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Reduced wavelet component energy-based approach for damage detection of jacket type offshore platform

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Abstract. Identification of damage has become an evolving area of research over the last few decades with increasing the need of online health monitoring of the large structures. The visual damage detection can be impractical, expensive and ineffective in case of large structures, e.g., offshore platforms, offshore pipelines, multi-storied buildings and bridges. Damage in a system causes a change in the dynamic properties of the system. The structural damage is typically a local phenomenon, which tends to be captured by higher frequency signals. Most of vibration-based damage detection methods require modal properties that are obtained from measured signals through the system identification techniques. However, the modal properties such as natural frequencies and mode shapes are not such good sensitive indication of structural damage. Identification of damaged jacket type offshore platform members, based on wavelet packet transform is presented in this paper. The jacket platform is excited by simple wave load. Response of actual jacket needs to be measured. Dynamic signals are measured by finite element analysis result. It is assumed that this is actual response of the platform measured in the field. The dynamic signals first decomposed into wavelet packet components. Then eliminating some of the component signals (eliminate approximation component of wavelet packet decomposition), component energies of remained signal (detail components) are calculated and used for damage assessment. This method is called Detail Signal Energy Rate Index (DSERI). The results show that reduced wavelet packet component energies are good candidate indices which are sensitive to structural damage. These component energies can be used for damage assessment including identifying damage occurrence and are applicable for finding damages' location.

Keywords: damage detection; jacket platform; wavelet transform; wavelet packet transform

1. Introduction

Offshore platforms in deep water are subjected to harsh marine environments, withstanding cyclic waves, severe storms, seaquakes and sea-water corrosion. The occurrence of damage in an offshore structure is inevitable during its lifetime. Then the field of health monitoring and damage detection has a great potential for applications in offshore structures. Therefore, aging of structures must be inspected at regular intervals in order to detect the initiation and growth of damages that may lead to catastrophic failure. Currently, divers or Remote Operated Vehicles (ROV) are employed for the purpose of visual inspection and local damage detection. However, the process of

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inspection and local detection for offshore structures, especially in deep water, is much more difficult than for land structures. The poor visibility and the concealment of damage by marine growth limit the effectiveness of process technically. In addition, the use of divers and ROVs are the most expensive options. So it is very useful to apply a global technique capable of assessing the health of offshore platforms in an automated fashion, providing advance warning of structural damages and minimizing maintenance costs. Also, the damage locations are requested to be provided prior to implementing the underwater inspection or local detection. In response to these requests, a substantial amount of activities related to the global health monitoring and damage detection for offshore platforms have been carried out during the past decades (Kim and Stubbs 1995).

Clearly the development of robust techniques for early damage detection is very important to predict and avoid possible occurrence of a catastrophic structural failure (Li *et al*. 2008). The methods for damage detection are commonly classified into four levels: Level 1: determination of the damage in structure, Level 2: determination of location of damage, Level 3: quantification of the severity of damage, and Level4: prediction of the remaining service life of structure (Asgarian *et al*. 2009). Damage identification techniques can be classified into either local or global methods. Most currently used techniques, such as visual, acoustic, magnetic field, eddy current, and etc. are effective yet locally in the nature. They require that the vicinity of the damage is known a priori and the portion of the structure being inspected is readily assessable. The global methods, on the other hand, quantify the healthiness of a structure by examining changes in its vibration characteristics. It is believed that these two methods should be used in a complementary way to effectively and correctly assess the condition of the health of a complicated structure. One core issue of the global vibration-based damage assessment methods is to seek some damage indices that are sensitive to structural damage. Indices that have been demonstrated with various degrees of success include natural frequencies, mode shapes, mode shape curvatures, the flexibility matrix, the stiffness matrix, etc (Ren and De Roeck 2002 a,b).

Farrar and Jauregui conducted a comparative experimental study of five damage identification algorithms applied to the I-40 Bridge (Farrar and Jauregui 1998 a,b). Kim and Stubbs proposed an algorithm to find the location and the size of the damage in jacket-type offshore structures with a Nondestructive Damage Detection (NDD) in large/complex structures via vibration monitoring (Kim and Stubbs 1995). Koh, See and Balendra suggested a method for identification of local damage of multi-story frame building in terms of changes in story stiffness (Koh *et al*. 1995). Shi et al. suggested a method to detect the location of damage using the elemental energy quotient difference and modal strain energy change and also this metod is used to quantify the damage based on sensitivity analysis. They proposed an algorithm to improve structural damage quantification based on modal strain energy change (Shi *et al*. 2000, Shi, Law *et al*. 2002). Mangal, Idichandy and Ganapathy used an experimental investigation on a laboratory model of a jacket platform, for exploring the feasibility of adapting vibration responses due to impulse and relaxation, for structural monitoring (Mangal *et al*. 2001). Xiang et al. proposed a method to detect location and severity of damage in jacket type offshore platforms via partial measurement of modal parameters of an experimental model platform under white-noise ground excitation (Shi *et al*. 2008).

Most of vibration-based damage assessment methods require the modal properties that are obtained from the measured signals through the system identification techniques such as the Fourier Transform (FT). There are a few inherent characteristics of FT that might affect the accuracy of damage identification. First, the FT is in fact a data reduction process and information about structural health might be lost during the processing. Second, the FT cannot present the time dependency of signals and it cannot capture the evolutionary characteristics that are commonly observed in the signals measured from naturally excited structures.

