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Acoustic Emission Signal Processing Technique to Characterize Reactor In-Pile Phenomena

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Abstract. Existing and developing advanced sensor technologies and instrumentation will allow non-intrusive in-pile measurement of temperature, extension, and fission gases when coupled with advanced signal processing algorithms. The transmitted measured sensor signals from inside to the outside of containment structure are corrupted by noise and are attenuated, thereby reducing the signal strength and the signal-to-noise ratio. Identification and extraction of actual signal (representative of an in-pile phenomenon) is a challenging and complicated process. In the paper, empirical mode decomposition technique is utilized to reconstruct actual sensor signal by partially combining intrinsic mode functions. Reconstructed signal will correspond to phenomena and/or failure modes occurring inside the reactor. In addition, it allows accurate non-intrusive monitoring and trending of in-pile phenomena.

INTRODUCTION

In-pile instruments are used to detect and measure various physical parameters of fuels and materials during irradiation [1]. An ability to gather information on reactor in-pile phenomena can provide much needed understanding of fuel performance, material degradation, etc. This information can be used to validate simulation codes, refine simulation models, and assist preventing developing failure. Repeatedly removing samples from a reactor to measurements is expensive, has the potential to disturb phenomena of interest, and only provides understanding of the sample's end state when each measurement is made [2].

In the case of nuclear fuels during irradiation, the physical structure and chemical composition change as a function of time and position within the fuel pellet. For example, fuel pellets can swell, crack (micro-cracking), and fission gases can be released. These conditions can vary with time in the reactor, temperature, and fuel burn-up [3]. Woolstenhulme [4] discussed that a non-fuel component (the bottom plate) of the first fuel plate frame assembly became separated from the rail sides. The separation of this component was determined to have been caused by the flow-induced vibrations, where vortex-shedding frequencies were resonant with a natural frequency of the bottom plate component. This gave way to amplification, fracture, and separation from the assembly. It may have been possible to detect the destructive vortex induced vibrations had a vibrational baseline and active vibration monitoring been in place.

The vibrational characterization of a reactor during operation will be beneficial to the reactor operators. A well-designed vibrational characterization of the reactor will provide a baseline that will enable the development of acoustic based communication devices, diagnostic and prognostic techniques for structural monitoring of the reactor core and the experiments contained within. Although there are active activities to characterize machines and equipment outside the reactor, there is no comprehensive vibrational characterization to monitor activities inside a reactor.

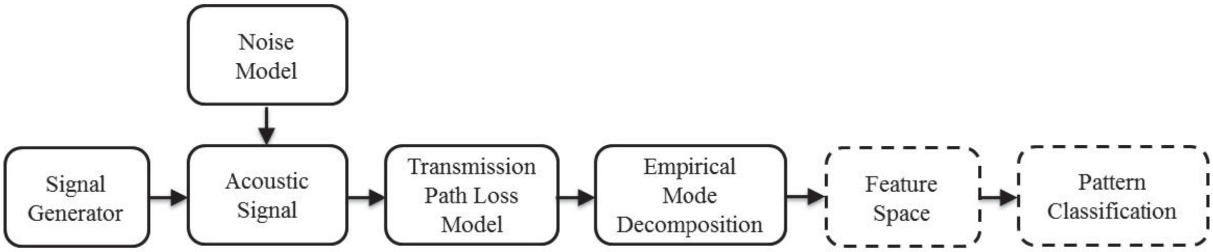


FIGURE 1. Proposed acoustic emission signal processing technique for in-pile phenomena characterization.

