Department of Environment, Land and Infrastructure Engineering

Master of Science in Petroleum Engineering

Structural Health Monitoring of Offshore Jacket Platforms Using Wavelet Packet Energy Rate Index

Supervisors:

Cecilia Surace

Marco Civera

Hamza Farroukh

S242221

Acknowledgment

Special thanks for my supervisor Cecilia Surace and her assistant, Marco Civera for their efforts in helping and guiding me to perform this thesis providing me all the support.

I am blessed to thank the Politecnico di Torino for giving us the opportunity to study and gaining engineering certificate. Not forgetting the other professors which taught us in professional and good manner.

Finally, I will like to thank my fiancé Nesrine Ltaifi for her support and all my family and friends.

Abstract

Vast structures like offshore platforms are highly susceptible to damage due to harsh ocean environment. The visual inspection of damage is difficult and not reliable since a large area of the platform covered by seawater. A scheduled and periodic maintenance could be a solution to detect the damage, but its time consuming, expensive, and not always reliable. Structural Health Monitoring provides information about the integrity of the structure on a continuous real time basis which allows an optimal use of the structure , achieving high safety conditions for the health of the people who work on it. Meanwhile, avoiding the occurrence of catastrophic failures.

In this thesis, we applied the wavelet packet energy rate index method in order to detect any damage on the platform. Starting from the relation between the damage existence and the adjustments in dynamic behavior of the system. Structural damage method based on mathematical operation called wavelet packet decomposition can provide an arbitrary time-frequency resolution.

In this study, we have simulated an offshore platform using the finite element software package Ansys (2015). We generated an impulse load on some parts of it in order to calculate the dynamic behavior of the system at normal conditions where no damage occurred. We induced some damage in order to study the dynamic response of the both cases. The ANSYS output signals, after performing transient analysis, are decomposed into wavelet components using Matlab software. Then we performed the calculation of energy components in order to determine the energy rate index on each node. The damage assessment based on energy rate index .The outcomes demonstrate that the WPT based component energies are great competitor lists that are delicate to identify the occurrence of structural damage and its location.

List of Figures:

Table of Contents

Chapter 1: Introduction

The main use of offshore platforms is during the exploration and exploitation of oil and gas reserves from the ocean. Oil and gas industries have spent a huge amount of money in developing this technology, where any failure of these structures will lead to catastrophic results such as loss of life of the workers on it, leakage of oil, or gas in the ocean will kill the marine life. These platforms installation used for drilling, preparing water or gas for injection into the reservoir, for processing oil and gas, cleaning the product water for disposal into the sea and accommodating the staff.

These structures are sensitive to water depth and subjected to different environmental conditions such as corrosion and fatigue effect, the flow of the seawater and tides, the pressure of the wind on the top sides and the impact of the waves. These structures need high investment and designed to work for 25 years or more (Harish et al 2010). For high reliability, damage inspection methods and monitoring are necessary. The complexity of detection the damage by eye since some structure parts are covered by water. Many methods has been used to give information about any abnormality existence in the structure such as magnetic resonance imaginary, X-rays and ultrasounds. They are proven methods characterized by high cost and time consuming (more downtime). Moreover, their application is periodic and scheduled. (Daniel Balageas 2005)

Structural health monitoring allows an optimal use of the structure by providing online monitoring to identify any abnormality occurrence, its location and severity.SHM is a process of implementing a technique towards excuting a harm discovery for aviation, civil or mechanical systems.SHM is based on the dynamic response of the structure over time in order to determine the current state of the system health. Its advantages for long-term identification of the ability of the structure to continue to perform its intended function in light of the inevitable ageing and degradation because of environmental conditions.SHM could be utilized for quick condition screening to give in close continuous, solid data about the performance of the system. (Charles R. Farrar, Keith Worden 2013)

Chapter 2: Structural Health Monitoring

2.1 Definition of Damage:

Damage can be described by certain changes brought into a framework that unfavorably influences its present or future performance. To identify damage, it is important to examine between the initial state of the framework which considered to be undamaged state and the recent state of the framework. Framework changes incorporate material as well as geometric property changes, changes in boundary conditions, and changes in framework network. All damage starts at the material dimension and material-level damage is available to some degree in all frameworks. Failure happens when the damage advances to a point where the framework can never again play out its expected capacity.

Damage can gather gradually over significant lots of time, as for the situation of damage related with fatigue and corrosion. Damage can likewise advance in all respects rapidly, as for the situation of critical fracture. (Charles R. Farrar, Keith Worden 2013)

Structural Health Monitoring is a rising innovation, managing the improvement of procedures and frameworks for the continuous monitoring, examination and damage discovery of structures, with minimum labour involvement.SHM enhances the performance of the structure. SHM includes the mix of sensors, potentially smart materials, information transmission, computational power, and handling capacity inside the structures. It permits to rethink the plan of the structure and the full administration of the structure its mythical being furthermore, of the structure considered as a piece of more extensive frameworks.(Daniel Balageas 2005)

2.2 Components of Structural Health Monitoring Process:

2.2.1 Operational Evaluation

In order to implement structural health monitoring strategy, it is important to justify the economic benefits and the enhancements on life-safety conditions. The identification of damage to be detected, including its type(corrosion,fatigue), threshold level and critical level before failure, can help in building robust damage detection technique. The awareness of the effects of operational and environmental conditions on the dynamic response of the structure can avoid misunderstanding of these changes, so not to consider that as a damage alarm.for example, a change in the mass of the system due to varying payload,or change in temperature. Some limitations on data acquisition while performing measurements on the in-situ structure related to economic considerations, environmental conditions, size of the structure and physical access. Therefore, it is necessary to evaluate all these aspects in order to choose the right type of sensors able to provide the detailed information required to detect the abnormality and develop a successful damage detection method. (Charles R. Farrar, Keith Worden 2013)