The structural damage is typically a local phenomenon, which tends to be captured by higher frequency signals. These higher frequencies normally are closely spaced but poorly excited. The Fourier analysis transforms the signals from a time-based or space-based domain to a frequency-based one.

Unfortunately, the time or space information may be lost during performing such a transform and it is sometimes impossible to determine when or where a particular event have taken place. To remove this deficiency, the short-time Fourier transform (STFT) was proposed by Gabor (1946) (Gabor 1946). This windowing technique analyzes only a small section of the signal at a time. The STFT maps a signal into a 2-D function of time or space and frequency. The transformation has the disadvantage that the information about time or space and frequency can be obtained with a limited precision that is determined by the size of the window. A higher resolution in time or space and frequency domain cannot be achieved simultaneously since once the window size is chosen; it is the same for all frequencies. The wavelet transform (WT) is precisely a new way to analyze the signals, which overcomes the problems that other signal processing techniques exhibit.

Wavelet functions are composed of a family of basic functions that are capable of describing a signal in a localized time (or space) and frequency (or scale) domain. The main advantage gained by using wavelets is the ability of performing local analysis of a signal, i.e., zooming on any interval of time or space. The use of local functions allows simultaneous, varying time-frequency resolution that leads to a multi-resolution representation for non-stationary data. Wavelet analysis is thus capable of revealing some hidden aspects of the data that other signal analysis techniques fail to detect. This property is particularly important for damage detection applications. Due to the time-frequency multi-resolution property, the WT has recently been demonstrated as a promising tool for damage assessment of machinery and structures. Staszewski and Tomlinson used the WT to detect a broken tooth in a spur gear (Staszewski and Tomlinson 1994).

Masuda et al illustrated that the cumulative damage of a building during an earthquake can be related to the number of spikes in the wavelet results (Sone *et al*. 1995). Gurley and Kareem outlined the usefulness and the applicability of the wavelet transform in earthquake, wind, and ocean engineering (Gurley and Kareem 1999). Wang and Deng developed a WT-based technique for analyzing spatially distributed structural response signals (Wang and Deng 1999). They found that response perturbations due to structural damage were discernible in wavelet components.

One possible drawback of the WT is that the frequency resolution is quite poor in the higher frequency regions. Hence, it still faces the difficulties when discriminating the signals containing close high frequency components. The wavelet packet transform (WPT) is an extension of the WT, which provides a complete level-by-level decomposition of signals. The wavelet packets are alternative bases formed by the linear combinations of the usual wavelet functions (Coifman and Wickerhauser 2002). Therefore, the WPT enables the extraction of features from the signals that combine the stationary and non-stationary characteristics with an arbitrary time-frequency resolution. Sun and Chang developed a WPT-based component energy technique for analyzing structural damage. The component energies were firstly calculated and then they were used as inputs into the neural network (NN) models for damage assessment (Sun and Chang 2002). Han et al proposed a damage detection index called wavelet packet energy rate index (WPERI), for the damage detection of beam structures(Han *et al*. 2005).

In this paper, the new method based on wavelet packet transform is proposed for damage identification of jacket platform. Dynamic signals are measured from finite element analysis result. It is assumed that this response is the measured response of actual structure. Dynamic signals are decomposed into wavelet packet components. Then DSERI for each damage scenarios is calculated. The results show that reduced wavelet packet component energies are good candidate indices that are sensitive to structural damage. In section 2 and 3, the background of wavelet and wavelet packet are presented. In section 4, methodology of damage detection is presented. Next section (section 5), numerical model, damaged scenarios and damage detection by using DSERI are presented. The results are presented in the last section.

2. Wavelet analysis

2.1. Continuous and discrete wavelets

Inaccurate results may be presented by the traditional Fourier analysis of the response data of general transient nature if the occurring time of damage is unknown. This, happens due to its time integration over the whole time span. In addition, progressive damage such as stiffness degradation due to mechanical fatigue and chemical corrosion could develop, therefore, a clear change in stiffness might not been found. The wavelet analysis can provide a time-frequency and multi-resolution analysis for non-stationary data. This method is efficient for damage detection of structures (Shinde and Hou 2005). In summary, a wavelet is an oscillatory, real or complex-valued function $\Psi(t) \in L^2$ (□) of zero average and finite length. Wavelets can be real or complex functions. Since real wavelets are useful to detect sharp signal transitions, this study deals exclusively with them (Lotfollahi-Yaghin and Koohdaragh 2011). Wavelet analysis starts by selecting among the existing wavelet families a basic wavelet function that can be a function of space x or time t. In this paper, it is considered that the independent variable is t, for damage localization of jacket platform members.

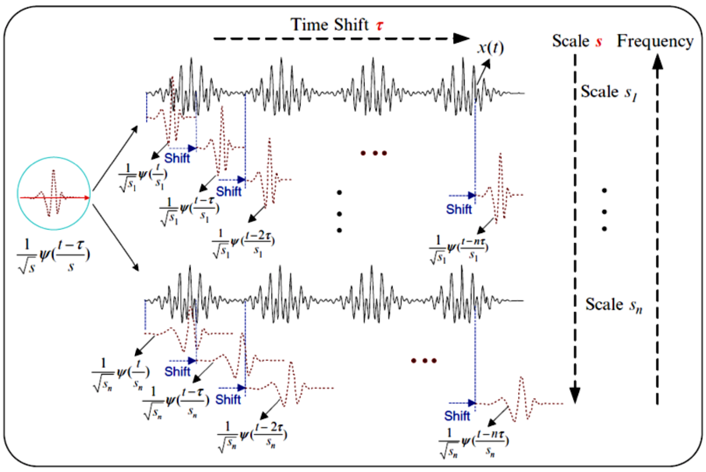


Fig. 1 wavelet transform

This basic wavelet function, called the 'mother wavelet' ψ(t), is then dilated (stretched or compressed) by *s* and transformed in space by τ to generate a set of basic functions $\Psi_{s\tau}(t)$ as demonstrated in Fig. 1 : (Lotfollahi-Yaghin and Koohdaragh 2011)