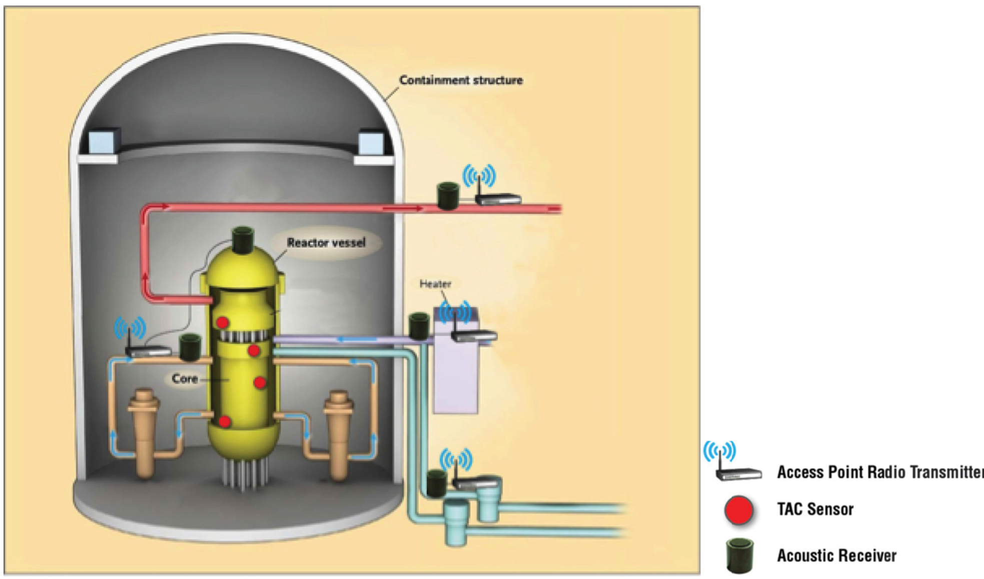


FIGURE 2. Proposed acoustic emission signal processing technique for in-pile phenomena characterization.

The paper proposes an acoustic emission signal processing technique (AESP) that would enable identification and classification of different in-pile phenomena and failure modes. Acoustic sensors, for example, Thermoacoustic Sensor (TAC) [5], can be configured to measure reactor temperature, extension, fission gasses, and pressure fluctuations [6]. The modules of the proposed approach will allow engineers to access raw data, process them using the empirical mode decomposition (EMD) technique, and extract information from the data while the experiment is still in progress inside the reactor. EMD has been widely used to extract actual signal information from noisy measured signals [7–9].

The paper is organized as follows: The modules of the proposed AESP technique are described in Section II. Brief discussions on the Gaussian noise and on transmission path loss models are presented in Sections III and IV respectively. The procedure to generate intrinsic mode functions (IMFs) by the EMD process is summarized in Section V. Section VI presents initial result and discussion. Finally, conclusion and future research activities are presented in Section VII.

PROPOSED APPROACH

The different modules of the proposed AESP technique, as shown in Fig. 1, include:

- *Signal Generator* will be used to generate acoustic emissions representative of different in-pile phenomena, in the absence of actual experimental data.
- A *Gaussian Noise model* is used to corrupt the sensor signal thereby changing the signal-to-noise (SNR) values.

- *Transmission attenuation* models will account for path loss between transmitted acoustic signal and external sensors receiving the signal.
- *Empirical mode decomposition technique* decomposes noisy signal into IMFs.
- *Feature Space and Pattern Classification* steps involve extracting appropriate features from the decomposed IMFs and design of classifier based on extracted features. Feature extraction and design of pattern classifier is currently beyond the scope of the paper.

GAUSSIAN NOISE MODEL

Fractional Gaussian noise is a generalization of white noise [10] and is implemented in the paper. It is closely linked with self-similar stochastic processes and random fractals both of which have been extensively considered in signal processing applications. It is expressed as incremental process of fractional Brownian motion and its statistical properties are controlled by a single parameter, H, known as the Hurst exponent. For detailed discussion on statistical properties of the noise model, refer [10]. The value H is within the range $[0,1]$ and $H = 0.5$ corresponds to white Gaussian noise.

