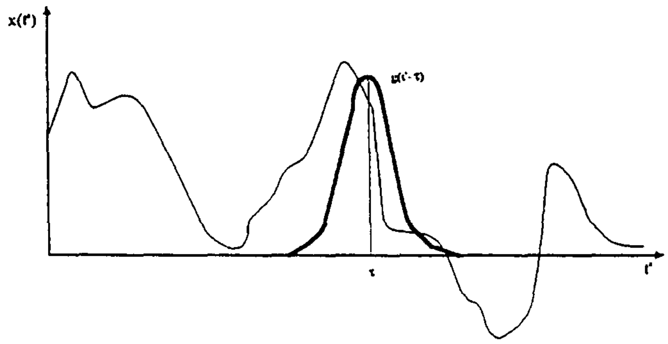

Figure 1. Short-time Fourier transform windowing process.

The STFT represents a compromise between time and frequency-based views of a signal and it provides some information about both. However, we can only obtain this information with limited precision, and that precision is determined by the size of the window. The fixed size window is the main drawback of the STFT (Figure 2). The STFT is limited by the uncertainty principle that does not allow achieving small resolution in time and frequency simultaneously. The resolution trade-off is that given an improvement in the time resolution, by using a short window, results in a loss of frequency resolution, and vice-versa. The Heisenberg inequality, that bounds the product of the bandwidth Δf and the time Δt, is given by

$$\Delta f \Delta t \geq \frac{1}{4\pi} \tag{2}$$

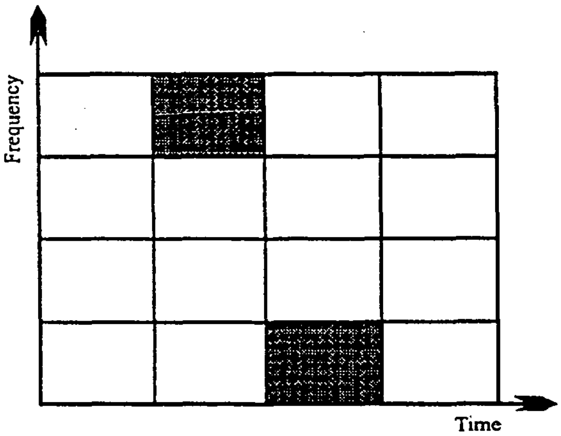

Figure 2. Bandwidth of STFT is uniform in the frequency domain

Usually the STFT plot representation is done by the so called STFT spectrogram which depicts a signal's energy distribution in the time-frequency domain [5].

The wavelet transform was introduced with the idea of overcoming the difficulties mentioned above. A windowing technique with variable-size region is then used to perform the signal analysis. Wavelet analysis allows the use of long time intervals where we want more precise low frequency information, and shorter intervals where we want high frequency information (Figure 3). The ability to perform local analysis is one of the most interesting features of the wavelet transform.

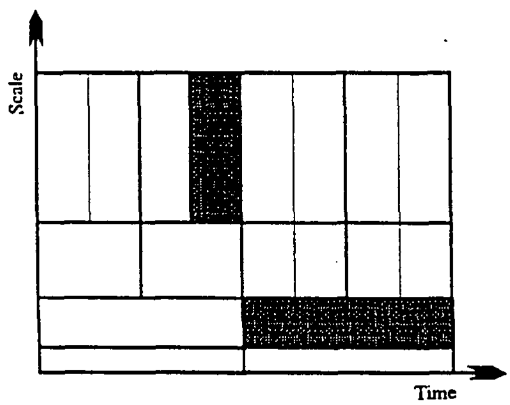

Figure 3. Bandwidth of the wavelet transform.