$$\Psi_{s,\tau}(t) = \frac{1}{\sqrt{s}}\Psi(\frac{t-\tau}{s}) \tag{1}$$

The function is centered at τ with a spread proportional to *s*. The wavelet transform (in its continuous or discrete version) correlates the function f(t), with $\Psi_{s,\tau}(t)$. The continuous wavelet transform (CWT) is the sum over all time of the signal multiplied by *s* and is a scaled and shifted version of a mother wavelet

$$C(s,\tau) = \frac{1}{\sqrt{s}}\int_{-\infty}^{\infty} f(t)\Psi(\frac{t-\tau}{s})dx = \int_{-\infty}^{\infty} f(t)\Psi_{s\tau}(t)dt \tag{2}$$

Where the scale (*s*) and the position (τ) are real numbers, and $s \neq 0$. The results of the transform are wavelet coefficients that show how well a wavelet function correlates with the signal which has been analyzed. Hence, sharp transitions in *f(t)* create wavelet coefficients with large amplitudes and this is the basis of the proposed identification method precisely. The inverse of CWT permits to recover the signal from its coefficients C (s,τ) and is defined as

$$f(t) = \frac{1}{K_\Psi}\int_{s=-\infty}^{s=\infty}\int_{b=-\infty}^{b=\infty} C(s,\tau)\Psi_{s\tau}(t)d\tau\frac{ds}{s^2} \tag{3}$$

Where the constant K_ψ depends on the wavelet type. One of the drawbacks of the CWT is that a very large number of wavelet coefficients *C(s,τ)* are generated during the analysis (Ovanesova 2004). Moreover, few wavelets have an explicit expression, and most are defined by recursive equations. It can be shown (Lotfollahi-Yaghin and Koohdaragh 2011) that the CWT is highly redundant, in the sense that it is not necessary to use the full domain of *C(s,τ)* to reconstruct *f(t)*. Therefore, instead of using a continuum of dilations and translations, discrete values of the parameters are used. The dilation is defined as $s = 2^j$ and the translation parameter takes the values of $\tau = k\,2^j$, where $(\mathrm{j},\ \mathrm{k}) \in \mathrm{Z}$, and Z is a set of integers. This sampling of the coordinates *(s,τ)* is referred as dyadic sampling because consecutive values of the discrete scales differ by a factor of 2 (Ovanesova 2004). Using the discrete scales, one can define the discrete wavelet transform (DWT)

$$C_{j,k} = \frac{1}{\sqrt{2^j}}\int_{-\infty}^{\infty} f(t)\Psi(\frac{t-k\,2^j}{2^j})\,dt = \int_{-\infty}^{\infty} f(t)\Psi_{j,k}(t)dt \tag{4}$$

The signal resolution is defined as the inverse of the scale $\frac{1}{s} = 2^j$, and the integer j is referred to as the level. As the level and the scale decreases, the resolution increases and smaller and finer components of the signal can be accessed. The signal can be reconstructed from the wavelet coefficients $C_{j,k}$ and the reconstruction algorithm is called the inverse discrete wavelet transform (IDWT)

$$f(t) = \sum_{j=-\infty}^{\infty} \frac{1}{2^{j/2}} \sum_{k=-\infty}^{\infty} c_{j,k}\, \psi(2^{-j}t - k). \tag{5}$$

Substituting $\psi(t)$ to $\phi(t)$ in Eq. (2) one obtains a function $D(s0, \tau)$

$$D(s_0,\tau) = \int_{-\infty}^{\infty} f(t) \frac{1}{\sqrt{s_0}} \phi(\frac{t-\tau}{s_0}) dt = \int_{-\infty}^{\infty} f(t) \phi_{s_0,\tau}(t) dt \tag{6}$$

The scaling function does not exist for every wavelet. The existence of the function $f(t)$ is important for the numerical implementation of the fast wavelet transform discussed later. Suppose now that the dyadic scale is used for s and τ, and consider the reference level of J. Applying Eq. (4) for this case, a set of coefficients are obtained.

$$cD_J(k) = \int_{-\infty}^{\infty} f(t) \Psi_{j,k}(t) dt \tag{7}$$

The coefficients $cD_J(k)$ are known as the level-J detail coefficients. Using the dyadic scale and level J, eq. (6) yields another set of coefficients

$$cA_J(k) = \int_{-\infty}^{\infty} f(t) \phi_{J,k}(t) dt \tag{8}$$

The new coefficients $cA_J(k)$ are known as the level-J approximation coefficients. Then $f(t)$ is reconstructed as

$$f(t) = \sum_{j=-\infty}^{\infty} \left(\sum_{k=-\infty}^{\infty} cD_j(k) \psi_{j,k}(t) \right) + \sum_{j=-\infty}^{\infty} cA_J(k) \phi_{j,k}(t, \tag{9}$$

Eq. (9) thus says that the original function can be expressed as the sum of its approximation at level J plus all its details up to the same level, i.e.

$$f(t) = A_J(t) + \sum_{j \le J} D_j(t) \tag{10}$$

For this study, we are interested in the detail signals. As it will be shown with the numerical examples, if *f(t)* is a response signal, typically the acceleration curve, the signals $D_j(t)$ contain the information necessary to detect the damages in the structure, see Fig. 2.