TRANSMISSION PATH LOSS MODEL

In broad terms, path loss (*PL*) is a measure of the average radio frequency attenuation suffered by a transmitted signal when it arrives at the receiver, after traversing a path of several wavelengths. A general *PL* model uses a parameter γ, to denote the power-law relationship between the separation distance and the received power. So, path loss (in decibels) can be expressed as [11]

$$PL(d) = PL(d_0) + 10\gamma \log(d/d_0) + \varepsilon \tag{1}$$

where d is the distance between the receiver antenna and the transmitting antenna, d_0 is the received-power reference point (default 1m), $\gamma = 2$ characterizes free space, and ε denotes the zero-mean Gaussian random variable of standard deviation σ.

In practical applications, the assumption of free space is not realistic. The signal traverses through different mediums with different attenuation factors before reaching the user located receiver. In case of a nuclear infrastructure, the environment is very different; the transmission medium is subjected to high temperature and radiation that can impact the path loss as seen in Fig. 2. For the purpose of demonstration, TAC sensors can be placed at different locations outside the reactor pressure vessel, acoustic waves generated by the TAC sensors are collected at different access points inside and outside the containment structure. The path loss observed at each access point will be different because piping, conduits, and concrete structure have different attenuation factor. In this case, (1) does not hold and multipath propagation model is required. A detail review on different path models is presented in [12]. A detailed formulation of path loss model for the sensor configuration shown in Fig. 2 is beyond the scope of this paper. Authors assume that on an average the received signal strength is 10% less than the actual transmitted signal.

EMPIRICAL MODE DECOMPOSITION

Empirical mode decomposition proposed by Huang et al. [13] deals with nonlinear and non-stationary signals. It is an intuitive, direct, and adaptive approach as it derives the basis function from the signal itself unlike the Fourier transformation and Wavelets.

The IMFs obtained from the decomposition of the signal $x(t)$ by EMD must obey two general assumptions; (i) each intrinsic mode must have the same number of extrema and zero crossings or differ at most by one and (ii) must be symmetric with respect to the local zero mean. These two assumptions assist in defining meaningful instantaneous frequency of an IMF. Based on these assumptions, the sifting procedure to obtain IMFs of the signal $x(t)$ is described as follows. Figure 3 shows the EMD process.

1. Identify all the maxima and the minima in the signal $x(t)$.
   Generate its upper and lower envelopes using cubic spline interpolation.
2. Compute the point-by-point local mean m_1 from upper and lower envelopes.

3. Extract the details, $h_1 = x(t) - m_1$.
4. Check the properties of h_1 and iterate k times, then $h_{1k} = h_{1(k-1)} - m_{1k}$ becomes the IMF once it satisfies some stopping criterion. It is designated as first IMF $c_1 = h_{1k}$.
5. Repeat steps 1 to 5 on the extracted data $r_1 = x(t) - c_1$.
6. The step 6 is repeated until all the IMFs and residual is obtained.

The stopping criterion, the normalized squared difference between two successive *sifting* operations is defined as,

$$SD_k = \frac{\sum_{t=1}^{T} |h_{k-1}(t) - h_k(t)|^2}{\sum_{t=1}^{T} h_{k-1}^2}\,. \tag{2}$$

The SD_k value is generally set between 0.2 and 0.3. The decomposed signal can be represented as,

$$x(t) = \sum_{n=1}^{N} c_n + r_N \tag{3}$$

where N is the total number of IMFs and r_N is the final residue which can be either the mean trend or a constant.