3. CONTINUOUS WAVELET TRANSFORM (CWT)[2],[7]

The class of functions that we are going to represent by the wavelet transform are those that are square integrable on the real line. This class is denoted as $L^2(R)$. Thus, the notation $f(x) \in L^2$ means

$$\int_{-\infty}^{\infty} |f(x)|^2 \, dx \, \langle \, \infty \, . \qquad (3)$$

The set of functions, that will be generated in the wavelet analysis, is obtained by dilating and translating a single prototype function $\psi(\mathbf{x})$ which is called a basic wavelet. This function is of oscillatory type and it is usually centered at the origin, that dies out rapidly as $|x| \to \infty$. Figure 4 shows an example of a wavelet.

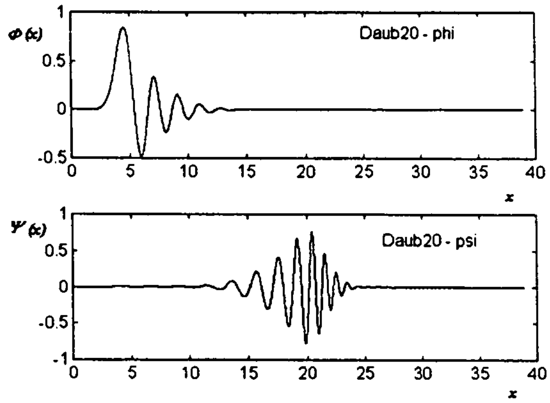

Figure 4. Daubechies wavelet basis function (Daub20)

The continuous wavelet transform is discussed in detail in Ref. [2,7].

The wavelet function denoted by the notation $\psi(\mathbf{x}) \in \mathbf{L}^2(\mathbf{R})$ has the parameters called translation b and dilation a that vary continuously. A set of wavelet basis functions, $\psi_{a,b}(\mathbf{x})$, can be generated by translating and dilating the basic wavelet $\psi(\mathbf{x})$ as

$$\psi_{a,b}(x) = \frac{1}{\sqrt{|a|}} \psi\left(\frac{x-b}{a}\right); \text{with } a, b \in R; a \neq 0 \qquad (4)$$

A "narrow" wavelet can access high frequency information and a wavelet that is more elongated can access low frequency information. This means that the parameter a corresponds to different frequencies. For better accuracy the time-interval should be relatively small to obtain high-frequency information and relatively wide for low-frequency information. These facts show that wavelet has a zoom-in and zoom-out capability, that is, the wavelet is flexible to provide a time-frequency window that contracts at high frequencies, as shown in Figure 3.

The continuous wavelet transform of a function $\mathbf{f} \in \mathbf{L}^2(\mathbf{R})$ is defined as

$$W_{a,b}(f) = \langle f, \psi_{a,b} \rangle = \int_{-\infty}^{\infty} f(x)\psi_{a,b}(x)dx. \tag{5}$$

The wavelet coefficients are given as the inner product of the function being transformed with each basis function. Considering that the wavelet $\psi(\mathbf{x})$ satisfies the admissibility condition

$$C_\psi = \int_{-\infty}^{\infty} \frac{|\hat{\psi}(\omega)|^2}{\omega} d\omega \langle \infty, \tag{6}$$

where $\hat{\psi}$ is the Fourier transform of ψ. Thus, we have

$$\hat{\psi}(0) = 0 \Rightarrow \int_{-\infty}^{\infty} \psi(x)dx = 0. \tag{7}$$

Then, the continuous wavelet transform $\mathbf{W}_{a,b}$ is invertible on its range, and the inverse transform is given by

$$f(x) = \frac{1}{C_\psi} \iint_{-\infty} W_{a,b}\psi_{a,b}(x) \frac{da\,db}{a^2}. \tag{8}$$

4. DISCRETE WAVELET TRANSFORM AND MULTIRESOLUTION ANALYSIS

The calculation of the wavelet coefficients using the continuous wavelet transform requires a considerable amount of work and it generates a large amount of data. The idea of using the Discrete Wavelet Transform (DWT) is to reduce this amount of work. The scales and positions are chosen based on powers of two, the so called dyadic scales and positions, and the analysis would be efficient and accurate.