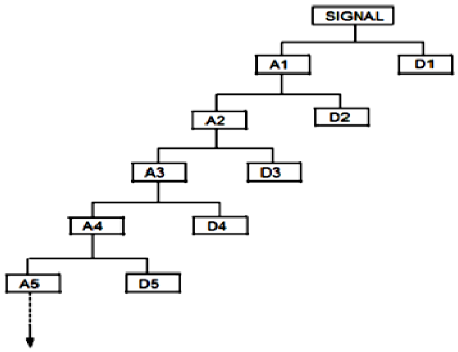


Fig. 2 Discrete wavelet transform decomposition tree

2.2. Wavelet packet transform

As a result of decomposition of only the approximation component at each level using the dyadic filter bank, the frequency resolution is low in lower-level, e.g., A1 and D1. DWT decompositions in a regular wavelet analysis may be lower. It may cause problems while applying DWT in certain applications, where the important information is located in higher frequency components. The frequency resolution of the decomposition filter may not be fine enough to extract necessary information from the decomposed component of the signal. The necessary frequency resolution can be achieved by implementing a wavelet packet transform to decompose a signal further. The wavelet packet analysis is similar to the DWT with the only difference that in addition to the decomposition of only the wavelet approximation component at each level, a wavelet detail component is also further decomposed to obtain its own approximation and detail components as shown in Fig. 3

At the top of the tree, the time resolution of the WP components is good but at an expense of poor frequency resolution whereas at the bottom of the tree, the frequency resolution is good but at an expense of poor time resolution. Thus with the use of wavelet packet analysis, the frequency resolution of the decomposed component with high frequency content can be increased. As a result, the wavelet packet analysis provides better control of frequency resolution for the decomposition of the signal. Wavelet packets consist of a set of linearly combined usual wavelet functions. The wavelet packets have the properties such as orthonormality and time-frequency localization from their corresponding wavelet functions. A wavelet packet Ψ^i_j, k is a function with three indices where integers *i*, *j* and *k* are the modulation, scale and translation parameters, respectively.

$$\psi^{i}_{j,k} = 2^{j/2} * \psi^{j}(2^{j/2}t - k), \quad i = 1,2,3,... \tag{11}$$

After *j* level of decomposition, the original signal *f(t)* can be expressed as

$$f(t)=\sum_{i=1}^{2^j} f_j^i(t) \tag{12}$$

The wavelet packet component signal $f_j^i(t)$ can be represented by a linear combination of wavelet packet functions $\Psi_{j,k}^i(t)$ as follows

$$f_j^i(t)=\sum_{i=1}^{2^j} c_{j,k}^i(t)\psi_{j,k}^i(t) \tag{13}$$

Where the wavelet packet coefficients $c_{j,k}^i(t)$ can be obtained from

$$c_{j,k}^i(t)=\int_{-\infty}^{\infty} f(t)\psi_{j,k}^i(t)dt \tag{14}$$

Providing that the wavelet packet functions are orthogonal

$$\psi_{j,k}^m(t)\psi_{j,k}^n(t)=0 \qquad if\, m\neq n \tag{15}$$

Each component in the WPT tree can be viewed as the output of a filter tuned to a particular basis function, thus the whole tree can be regarded as a filter bank. At the top of WPT tree (lower level), the WPT yields a good resolution in the time domain but a poor resolution in the frequency domain. At the bottom of WPT tree (higher level), the WPT results in a good resolution in the frequency domain, yet a poor resolution in the time domain. The wavelet transform tree is shown in Fig. 3 and the decomposition formulation of signal *f(t)* is

$$F(t)=AAA3+DAA3+ADA3+DDA3+DAD3+ADD3+DDD3 \tag{16}$$

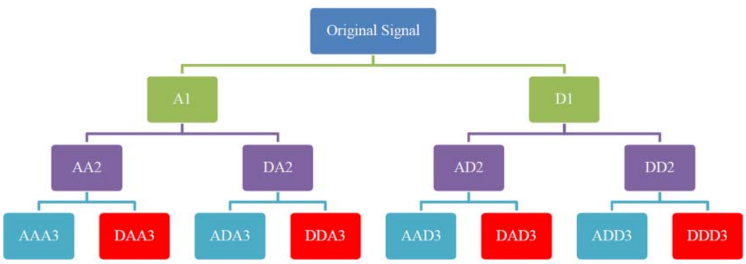


Fig. 3 Wavelet packet decomposition tree

3. Detail signal energy rate index

The feasibility of applying the WPT to the vibration signals was investigated by Yen and Lin (2000). They defined a wavelet packet node energy index and concluded that the node energy representation could provide a more robust signal feature for classification than using the wavelet packet coefficients directly.