2.2.2 Data Acquisition

Choosing the efficient sensing technology,leads to accurate informations of the dynamic response of the system. The data acquisition process is identified with the determination of the excitation method, types, number and location of sensors utilized, and type of the information transmitted. Sensors read the dynamic signals and should be located near the expected damage position. The measurement of the data for variable mass structure under different temperatures, or during high wind velocity or waves motion, shows the importance of data normalisation in damage detection technique. Data normalisation is the procedure utilized in SHM to differentiate between the data extracted from the sensors that are influenced from the EOVs and from those influenced by damage happened on structures. Data cleansing is a selective process utilized to see if the data can pass on or it must be refused from this feature selection process. The data cleansing process is dependent on the commands selected by experts based on their experience and knowledge to directly connect to data acquisition. Filtering and resampling which are signal-processing techniques can also be considered as data cleansing procedures. Data compression is defined as reduction of dimension of measured data keeping the high quality data needed to apply SHM.in order to increase the reliability of data acquired, data fusion which combines information from multiple sources is used. (Charles R. Farrar, Keith Worden 2013)

2.2.3 Feature Selection

Identification of data feature is the most important part in SHM lead us to distinguish between undamaged and damaged systems.it is a quantity extracted from the measured system response information that identify the presence of abnormality in the system. These features changes considerably in their complexity. The majority of damage detection studies that were done in the past on offshore oil platforms shows changes in basic modal properties (resonance frequencies and mode shapes) that are extracted from measured acceleration response time histories. Numerical modelling approaches were used; examine the changes in the predicted modal properties simulated with in the finite element approach and the estimated modal properties from measured system response. This approach allows one to identify the damage, locate and estimate the severity of damage. (Charles R. Farrar, Keith Worden 2013)

2.2.4 Statistical modelling for feature discrimination

Statistical model advancement is worried about the usage of algorithms that work on the extracted feature to measure the damage condition of the structure; they are the premise of the SPR approach. Using machine-learning techniques the statistical model are derived. The machine-learning algorithm consists of two types:

Supervised learning algorithm include group classification and regression analysis. Unsupervised learning algorithm include outlier and novelty detection method.

Statistical models are used to apply two kinds of structural health monitoring which are protective monitoring and predictive monitoring. Using damage sensitive feature to detect failure and shut the system down before any catastrophic failure happen is called the protective monitoring. While the predictive monitoring using trends in data feature to forecast when the damage will arrive at critical value. (Charles R. Farrar, Keith Worden 2013)

2.3 Local Versus Global Damage Detection:

The majority of damage detection methods are non-destructive evaluation based; they characterized by visual or localized experimental methods such as acoustic, magnetic field, radiography, eddy currents, thermal field methods. The drawback of these methods that they can detect the damage on and near the surface of the structure. Global damage detection methods can be applied to huge and complexed structures... with the innovation and researches a new development of methods that compare changes in the vibration characteristics of the structure. The fundamental concept of vibration-based damage detection is that abnormality existence will affect the stifness, mass or energy dissipation properties of a framework, which,also affects the measured global dynamic response properties of the framework. (Charles R. Farrar, Keith Worden 2013)

Chapter 3: Signal Analysis Techniques

3.1 Wavelet Analysis

Wavelet analysis becomes very important in signal processing, it has been effectively connected in numerous applications, for example : transient analysis , image analysis and many other applications.it expands functions in terms of wavelets which are generated in form of translations and dilations of the mother wavelet .it gives a multi-resolution in time-frequency domain for processing non-stationary data unlike the traditional Fourier analysis when analyzing the response data of general transient nature without knowing when the harm happened , erroneous outcomes might be exhibited because of its time incorporation over the entire time length. Along these lines, wavelet analysis can be viably connected for structural health monitoring. (Lotfollahi-Yaghin ET al.2011)

$W_f(a,b)$: Continuous wavelet transform of a signal f(t)

It can be defined as:

$$W_f(a,b) = \frac{1}{\sqrt{a}}\int_{-\infty}^{+\infty} f(t).\overline{\Psi}\left(\frac{t-b}{a}\right)dt \qquad (1)$$

Where 'a' is the dilation parameter and 'b' is the translation parameter in which both parameters are real and a>0 . '$\overline{\Psi}$' is the conjugate of a mother wavelet function 'Ψ' .

The mother wavelet 'Ψ' needs to fulfill certain tolerability condition to guarantee presence of the inverse wavelet transform. The dilation parameter 'a' and the translation parameter 'b' are likewise alluded as the scaling and shifting parameters separately and assume a vital job in the wavelet analysis. By differing the estimation of translation parameter 'b', a signal is inspected by the wavelet window piece by piece restricted in the area of 't=b' thus the non-stationary nature of the data can be analyzed which is like the Short Time Fourier Transform (STFT). By fluctuating the estimation of dilation parameter 'a', the data divide in the area of 'b' can be inspected in various resolutions thus a time differing frequency content of the signal can be uncovered by this multi-resolution examination, a component the STFT doesn't have. The signal analysis by using continuous wavelet transform maps on a Time-Scale plane. The idea of scale in Wavelet analysis is like the idea of frequency in Time-Frequency examination. The scale is contrarily relative to the frequency. Playing out the reverse wavelet transform on the wavelet transform of a signal, the initial signal can be recreated with no loss of information

3.2 (DWT): Discrete Wavelet Transform

In order to make quick calculations of wavelet transform, the DWT has been developed which depends on subband coding. It is simple to apply and decreases the calculation period and assets required. The signals are interpreted by means of a set of mother wavelets (basis functions) which are connected together by simple scaling and translation according to continuous wavelet transform. Because of DWT, a time scale representation of the computerized signal is gotten utilizing advanced separating systems. The signal to be investigated is gone through filters with various cutoff frequencies at different scales. Meanwhile, the signal can be broke down by going it through an investigation filter bank pursued by a decimation activity. At the point when the signal goes through these filters, it is part into two groups. The low pass filter, which relates to an averaging operation, extricates the coarse data of the signal. The high pass filter, which relates to a differencing operation, separates the detail data of the signal. Two then obliterates the yield of the separating activities or filtering. Filters are a standout amongst the most generally utilized signal processing capacities. Wavelets can be acknowledged by emphasis of filters with rescaling. Mallat-tree decomposition or Mallat algorithm is registered by successive low pass and high pass filtering of the discrete signal as function of time .The half band filters produce signals spreading over just a large portion of the frequency band after each decomposition which increase the frequency resolution to double it at the same time the uncertainty in frequency decreases by half. From The length of the signal, we can estimate the maximum number of decomposition levels. Then the initial signal can be reconstructed as the dyadic wavelet filter family forms an orthonormal basis. (Gokhale ET Khanduja 2010) (Civera et al 2018)

3.3 (WPT) Wavelet Packet Transform

by level decomposition of a signal from the time area into the frequency space. The wavelet packet decomposition is a wavelet transform characterized by further decomposition of the signal, unlike discrete wavelet transform, in which the signal is passed through more filters. Not only the approximation confidents are decomposed but also the detail ones .It gives level utilizing a recursion of filters decimation tasks prompting the decline in time resolution and increment in frequency resolution. In wavelet examination, a signal is part into an approximation and a detail coefficient. The approximation coefficient is then itself part into a second-level estimation coefficients and detail coefficients, and the procedure is rehashed.