An efficient algorithm to perform the DWT was introduced by Mallat and is well known in the signal processing area as two-channel sub-band coder. It is also known as Multiresolution Analysis (MRA), and was formulated based on the study of orthonormal compactly supported wavelet functions. The discrete representation of an orthonormal, compactly supported wavelet basis of $\mathbf{L}^2(\mathbf{R})$ is formed by dilation and translation of a single function $\psi(\mathbf{x})$, called the wavelet function

$$\psi_{j,k}(x) = 2^{\frac{-j}{2}} \psi(2^{-j}x - k);\ j,k \in Z; \tag{9}$$

where Z is the set of integers. The function ψ has M vanishing moments up to order M-1, and it satisfies the following " two-scale" difference equation

$$\psi(x) = \sqrt{2}\sum_{k=0}^{L-1} g_k \psi(2x-k). \qquad (10)$$

The wavelet function $\psi(\mathbf{x})$ has a companion, the scaling function $\phi(\mathbf{x})$, which also forms a set of orthonormal bases of $\mathbf{L}^2(\mathbf{R})$.

$$\phi_{j,k}(x) = 2^{\frac{-j}{2}}\phi(2^{-j}x-k); j,k \in Z. \qquad (11)$$

The scaling function satisfies

$$\int_{-\infty}^{\infty}\phi(x)dx = 1 \qquad (12)$$

and the two-scale difference equation

$$\phi(x) = \sqrt{2}\sum_{k=0}^{L-k} h_x \phi(2x-k) . \qquad (13)$$

In wavelet representation the coefficients $\mathbf{g}_k$ behave like a low-pass filter and $\mathbf{h}_k$ behave like a high-pass filter. These two filters are related by

$$g_k = (-1)^k h_{L-k}; k = 0,1..., L-1, \qquad (14)$$

and are called *Quadrature Mirror Filters* (QMF).

The dilation function of the discrete wavelet transform can be represented as a tree of low-pass and high pass-filters. The original signal is successively decomposed into components of low resolution, while the high frequency components are not analyzed any further. The maximum number of dilations that can be performed is dependent on the input size of the data to be analyzed, with 2N data samples enabling the breakdown of the signal into N discrete levels, using the discrete wavelet transform.

5. DATA ANALYSIS AND VISUALIZATION SYSTEM

The reactor data analysis and visualization were performed using the MATLAB™ Wavelet, Signal and Graphics Toolboxes. Several steps were performed during the data analysis, such as pre-processing the data, DWT and MRA analysis.

In the pre-processing stage the raw data were formatted and converted to ASCII type to be used with the MATLAB Toolbox Data Analysis System (Figure 5).

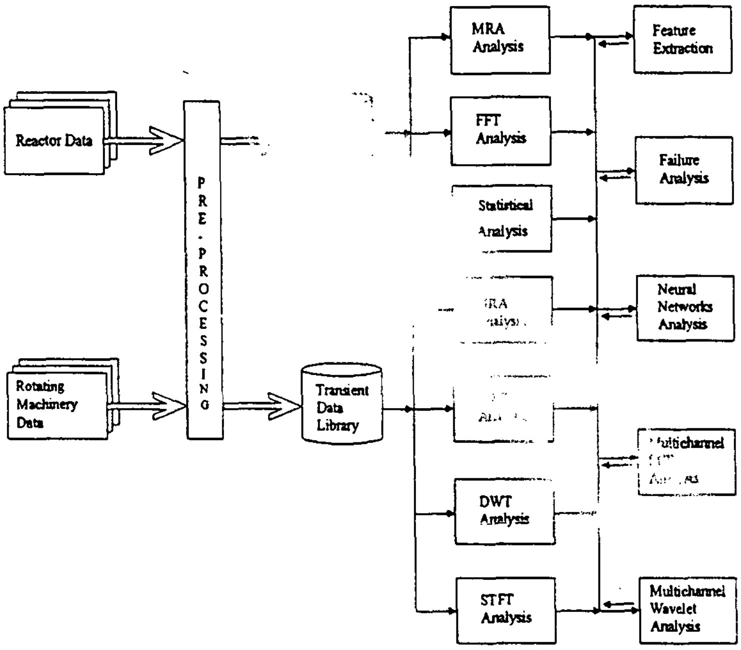

Figure 5. MATLAB data aanalysis system toolbox.