In this study, the detail signal energy rate index is proposed to identify the locations of the damage. To do that, the signal energy E_t at *j* level is first defined as

$$E_{f_j} = \int_{\infty}^{\infty} f^2(t)dt = \sum_{m=1}^{2^j}\sum_{n=1}^{2^j}\int_{\infty}^{\infty} f_j^m(t) f_j^n(t)dt \tag{17}$$

Substituting Eq. (14) into Eq. (19) and using the orthogonal condition Eq. (16) yields

$$\mathrm{E}_{\mathrm{f_j}} = \sum_{\mathrm{i=1}}^{2^{\mathrm{j}}} \mathrm{E}_{\mathrm{f_j^i}} \tag{18}$$

Where the wavelet packet component energy $E_{f_j^i}$ can be considered to be the energy stored in the component signal $f_j^i(t)$

$$E_{f_j^i} = \int_{\infty}^{\infty} f_j^i\ (t)^2 dt. \tag{19}$$

It can be seen that the component signal $f_j^i(t)$ is a superposition of wavelet functions $\Psi_{j,k}^i(t)$ of the same scale as *j* but translated into the time domain $-\infty < k < \infty$. In physical terms, Eq. (20) illustrates that the total signal energy can be decomposed into a summation of wavelet packet component energies that correspond to different frequency bands. According to (Han *et al*. 2005), the WPERI is a good candidate to indicate the structural damage. So, in the presented paper, the authors proposed a new method based on wavelet packet decomposition, called as DSERI (detail signal energy rate index) for damage detection in jacket type offshore structure. The rate of signal wavelet packet energy at *j* level of detail signals that is shown in Fig. 3. in red (for example j=3) are defined as

$$\Delta(\mathrm{E^D_{f_j}}) = \sum_{\mathrm{i=1}}^{2^{\mathrm{j}}} \frac{\left|(\mathrm{E^D_{f^i_{jcc}}})_{\mathrm{b}} - (\mathrm{E^D_{f^i_j}})_{\mathrm{a}}\right|}{(\mathrm{E^D_{f^i_j}})_{\mathrm{a}}} \tag{20}$$

Where $(E^D_{f_j^i})_a$ is the component energy of detail signals $(E^D_{f_j^i})$ at *j* level without damage, and $(E^D_{f_j^i})_b$ is the detail signals energy ($E^D_{f_j^i}$) with some damage. It is assumed that structural damage would affect the wavelet packet component energies and consequently alter this damage indicator. It is desirable to select a DSERI that is sensitive to the changes of signal characteristics.

4. Methodology of damage detection

Continuous monitoring is assumed have been carried out for offshore platforms, which are highly susceptible to damage due to the sea corrosive environment, continuous action of waves and damages due to fatigue and boat impact. Also, since a major part of the structure is under water and covered by marine growth, even a trained diver cannot easily detect damage in such a structure. In this paper, vibration criterion is adopted for structural monitoring of jacket type offshore platforms. Damage in the system causes a change in dynamic properties of a system. The structural damage is typically a local phenomenon, which tends to be captured by higher frequency signals. In this paper DSERI is suggested for damage detection of this type of structures.

Two assumptions are adopted in this study: (1) the reliable undamaged and damaged structural models are available; (2) the structure is subjected to wave action (for example specific wave height *(H_s)* =12 *m*, period (T_s) =10 *sec*). Thirty of sensors are utilized (6 sensor in each level of jacket platform). Vibration signals need to be measured on the structure. Vibration signals are extracted from finite element model analysis using ANSYS software and then processed using the WPT. The level of wavelet packet decomposition is determined through a trial and error analysis using undamaged and damaged structural models. Then the wavelet packet energy rates of detail signals are computed.

5. Numerical studies

Numerical study is performed for an existing five stories offshore platform in Persian Gulf with six legs located at a water depth of 70.2 m. Considered offshore platform consists of a three-level deck, main legs, embedded piles in soil, horizontal and vertical bracing members. Platform members are modeled using PIPE59 elements of ANSYS which takes into account hydrodynamic loading. The deck weights are modeled using concentrated mass elements MASS21. The FE model is shown in Fig. 4. To simulate the damage, three damage scenarios with different location are considered. The damage severities are implemented by reducing the stiffness of specific elements. As illustrated in previous section, a sufficiently high level of decomposition is required to obtain the sensitive component energies. For the simulated structures, the decomposition level is set to be 4 where a total of 16 component energies are generated.

In order to study the effect of decomposition level, as shown in (Lotfollahi-Yaghin *et al*. 2010), the decomposition level is also set to be 5 where a total of 32 component energies are generated. It is found that both results seem similar, which indicates that 4 decomposition level is enough and better than 5 decomposition level. After decomposing the signals, the detail signal energy rate indices $\Delta(E_{f_j}^D)$ are calculated by Eq. (20).

The undamaged structure is denoted as *J0*. The other three different damage scenarios, denoted as J1, J2 and J3, are described as follows: (1) J1: stiffness reduced 10%,20%,30%,40%,50% and 60% in the 33th and 36th elements; (2) J2: stiffness reduced 10%, to 60% in the 33th element; and (3) J3: stiffness reduced 10%,20%,30%,40%,50% and 60% in the 45th and 48th elements. They are shown in Fig. 3. For every damaged structure, the histogram can be drawn. The damage location can be intuitively shown in histograms. Histograms of three damaged structures; J1, J2 and J3 are shown in Fig. 5 and 7 respectively. In Fig. 5, it can be seen that the detail signal energy rate indices of wavelet packet decomposition appeared in 33th and 36th elements and their amount were larger than other elements, then it can be suspected that this elements are damaged. In Fig. 6, it can be seen that the DSERI in 33th element are larger than another elements then it can be suspected that these elements are damaged. In all above figures, the same result can be obtained for J3 model.