While in the wavelet decomposition, the signal splits in both approximations and details, which gives more than 2^{2n-1} approaches to represent the signal. At the point when the WT is summed up to the WPT, not exclusively can the low pass filter yield be iterated through further decomposition, however the high pass filter can be iterated also. This capacity to repeat the high pass filter yields implies that the WPT takes into consideration more than one basis function at a given scale, versus the WT, which has one basis function at each scale. The arrangement of wavelet packets overall make up the total group of possible bases, and numerous potential bases can be built from them. On the off chance that all low pass and high pass filters are iterated, the optimal sub band tree structuring is obtained. The time resolution is good at the top of the tree with poor frequency resolution while the time resolution is poor at the bottom of the tree with high frequency resolution. In other words, wavelet packet decomposition of the signal is useful in order to get better control of frequency resolution. (Lotfollahi-Yaghin ET al.2011) (Jian-Gang Han et al 2005)

3.4 Wavelet packet analysis

A linear combination of usual wavelet functions can defines the wavelet packets, which acquires the properties and attributes of its corresponding wavelet functions. For example, orthonormality and time frequency localization.

A wavelet packet can be described based on three integers, which are:

i-is the modulation parameter.

j-is the scale parameter.

k-is the translation parameter.

$$\psi_{j,k}^{i} = 2^{j/2} * \psi^{j}\left(2^{j/2}t - k\right), \quad \text{i=1,2,3,...} \tag{2}$$

From these relationships, we can obtain the wavelet functions:

$$\psi^{2j}(t) = \sqrt{2}\sum h(k)\psi^{i}(2t-k) \, , \tag{3}$$

$$\psi^{2j+1}(t) = \sqrt{2}\sum g(k)\psi^{i}(2t-k) \, , \tag{4}$$

The mother wavelet function is the first wavelet:

$$\psi^{i} = \psi \tag{5}$$

h(k) and g(k),which are discrete filters, are the quadrature mirror filters associated with the scaling function and the mother wavelet function. Some mother wavelets are developed in order to satisfy the invertibility and orthogonality properties. A Belgian woman, Ingrid Daubechies, the inventor of compactly supported orthonormal wavelets, is very well known by her researches in wavelets in which she developed a family of mother wavelets based on the solution of a dilation equation and made DW analysis applicable. The wavelet packet decomposition characterized by complete decomposition at each level, which provides a better resolution in the high frequency region.

Jth and the (j+1)th level components have the following recursive relations:

$$f_{j}^{i}(t) = f_{j+1}^{2i-1}(t) + f_{j+1}^{2i}(t) \, , \tag{6}$$

$$f_{j+1}^{2i-1}(t) = Hf_{j}^{i}(t) \, , \tag{7}$$

$$f_{j+1}^{2i}(t) = Gf_{j}^{i}(t) \, , \tag{8}$$

In which G and H are the filtering-decimation operators related to the discrete filters g(k) and h(k)

$$G\{0\}=\sum_{k=-\infty}^{\infty} g(k-2t) \, , \tag{9}$$

$$H\{0\}=\sum_{k=-\infty}^{\infty} h(k-2t) \ , \qquad (10)$$

The original signal f(t) and after the decomposition at jth level can be represented by:

$$f(t)= \sum_{i=1}^{2j} f_j^i(t) \ , \qquad (11)$$

$f_j^i(t)$ which is the wavelet packet component signal can be expressed by a linear combination of wavelet packet functions

$$f_j^i(t) = \sum_{i=1}^{2j} c_{j,k}^i\,(t)\psi_{j,k}^i(t) \ , \qquad (12)$$

Where $c_{j,k}^i$ are the wavlet packet coefficients we can get from:

$$c_{j,k}^i(t) = \int_{-\infty}^{\infty} f(t)\,\psi_{j,k}^i(t)dt \ , \qquad (13)$$

Giving the orthogonality of wavelet packet functions:

$$\psi_{j,k}^m(t)\psi_{j,k}^n(t) = 0 \qquad \text{if } m\neq n \qquad (14)$$

(Jian-Gang Han et al 2005) (Lotfollahi-Yaghin ET al.2011)