6. ANALYSIS OF NEUTRON DETECTOR AND PROCESS SENSOR SIGNALS FROM A PRESSURIZED WATER REACTOR

During the past decade wavelet transforms have been applied successfully to many problems in science and engineering. The integration and application of these methods to nuclear power plants is still under development. Some results of application to data from an operating pressurized water reactor (PWR) are presented in this section.

The nuclear power plant data, analyzed in this research, are measurements from flow and pressure transmitters from a PWR showing strong and irregular flow dips. The in-core flux detector signals, monitored during the full power reactor operation, are also analyzed. The nuclear power plant data analysis, using the wavelet and STFT techniques, pursues the detection and characterization of transients in the data. The detection of time dependency and stationary characteristics of fuel channel vibration, the estimation of the frequency contents of the transient signals, and the identification of signal changes are presented.

Figure 6 shows the time-amplitude signal for an in-core neutron detector. The FFT spectrum is plotted in Figure 7. Figure 8 shows the results obtained using MRA and STFT techniques and Figure 9 shows the discrete wavelet transform analysis.

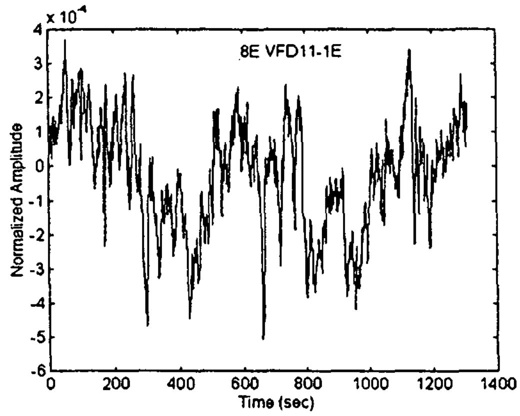

Figure 6. Time-Amplitude plot from in-core neutron detector (ID#5 Code: 8EVFD11-1E).

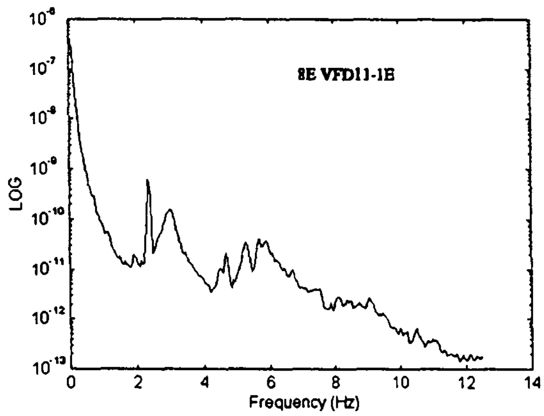

Figure 7. Auto power spectrum from the in-core neutron detector (ID#5 Code: 8EVFD11-1E)

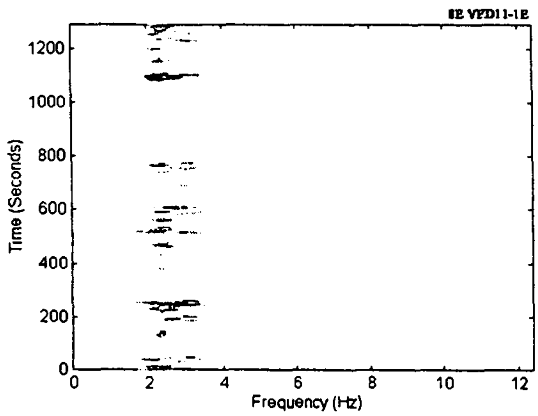

Figure 8. STFT and MRA contour plot for the detail level 3 in-core fuel assembly vibration signal (ID #5 Code: 8EVFD11-1E).