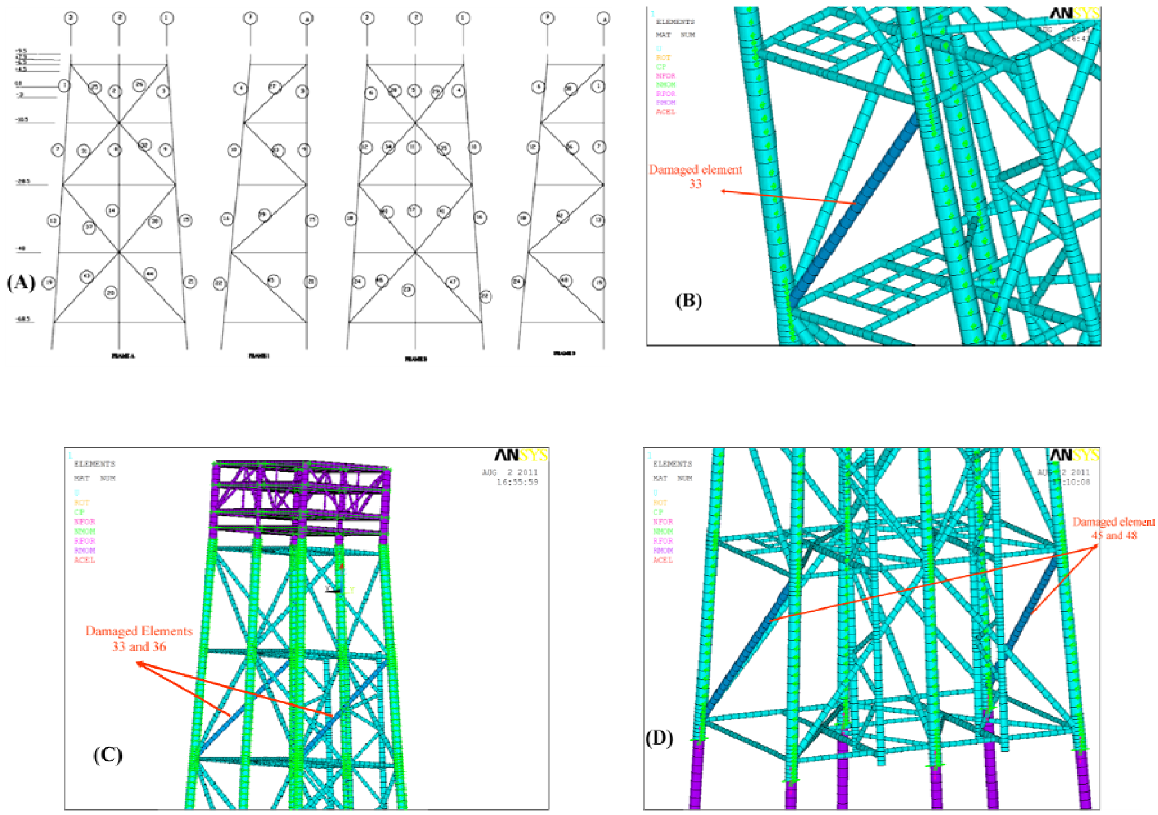


Fig. 4 FE modeling of jacket, (a) Jacket elements number, (b) J1 model, (c) J2 model and (d) J3 model