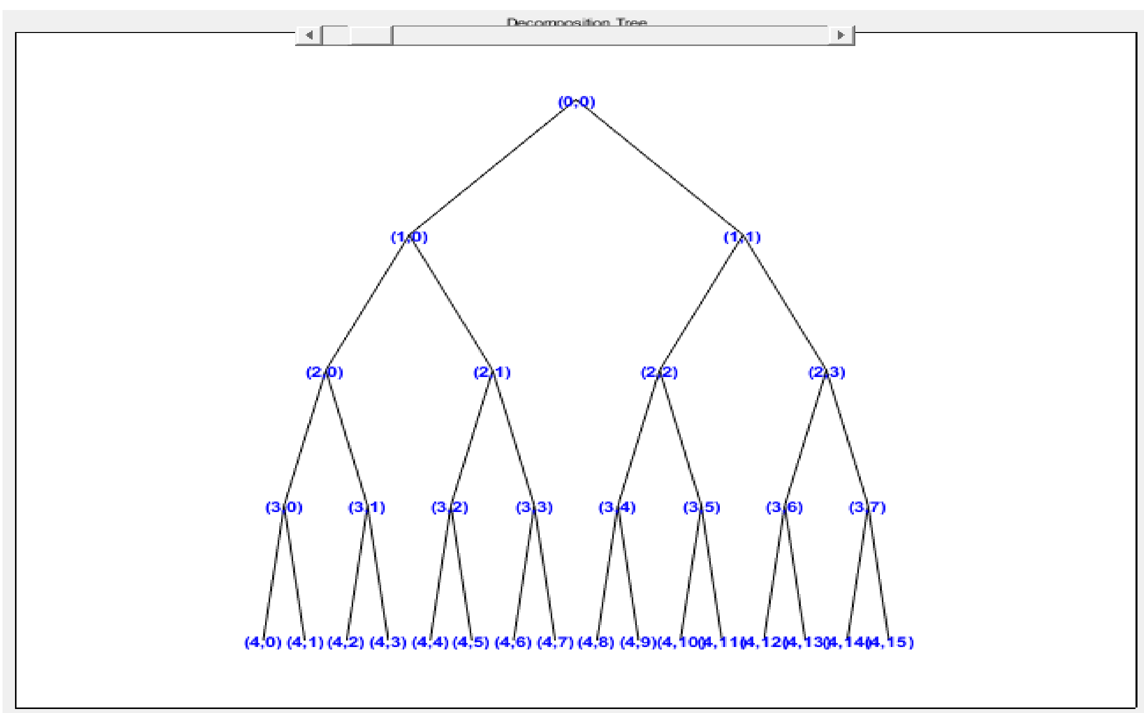

Figure.1 Decomposition of input signal to the 4th level

3.5 Wavelet packet energy rate index

In order to make the application of the WPT feasible to the vibration signals, Yen and Lin introduced a wavelet packet node energy index .The node energy could give a more robust signal feature for classification.in 2002, Chang defined a wavelet packet component energy index, which is useful for neural network models for damage assessment. The wavelet packet energy index is a good technique in investigation the occurrence of a damage, its location and how much severe.

The signal energy E_f at j level is expressed by :

$$E_{fj} = \int_{-\infty}^{\infty} f^2(t)dt = \sum_{m=1}^{2^j} \sum_{n=1}^{2^j} \int_{-\infty}^{\infty} f_j^m(t) f_j^n(t)dt. \quad (15)$$

Using the orthogonal condition Eq.(14) and substituting Eq.(12) in Eq.(15) gives

$$E_{fj} = \sum_{i=1}^{2^j} E_{f_j^i} , \quad (16)$$

Where $E_{f_j^i}$ represents the energy stored in the component signal f_j^i(t)

$$E_{f_j^i} = \int_{-\infty}^{\infty} f_j^i(t)^2 \, dt . \quad (17)$$

The component signal $f_j^i(t)$ is a superposition of wavelet functions $\psi_{j,k}^i(t)$ and it can noticed that they have almost the same scale as j but diiferent translation into the time domain ($-\infty < k < \infty$). This illustrates that $E_{f_j^i}$ is the energy stored in a frequency band defined by the wavelet functions $\psi_{j,k}^i(t)$.from Eq, we can see that the summation of wavelet packet component energies which belongs to different frequency bands is the total signal energy .

The high sensitivity of energy components provide a good index to analyze the signal characteristics. WPERI is a successful technique used in the process of detecting the occurrence of abnormality in structure; moreover, it can detect the severity and the location of harm. $\Delta(E_{f_j})$ is wavelet packet rate energy index at jth level obtained by :

$$\Delta\ (E_{f_j}) = \sum_{i=1}^{2^j} \frac{|\left(E_{f_j^i}\right)_b - \left(E_{f_j^i}\right)_a|}{\left(E_{f_j^i}\right)_a} \tag{18}$$

Where $\left(E_{f_j^i}\right)_b$ represents the damaged signal component energy at the level

$\left(E_{f_j^i}\right)_a$ represents the undamaged signal component energy at jth level.

The wavelet packet component energies would be affected by assuming structural damage .it is a good indicator for structural damage detection.(Lotfollahi-Yaghin Et Al 2011), (Asgarian et al 2014) (Jian-Gang Han et al 2005)

Chapter 4: Numerical Study Of Offshore Platfrom

In order to perform the damage detection method based on wavelet packet energy rate index and to check its validity on offshore platforms,the simulated platform without damage and with some assumed damage elements are identified.

4.1 Simulated Structure Description

The geometrical model built by using the finite element software package Ansys. The deck was modeled with a net of beam elements and quadrilateral plate elements. It is considered as shell with each side length of 13 meters. The base of the platform held by four legs with 30 meters long under the soil. A small connection having a height of 2.5 meters connects the foundation with the first steel layer. The elevations from the deck until the first steel layer are 50 meters, 38 meters, 30 meters, 21.7 meters, 12.5 meters and the connection of 2.5-meter height. The displacement responses under an impulse load are measured on 32 different node positions. (Ruotolo et Surace 1997)(Surace et al 1999)