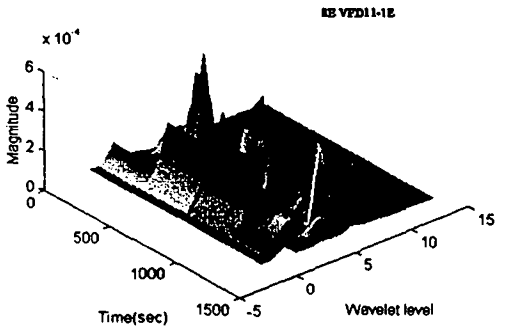

Figure 9. Three-dimensional DWT plot for the in-core fuel assemblyvibration signal (ID #5 Code: 8EVFD11-1E).

The results obtained from the analysis of flow and pressure signals are shown in Figures 10-13.

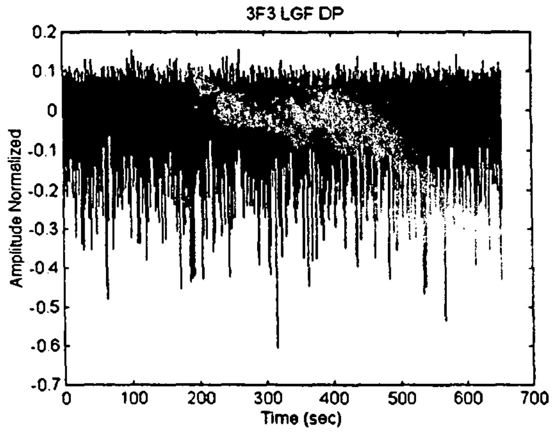

Figure 10. Time-amplitude plot of the flow sensor (Code:3FLGFDP).

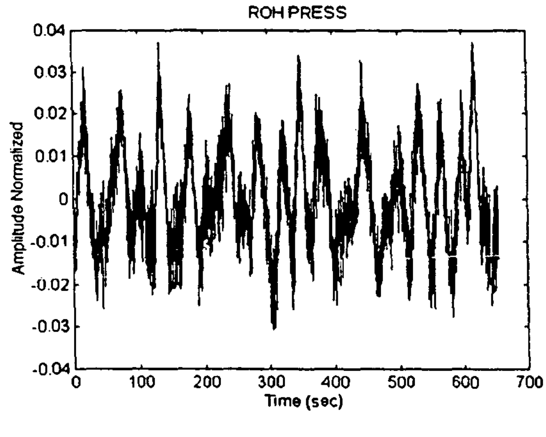

Figure 11. Time-amplitude plot of the pressure sensor.

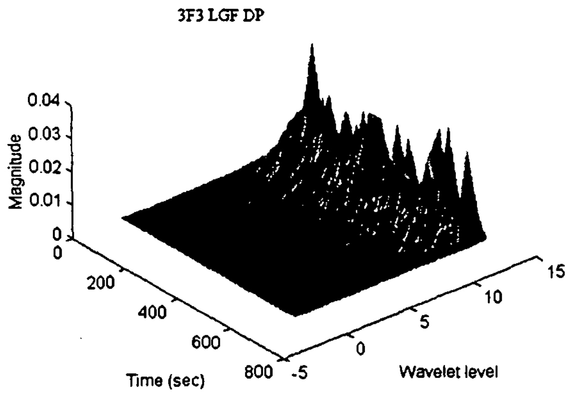

Figure 12. Three-dimensional plot of the DWT power spectrum for the flow sensor signal using Daubechies 20 wavelet(Code:3FLGFDP)