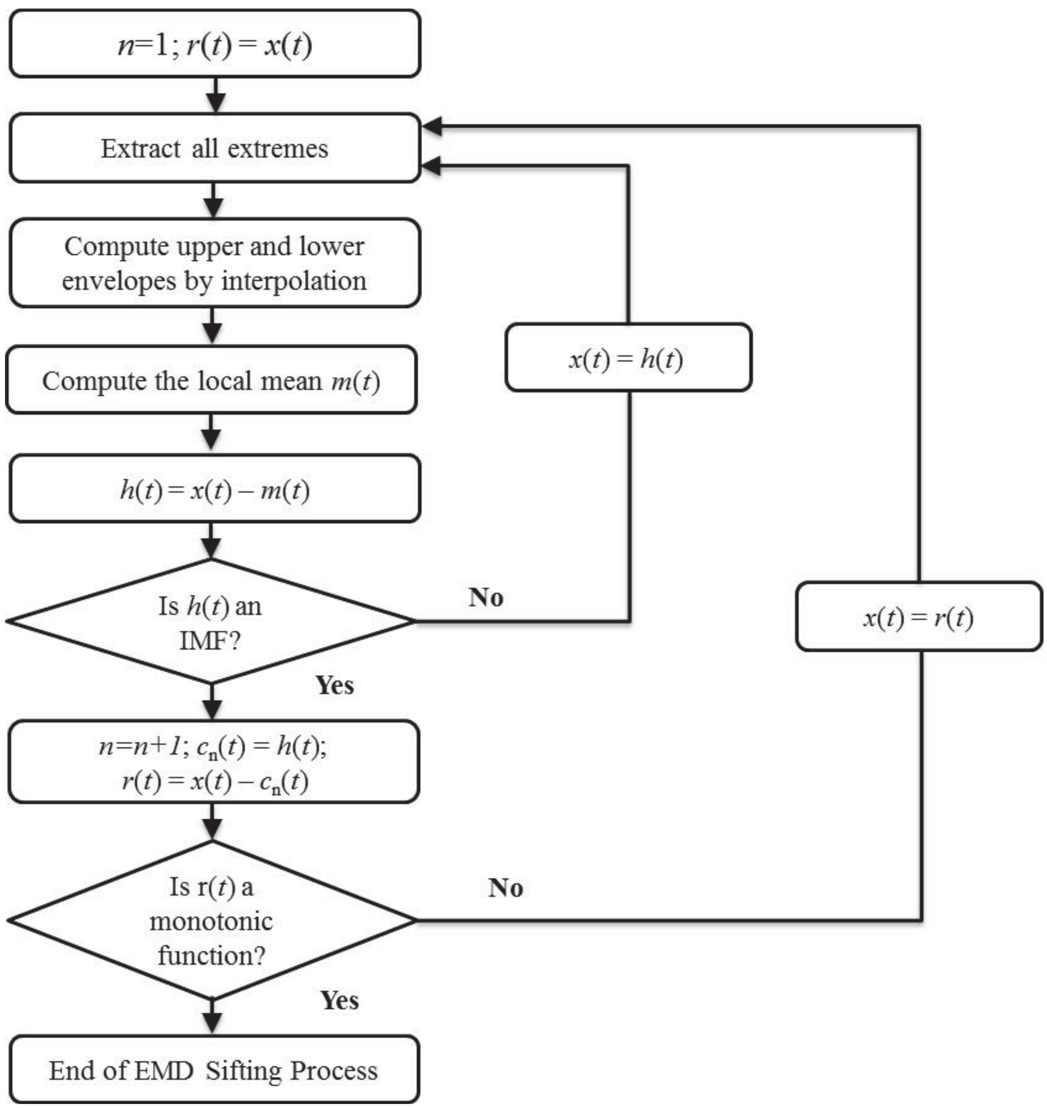


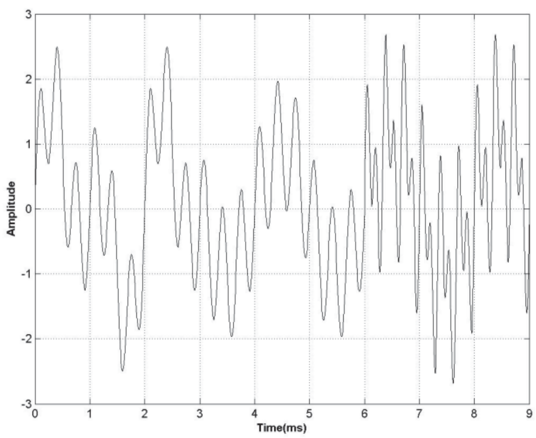
FIGURE 3. Signal decomposition using EMD.