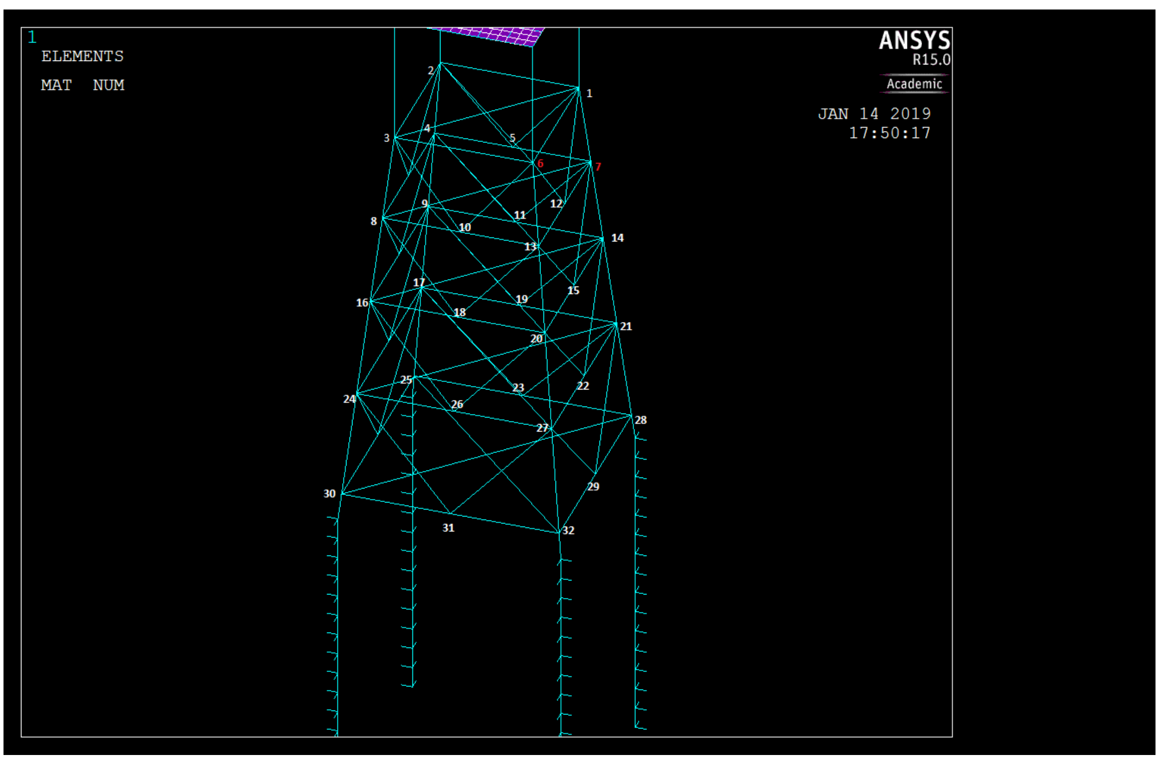

Fig.2 Geometrical model of the steel jacket platform.

4.2 Damage assumptions and locations

In order to validate the effectiveness of the wavelet packet energy rate index to detect the harm in the structure, we generate two different damage scenarios with different severity and locations in our structure. The damage severities described by reduction in stiffness of certain element.

The first damage scenario proposed is reducing the stiffness by 40% in the upper side of the platform as shown in the figure (3) indicated by red color.

The second damage scenario characterized by decreasing the stiffness by 60% in the below side of the first damage location assumption, in order to see the effect of this damage on whole the structure, it is shown in the figure(3) indicated by yellow color.

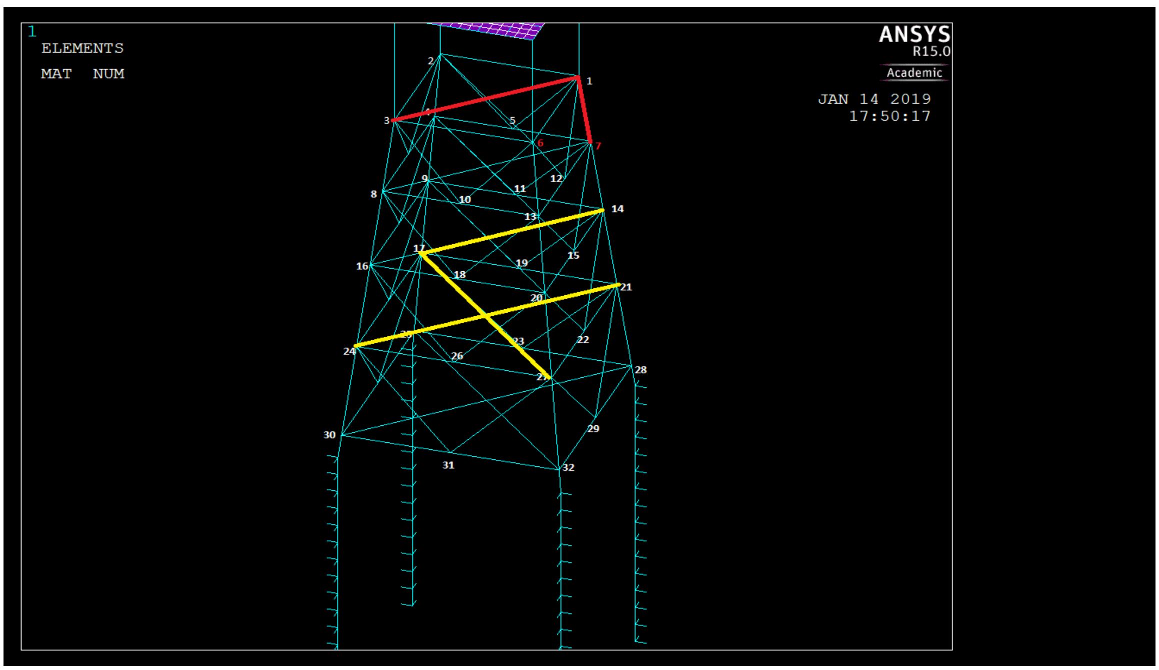

Fig.3 The location of damage introduced

4.3 Load generation and position

We have applied on the model an impulse load of 15 kN to excite the system in order to study the displacement dynamic response on each node .The time dependent force is well explained in the figure 4(a) and its location as shown in figure 4(b).

