ARTICLE IN PRESS

Advanced Powder Technology xxx (2018) xxx–xxx

Contents lists available at ScienceDirect

Advanced Powder Technology

journal homepage: www.elsevier.com/locate/apt

Original Research Paper

Silo quake response spectrum of iron ore train load out bin

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ARTICLE INFO

Article history:
Received 18 May 2017
Received in revised form 22 July 2018
Accepted 30 July 2018
Available online xxxx

Keywords:
Silo
Silo quaking
Response spectrum
HHT
HMS

ABSTRACT

Silo quaking is a very complex industrial phenomenon and is often occurred in silo structures during discharge. There are three variants of the silo quaking phenomenon such as silo honking, silo shock and silo pulsation. Accelerometers are often used in practice to measure the responses of the structure. The accelerations generated by the silo structure during discharge are of non-linear and non-stationary nature. Therefore traditional algorithm, such as Fast Fourier Transform, which was designed to analyse linear and stationary signals and often used to analyse the collected acceleration data, is not suitable for signals generated by the silo structure during discharge. In the present research, Hilbert-Huang Transform and Hilbert Marginal Spectrum created by Norden Huang, a mathematician at NASA to analyse non-linear and non-stationary signals, were used to analyse the accelerograms collected from the experimental silo. The results revealed the existence of a silo quake spectrum which lays a solid foundation for further research into the silo quaking phenomenon and especially structural design methods to mitigate the effects of silo quaking on the silo structure.

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1. Introduction

Accelerometers are devices designed to measure the accelerations of a moving or vibrating body. Such devices can be found in the various field of engineering for example earthquake, structural health monitoring and vibrating machinery. The acceleration signals are often processed using a traditional algorithm, such as Fast Fourier Transform (FFT), which is an algorithm to transform signals from time domain to frequency domain [1]. As mentioned by He and Yi [2], FFT is more suited to stationary signal processing and feature extraction. The effectiveness of FFT algorithm decreases when processing non-linear and non-stationary problems according to He and Yi [2]. However, in most natural processes, the data is likely to be both non-linear and non-stationary [3]. Silo discharge under gravity is one of the natural processes and often associated with vibrations named silo quaking.

Silo quaking is a term used to describe the vibration characteristics of silos and their supporting structures during discharge. During discharge, it has been observed by various researchers such as Firewicz [4], Buick, Chavez-Sagarnaga, Ooi, Pankaj, Campbell and Greated [5] and Bennett and Kmita [6] that the flow is intermittent and pulsating. Furthermore, during discharge and filling, the total mass of the silo structure is constantly changing thus affecting the dynamic response characteristics of the silo structure. Thus a process of such complexity is best described as being non-linear and non-stationary.

There are three types of silo quakes such as silo honking, silo shock and silo pulsation [7]. The quaking causes several problems, which could lead to structural connections failure, reduced fatigue life of structural connections, computer data corruption, on-site personnel discomfort and health related issues, loss of production, increase in maintenance costs and catastrophic failure as noted by Chou, Chuang, Smid, Hsiau and Kuo [8]. It is believed that pulsation loads occur in most bins, whether the induced pulsating loads cause silo quake depend on the severity of the load, natural frequencies of the bin and its supporting structure [9].

In this paper, the Hilbert-Huang Transform (HHT) algorithm and Hilbert Marginal Spectrum (HMS) are proposed as alternative and more suitable methods in analysing acceleration signals resulting from silo quaking phenomenon. HHT is an empirically based data analysis method and consists of two parts, empirical mode decomposition and Hilbert spectral analysis. HHT was created in 1996 by Norden E. Huang, a mathematician at the National Aeronautics and Space Administration (NASA) and has been adopted in many research areas [3].

2. Hilbert-Huang Transform and Hilbert Marginal spectrum

The analysis methods prior to the development of Hilbert-Huang Transform (HHT) were either for linear but non-stationary, or

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https://doi.org/10.1016/j.apt.2018.07.026
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Please cite this article in press as: P. Tu et al., Silo quake response spectrum of iron ore train load out bin, Advanced Powder Technology (2018), https://doi.org/10.1016/j.apt.2018.07.026

non-linear but stationary and statistically deterministic [10]. However the data from real-world processes are non-linear, non-stationary and stochastic. Thus Hilbert-Huang Transform (HHT) was developed to address the need to analyse nonlinear and non-stationary signals that occur in natural processes. The HHT algorithm consists of two parts, empirical mode decomposition (EMD) and Hilbert transform (HT).

2.1. Empirical mode decomposition

Empirical mode decomposition is based on an assumption that any data consists of simple intrinsic modes of oscillations where each intrinsic mode represents a simple oscillation. The oscillation is assumed to be symmetric with respect to the local mean and different modes of oscillation superimposed to form the final complicated data. Each mode of oscillation is represented by an intrinsic mode function (IMF). An IMF has to satisfy the following conditions [2]:

1. The number of extrema and the number of zero-crossings must either equal or differ at most by one.
2. The mean value of the envelopes defined by the local maxima and the local minima is zero.