INITIAL RESULT

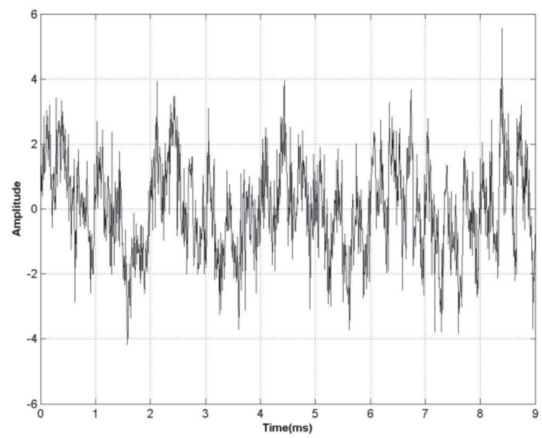
A signal is simulated; see Fig. 4(a), to represent a typical acoustic signal measured by an acoustic sensor. The simulated signal is corrupted with the Gaussian noise model as described in Section III. The noisy signal in Fig. 4(b) is subjected to attenuation as it is transmitted via different medium. It is assumed that the signal strength of the received signal is 10% less than the actual transmitted signal strength.

The noisy attenuated acoustic signal is decomposed to generate IMFs as per the EMD process. EMD of the signal results in IMFs c1 to c13 and a residual component as shown in Fig. 5. Each IMF represents a particular frequency component in the actual signal. However, the number of IMFs generated depends on user-defined stopping criteria. After obtaining the IMFs, energy information of each IMF is computed, as seen in Fig. 6, based on the energy model in [14]. From the energy information in Fig. 6, the IMFs c4 to c13 has more energy compared to IMFs c1 to c3. Therefore, based on this empirical observation, IMFs c4 to c12 are combined along with residual component to reconstruct the actual simulated signal. Figure 7 shows the reconstructed signal (top) and the simulated signal (bottom).

Based on simple energy information of IMFs, an accurate reconstruction of simulated acoustic signal is possible and is demonstrated. However this approach requires further rigorous evaluation.



(a)



(b)

FIGURE 4. (a) Simulated sensor signal and (b) Simulated sensor signal with Gaussian noise.

CONCLUSION AND FUTURE RESEARCH

The paper proposed an acoustic emission signal processing technique to recover actual information from the noisy and attenuated sensor signal. The proof-of-concept of the proposed technique was demonstrated via simulation. Empirical mode decomposition technique was used to decompose noisy signal into IMFs and recovery useful information by partially combining IMFs based on the energy model. The reconstruction obtained accurately represents the actual information.

The proposed approach lacks rigorous evaluation based on different path loss models and noise models, which is part of future research.