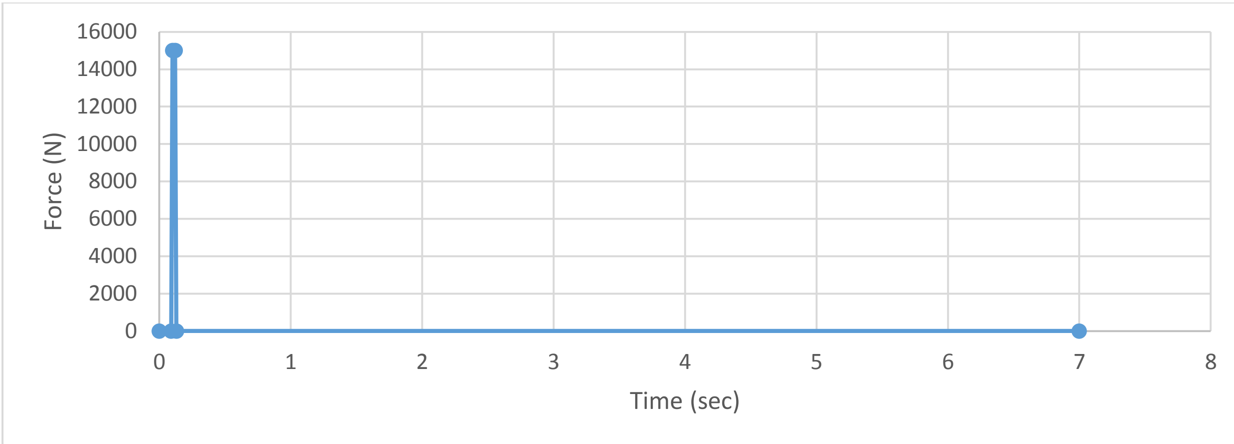

Fig.4(a) Time dependent force

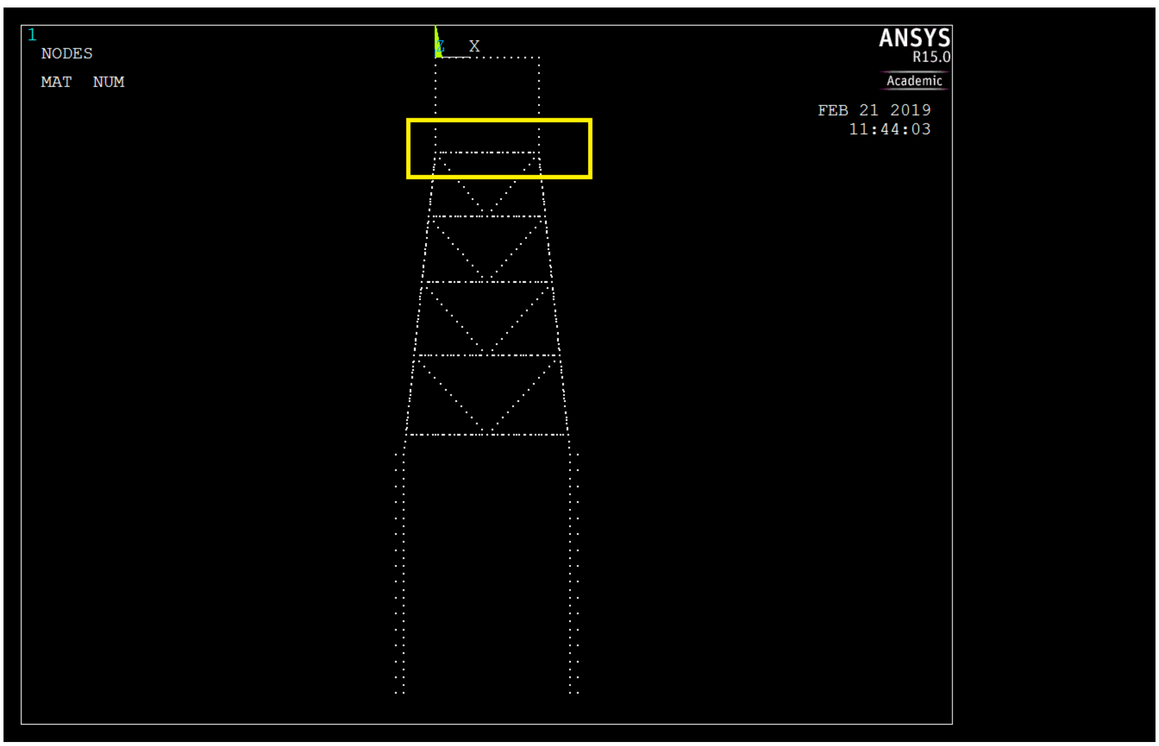

Fig.4(b) Location of the impulse load applied

4.4 Measurment of Dynamic Response

Using the software ANSYS(2015),we have introduced the model after defining the geometry, choosing element type and material properties, applying mesh and boundary conditions. We performed Transient analysis in order to obtain the dynamic response of the simulated model.

First, we did transient analysis for the undamaged structure under the effect of impulse load we already defined. We have recorded the displacement along X-axis and Z-axis as shown in figures 5(a) ,5(b) respectively :