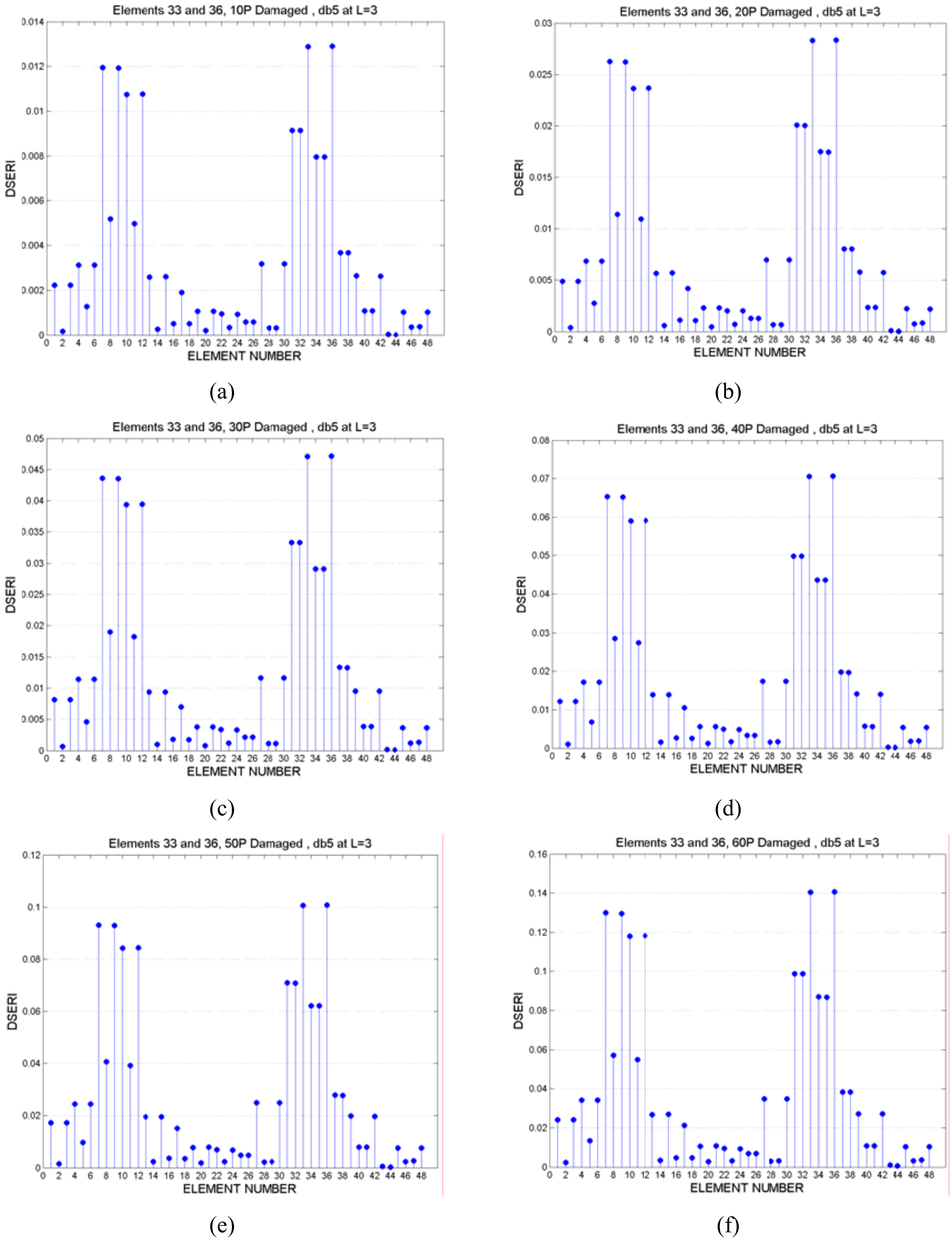
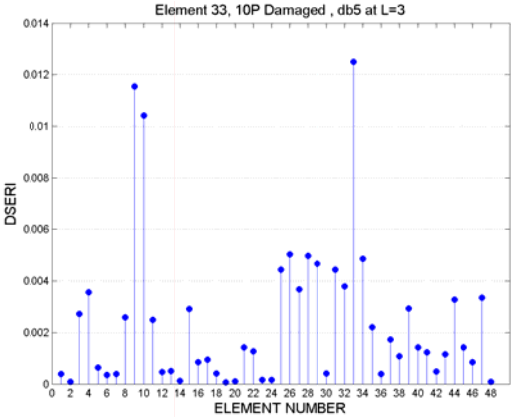
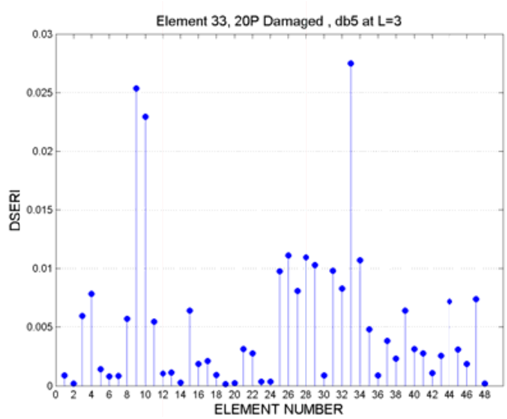


Fig. 5 Damage detection of J1 model, (a) 10% damaged, (b) 20% damaged, (c) 30% damaged, (d) 40% damaged, (e) 50% damaged and (f) 60% damaged



(a)



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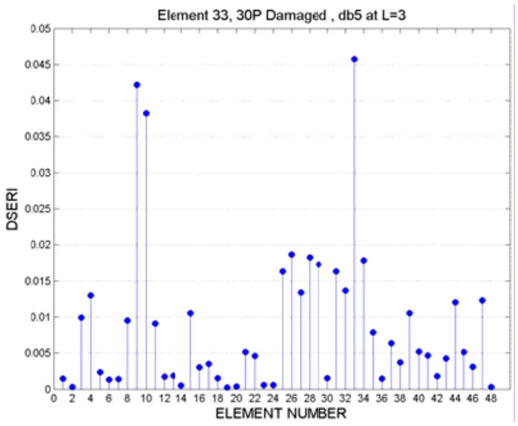

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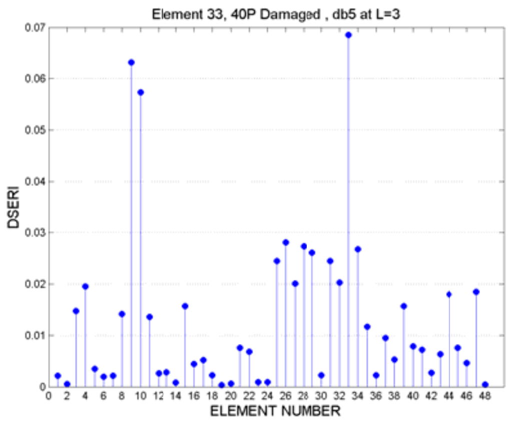

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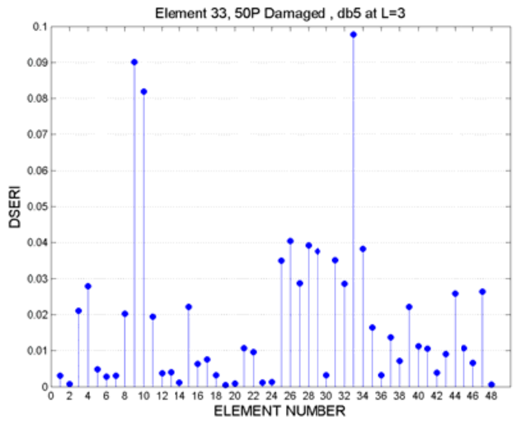