According to Huang, Shen, Long, Wu, Shih, Zheng, Yen, Tung and Liu [10], the first condition is similar to the narrowband requirements for stationary Gaussian process whereas the second requirement was invented to that the instantaneous frequency will not have unwanted fluctuations induced by asymmetric waveforms. The practical implementation of EMD or sifting process outlined by Su and Chuang [11] for a given signal $x(t)$ is as follows:

1. Identify the extrema of the signal $x(t)$, and generate the upper and lower envelops defined by the cubic spline interpolation of the extrema point.
2. Compute the mean, $m(t)$ by averaging the upper and lower envelops and compute the first component $h(t) = x(t) - m(t)$
3. If the first component is not an IMF then let $h_1(t)$ be the new data set and repeat step 1 and 2 until an IMF is found.
4. The first IMF component $h_1(t)$ is called $c_1(t)$. Therefore $r_1(t) = x(t) - c_1(t)$. Repeat steps 1–3 until the $r_N(t)$ obtained is monotonic.

At the end of the sifting process, the original data $x(t)$ is decomposed into a set of IMFs satisfying Eq. (1)

$$x(t) = \sum_{j=1}^{N} c_j + r_N \tag{1}$$

Despite the usefulness of EMD, it suffers a major drawback called mode mixing as identified by Wu and Huang [12] and especially when it is applied to noisy data as demonstrated by Wang, Zhang, Yu and Zhang [13]. Mode mixing is defined as a single IMF either consisting of signals of disparate scales or signals of the similar scale residing in different IMF. The presence of mode mixing causes serious aliasing in the time-frequency distribution and also makes the physical meaning of each IMF unclear [12].

In order to overcome the scale separation problem the Ensemble Empirical Mode Decomposition (EEMD) was introduced by Wu and Huang [12]. The EEMD algorithm defines the true IMF components as the mean of an ensemble of trials where each trial consists of the signal plus a white noise of finite amplitude. The development of the EEMD algorithm was inspired by the work initiated by Flandrin, Gonçalves and Rilling [14] where it was demonstrated that added noise could help data analysis. According to Wu and Huang [12] the added white noise series cancel each other in the final mean of the corresponding IMFs. The mean IMFs stay within the natural dyadic filter windows thus reducing the chance of mode mixing. The practical implementation of EEMD as per Wu and Huang [12] is as follows:

1. Add a white noise series to the targeted data as shown in Eq. (2) where $w_i(t)$ is different realisations of Gaussian noise.
2. Decompose the data $x_i(t)$ with added white noise into IMFs.
3. Repeat step 1 and 2 with different white noise series each time.
4. Obtain the means of corresponding IMFs of the decompositions as the final result.

$$x_i(t) = x(t) + w_i(t) \tag{2}$$

According to Torres, Colominas, Schlotthauer and Flandrin [15] the resulting decomposition from the EEMD algorithm solves the EMD mode mixing problem, however it creates some new ones. In order to address the issue associated with EEMD, Torres, Colominas, Schlotthauer and Flandrin [15] proposed the following modifications to the original EEMD algorithm:

1. Decompose by EMD over I iterations to obtain the first mode and compute

$$\widetilde{IMF}_1(t) = \frac{1}{I}\sum_{i=1}^{I} IMF_1^i(t) = \overline{IMF}_1(t) \tag{3}$$

2. Calculate the first residue $r_1(t)$ where $k = 1$

$$r_1(t) = \mathrm{x(t)} - \widetilde{IMF}_1(t) \tag{4}$$

3. Decompose realisation $r_1(t) + \varepsilon_1 E_1 w_i(t)$, where ε is the noise standard deviation, I is the ensemble size, E is the mode obtained by EMD and $w_i(t)$ is the noise data, to obtain their first EMD mode and define the second mode

$$\widetilde{IMF}_1(t) = \frac{1}{I}\sum_{i=1}^{I} E_1(r_1(t) + \varepsilon_1 E_1 w_i(t)) \tag{5}$$

4. Calculate the k residue for $k = 2$ to K

$$r_k(t) = r_{k-1}(t) - \widetilde{IMF}_\mathrm{k}(t) \tag{6}$$

5. Decompose realisation $r_k(t) + \varepsilon_k E_k w_i(t)$ to obtain their first EMD mode and define the $(k + 1)$th mode

$$\widetilde{IMF}_{\mathrm{k}+1}(t) = \frac{1}{I}\sum_{i=1}^{I} E_1(r_k(t) + \varepsilon_k E_k w_i(t)) \tag{7}$$

6. Repeat steps 4 to 5 until the obtained residual can no longer be decomposed

$$R(t) = x(t) - \sum_{k=1}^{K} \widetilde{IMF}_\mathrm{k}(t) \tag{8}$$

$$x(t) = \sum_{k=1}^{K} \widetilde{IMF}_\mathrm{k}(t) + R(t) \tag{9}$$

Colominas, Schlotthauer and Torres [16] proposed further improvements to their complete ensemble EMD with adaptive noise (CEEMDAN) model to eliminate the residual noise in the modes and spurious modes. The residual noise in the modes was determined by subtracting the estimated local mean from the original signal as per Eq. (10).

$$\tilde{d}_1 = x - \langle M(x_i)\rangle \tag{10}$$

$$x^{(i)} = x + w^{(i)} \tag{11}$$

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