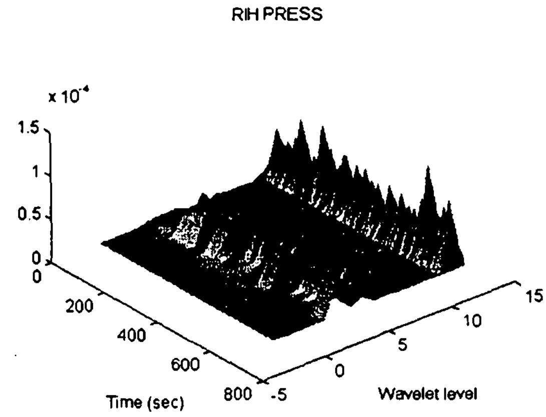

Figure 13. Three-dimensional plot of the DWT power spectrum for the pressure sensor signal using Daubechies 20 wavelet

7. CONCLUDING REMARKS

The application of wavelet and STFT transforms in nuclear power plant sensor signal analysis brought about a new insight into signature characterization when the system is under steady state or transient operation. The analysis method developed also pursued the detection and characterization of transients in a 515 MWe commercial PWR. The estimation of the frequency contents of the flow and pressure signals was made before, during and after the transients. The definition of time dependency and stationary characteristics of the fuel channel vibration and the estimation of the coherence and correlation functions between monitored sensor signals, were performed to reveal the dominant frequencies triggering the dips and spikes at the transmitter's output.

The fuel assembly vibration analysis was performed using the discrete wavelet and the STFT transforms, and the combined results from these techniques showed their potential for monitoring and diagnosis of possible sensor signal anomalies in the time-frequency domain. The DWT power spectrum obtained during the fuel assembly vibration data analysis showed that some anomalies were found at very low frequency ranges (low wavelet level < 0.2 Hz).

The primary goal of the analysis of the flow and pressure sensor signals was to define the frequencies where most of the spikes and dips that occur in the signals. To accomplish this objective, the discrete wavelet transform was used. The wavelet coefficients, that represent the transients, were visually portrayed in 3-D plots. The peaks in the wavelet power spectrum were associated with the time-scale or time-frequency domain.

The results obtained from the flow sensor analysis lead to the conclusion that most transient features are localized in the frequency range 3-12 Hz. The pressure sensor showed small anomalies at a frequency range 10-12 Hz and at low frequencies (<0.2 Hz).

The method introduced and developed in this research brought a new insight into the stationary and non-stationary data analysis activities for nuclear power plant systems.

AKNOWLEDGMENTS

We would like to thank the "Conselho Nacional de Pesquisas – CNPq" and "Comissão Nacional de Energia Nuclear - CNEN (Brasil)" for supporting this research.

REFERENCES

[1] S. Mallat, "A Theory for Multi-Resolution Signal Decomposition: The Wavelet Representation," IEEE Transaction on Pattern Analysis and Machine Intelligence, Vol. 11, No. 7, 674-693, July 1989.

[2] I. Daubechies, "Ten Lectures on Wavelets," Philadelphia, PA: Society for Industrial and Applied Mathematics, 1992.

[3] D. Gabor, "Theory of Communication," Journ. IEE, Vol. 93, No. III, pp. 429-457, London, November 1946.

[4] S. Qian and D. Chen, "The Joint Time-Frequency Analysis - Methods and Applications," Prentice-Hall, Englewood Cliffs, NJ, 1996.

[5] F. Hlawatsch and G. F. Bourdreaux-Bartels, "Linear and Quadratic Time-Frequency Signal Representations," IEEE Signal Processing Magazine, pp. 21-67, April 1992.

[6] C. K. Chui, "An Introduction to Wavelets," Academic Press, Boston, 1992.

[7] A.A. da Silva, "An Integrated Approach for Plant Monitoring and Diagnosis Using Multiresolution Wavelet Analysis," Ph.D. Dissertation, The University of Tennessee, December 1997.

Aucyone Da Silva

MARCON 99

Maintenance And Reliability CONference

PROCEEDINGS

May 10–12, 1999
Knoxville, Tennessee USA

UT

Sponsored by
Maintenance and Reliability Center
College of Engineering
The University of Tennessee, Knoxville

Volume 2 of 2