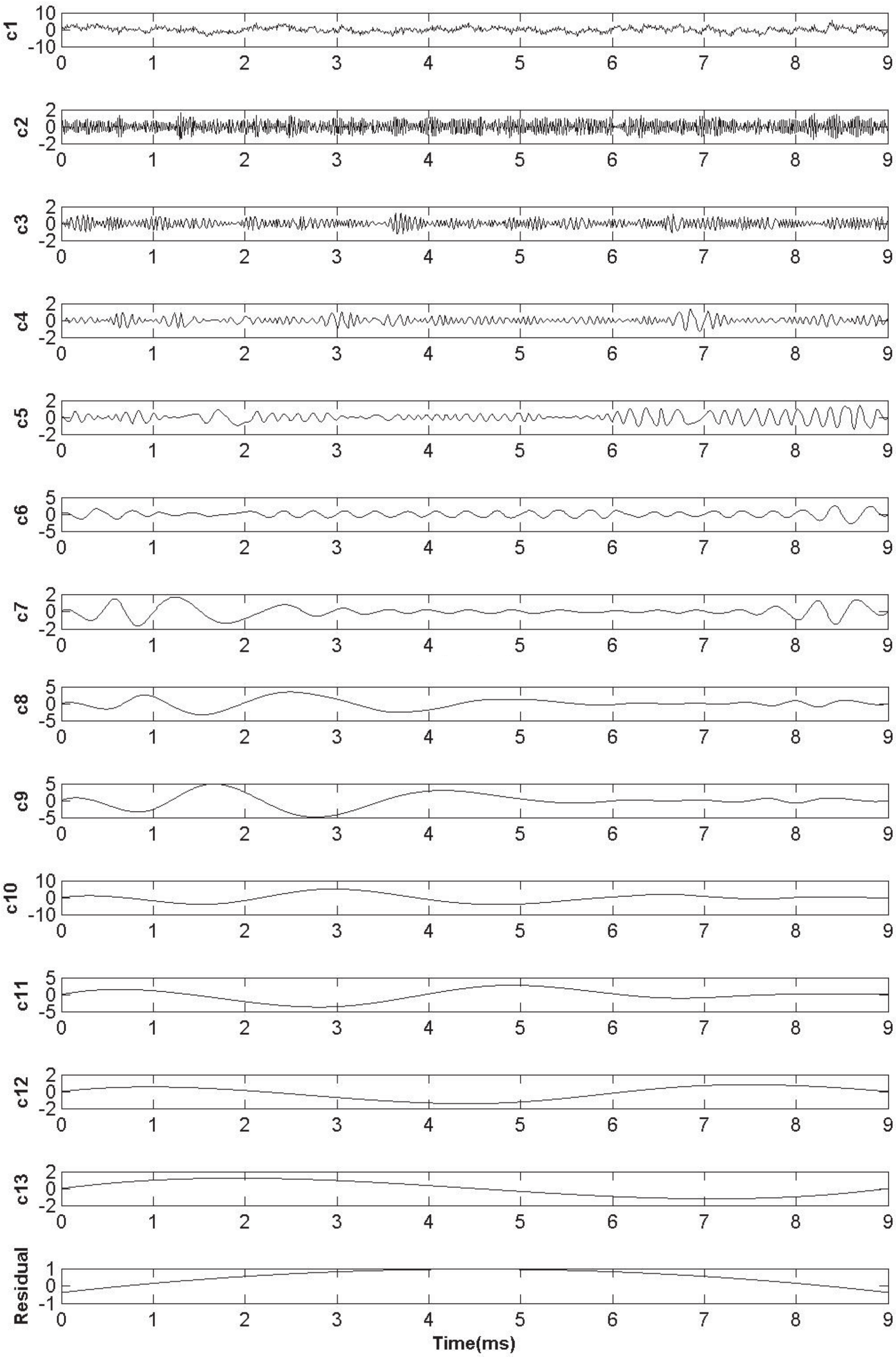


FIGURE 5. IMFs of simulated noisy signal (IMFs c1 to c13 and the residual component.