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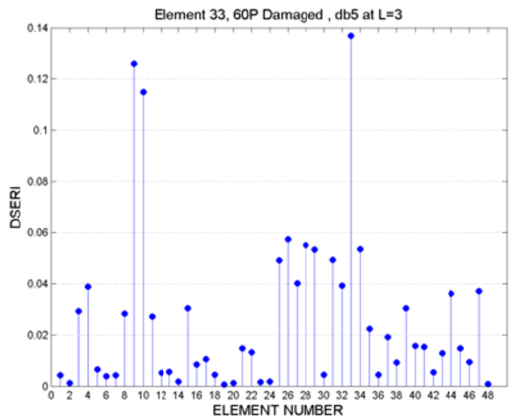
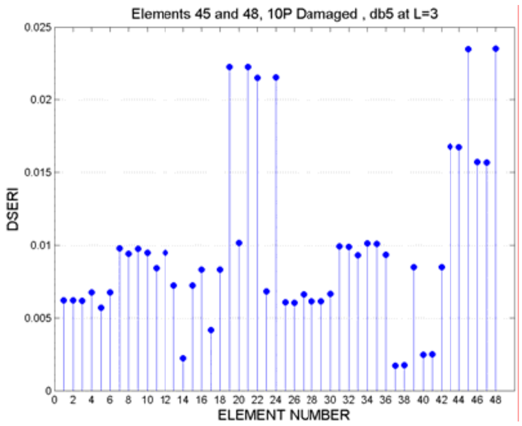
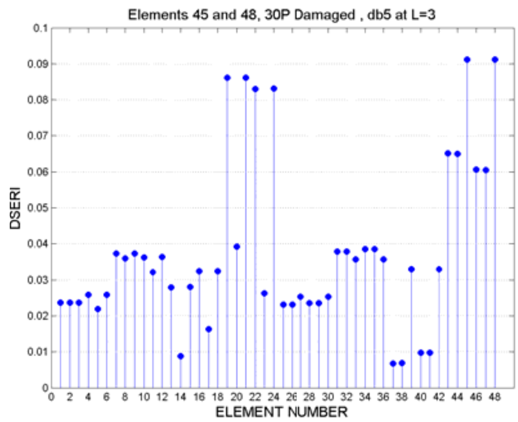


(f)

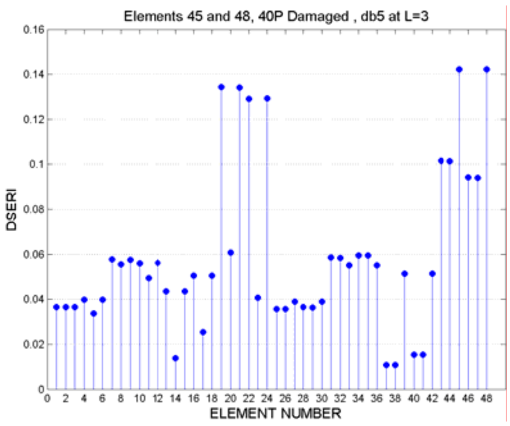
Fig. 6 Damage detection of J2 model, (a) 10% damaged, (b) 20% damaged, (c) 30% damaged, (d) 40% damaged, (e) 50% damaged and (f) 60% damaged



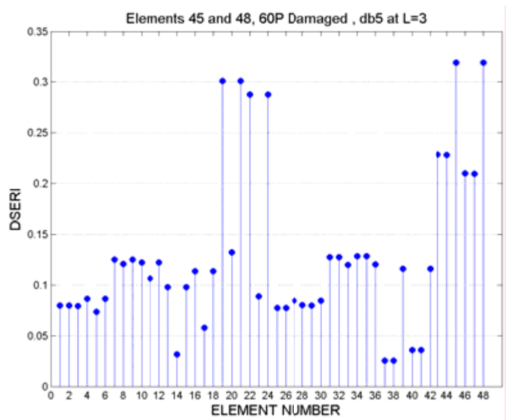
(a)



(b)



(c)



(d)

Fig. 7 Damage detection of J3 model, (a) 10% damaged, (b) 30% damaged, (c) 40% damaged and (d) 60% damaged

6. Conclusions

In this paper, the sensitivity and the variability of a wavelet packet based on new method (DSERI) for damage detection of jacket type offshore platforms are investigated. DSERI methods based on eliminating approximation components of wavelet packet at terminal node are proposed. Proposed damage identification procedure requires three steps of computation: (1) wavelet packet decomposition; (2) DSERI of each element calculation; and (3) damage location identification. These calculations are rather straightforward; hence on-line implementation is possible if the reference information is available. Investigating different wavelets in several scales and analyzing levels, demonstrates that wavelets db, coif, and sym are useful for damage detection. In this research, db5 (Daubechies wavelet) performs better in terms of damage detection in marine platforms. With regard to selecting the decomposition level, the lower decomposition level which can correctly identify damage location is important since the lower decomposition level will reduce the computation efforts.

The sensitivity of this method to the change of structural member stiffness is derived through performing analysis on an actual platform. Results show that the reduced wavelet packet component energy is significantly sensitive to the stiffness change. The wavelet packet ratio index of reduced wavelet packet energy in the damaged elements is larger than other elements; therefore DSERI is a good indicator for damage location detection. Due to occurrence of the damage in one of the vertical bracings of the sample offshore platform, leg elements and vertical bracings of the damaged level and its upper and lower stories, also the horizontal bracings of the damaged level are suspected as damaged elements.

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