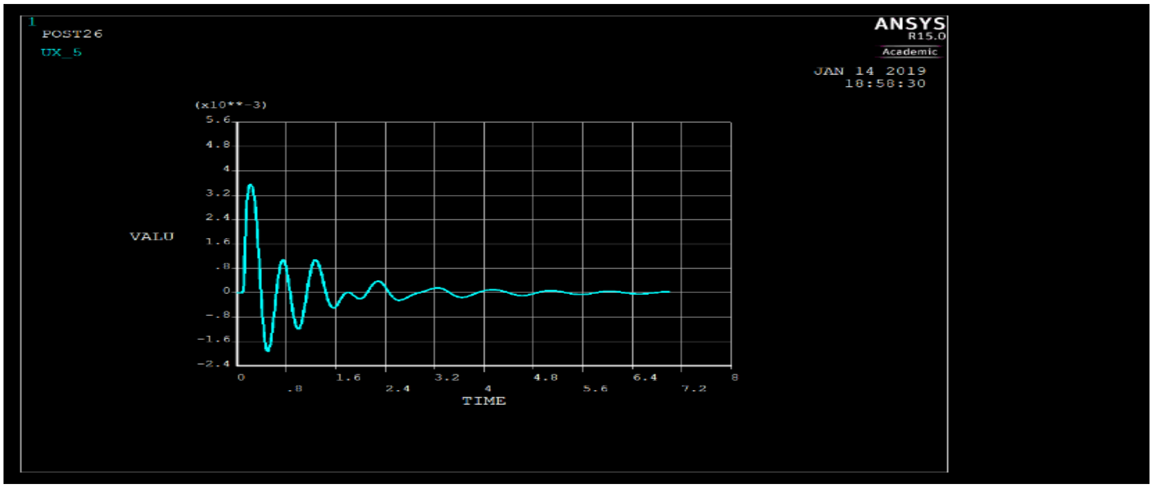

Fig.5(a) displacement along x-axis for node 5

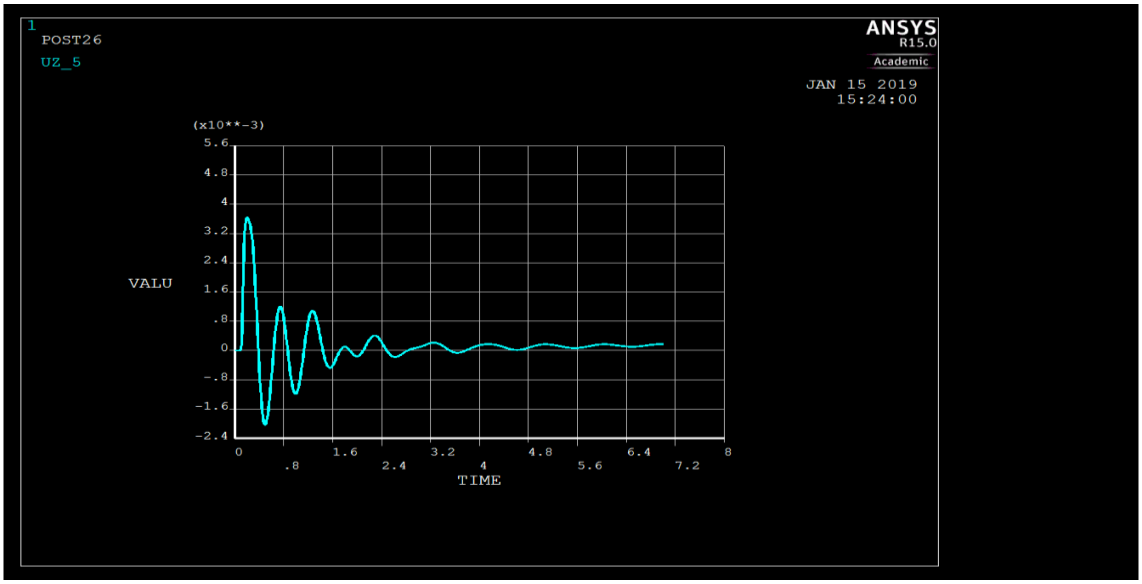

Fig.(b) displacement along z-axis for node 5

4.5 Transient analysis using ANSYS

The steps followed in order to perform transient analysis using Ansys(2015) are:

1.go to solution in the ANSYS toolbar, select analysis type, click new analysis, choose Transient , full solution method.

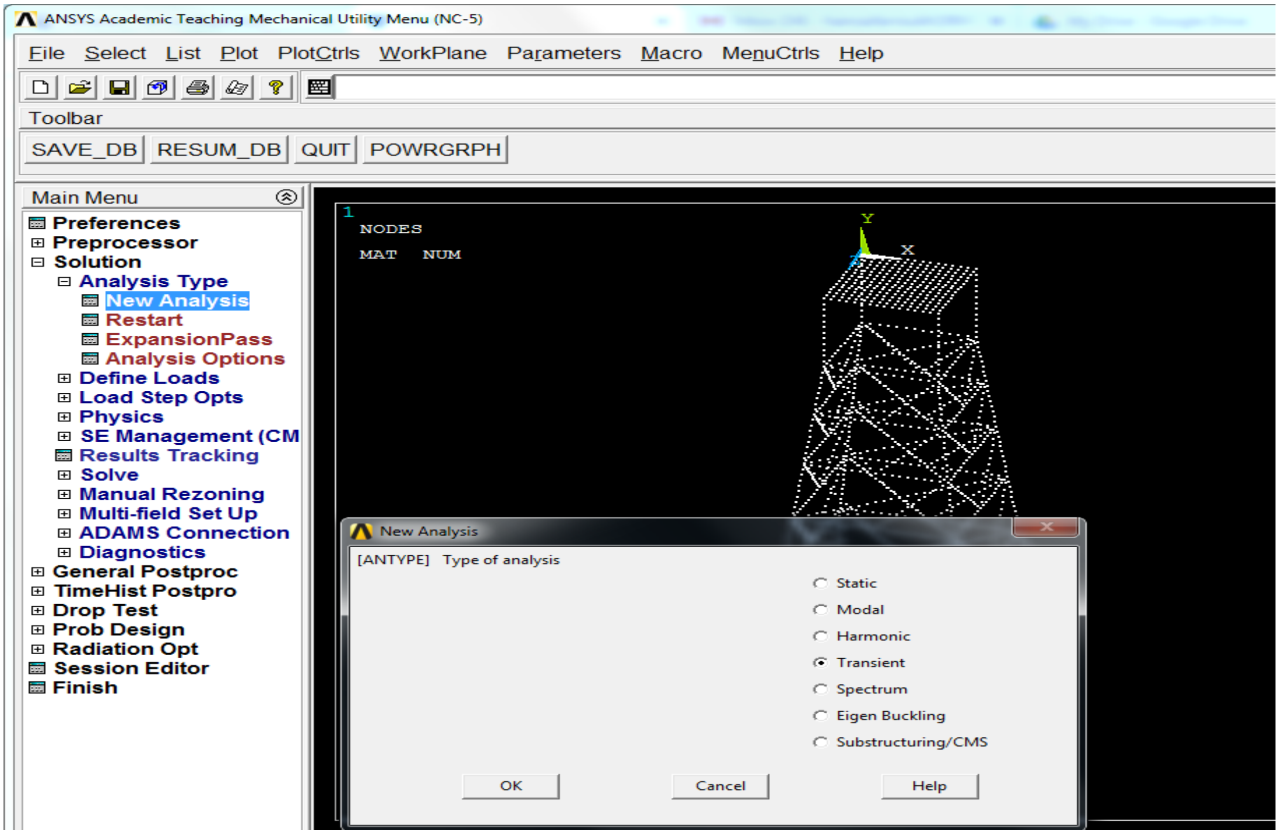

Fig.6(a) selecting the new analysis type by ANSYS

2. After clicking on transient new analysis ,it appears on the toolbar , Sol'n Controls, define analysis options as small displacement transient, time at the end of loadstep.after running the model many times, we got the minimum time to represent the dynamic response of the given model under the given impulse load is 7 seconds , click on Time increment by 0.01, in the frequency area, select Write Every Nth substep.