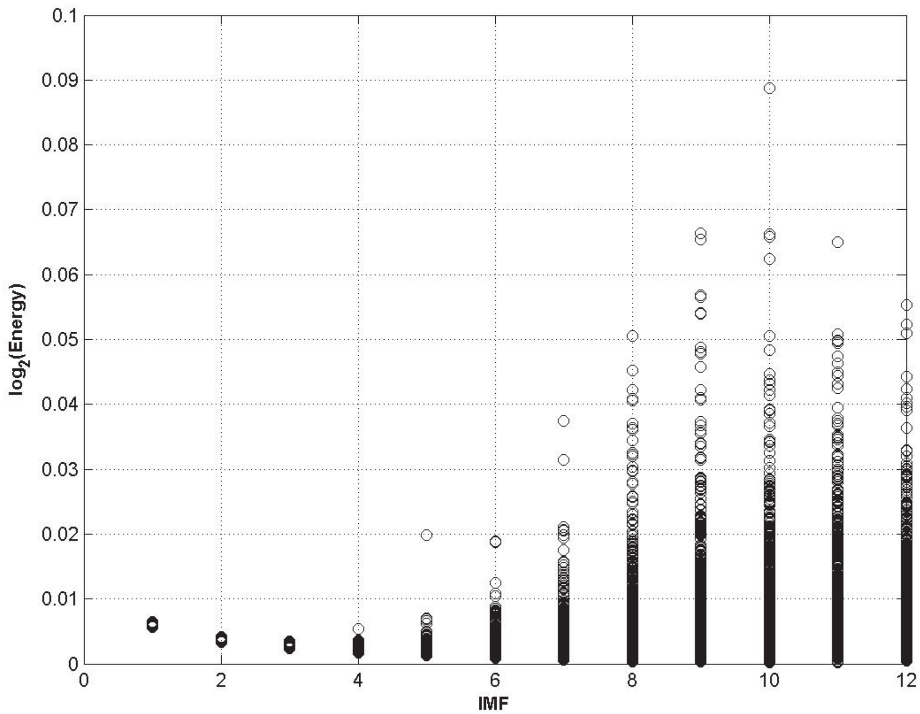


FIGURE 6. Energy of each IMF.

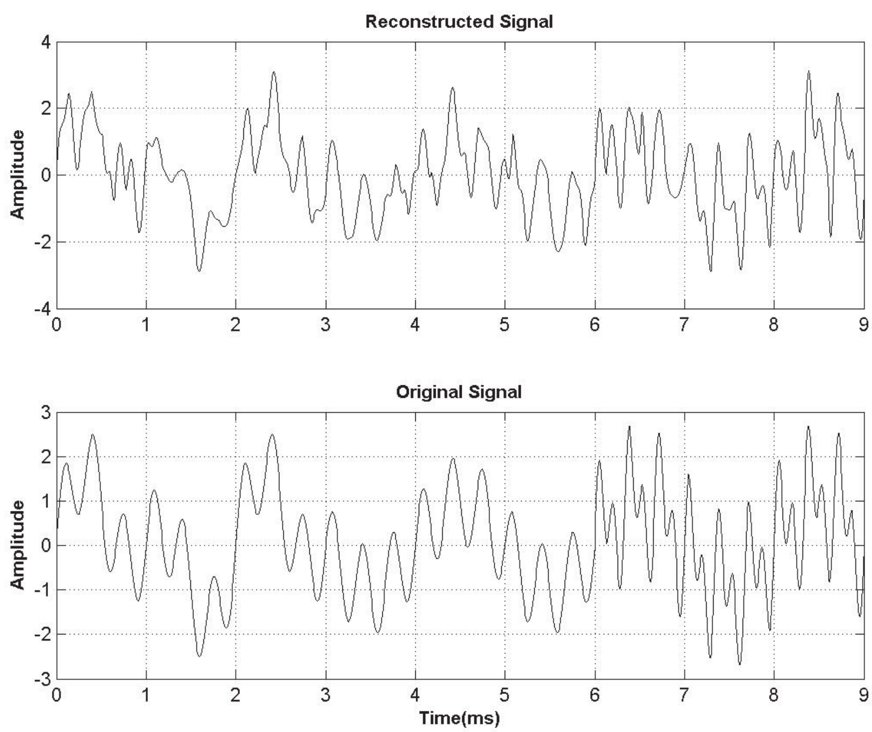


FIGURE 7. Reconstructed sensor signal by combining IMFs c4 to c13 and residual component (top) and simulated sensor signal (bottom).

DISCLAIMER

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