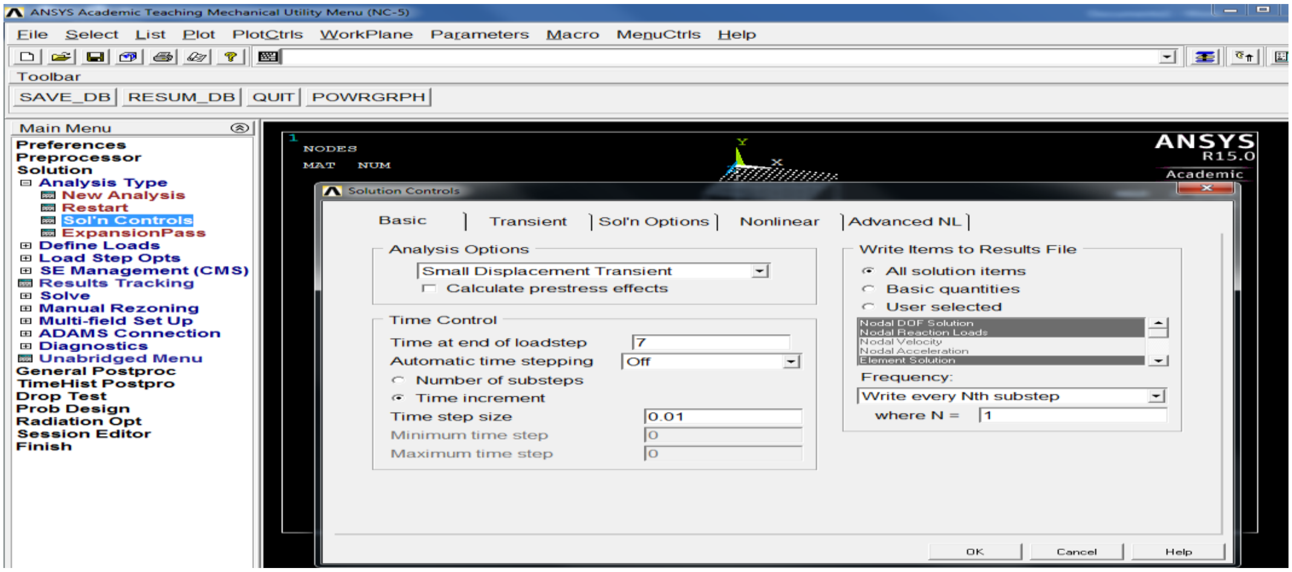

Fig.6(b) setting solution controls

3. go to Transient , select Ramped loading, assuming damping coefficients Alpha and Beta 0.002 and 0.02 respectively for huge structures.

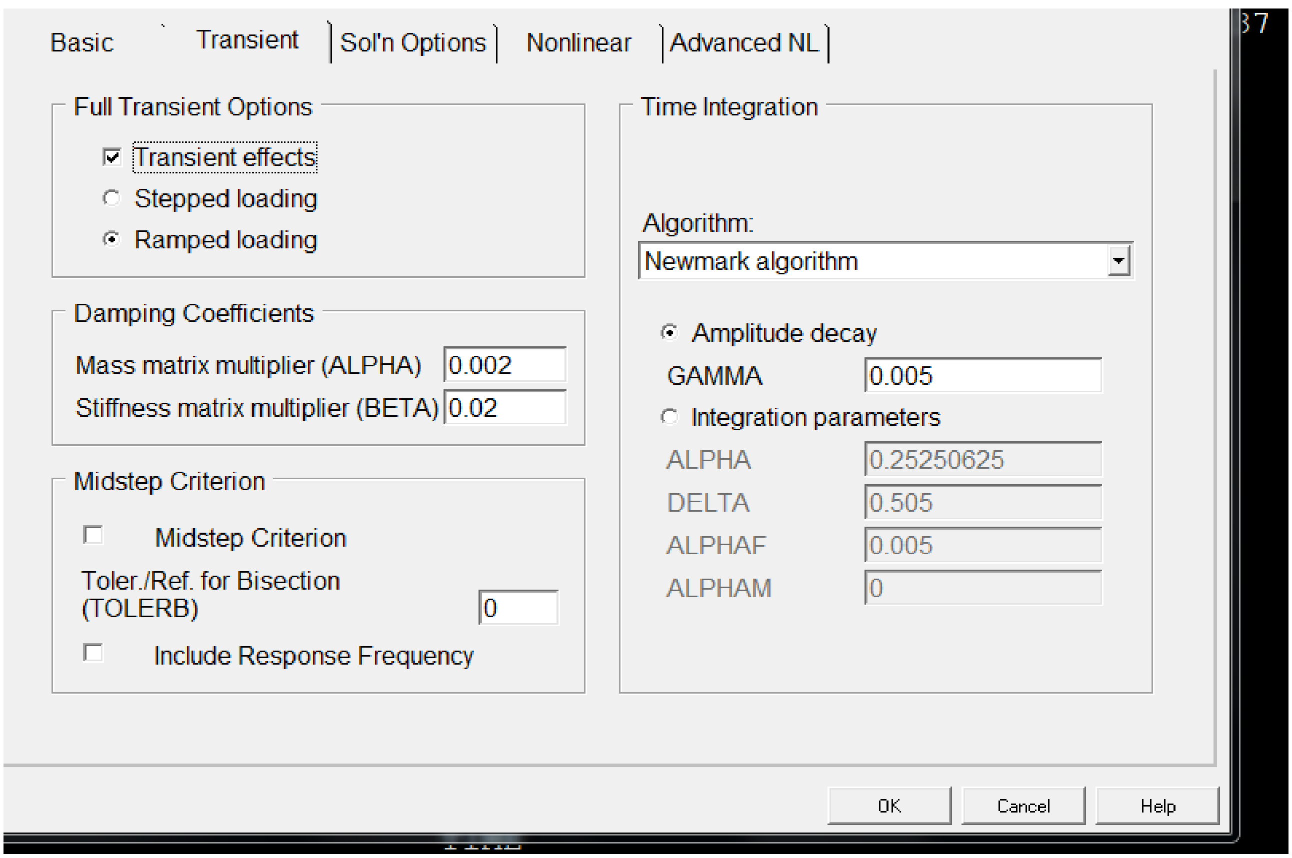

Fig.6(c) illustration of setting constraints

4.Generate a time dependent load using ANSYS, from the toolbar above ,select Parameters, Array parameters, Define/Edit , add parameter , select table array, 6 number of rows and 1 number of columns.

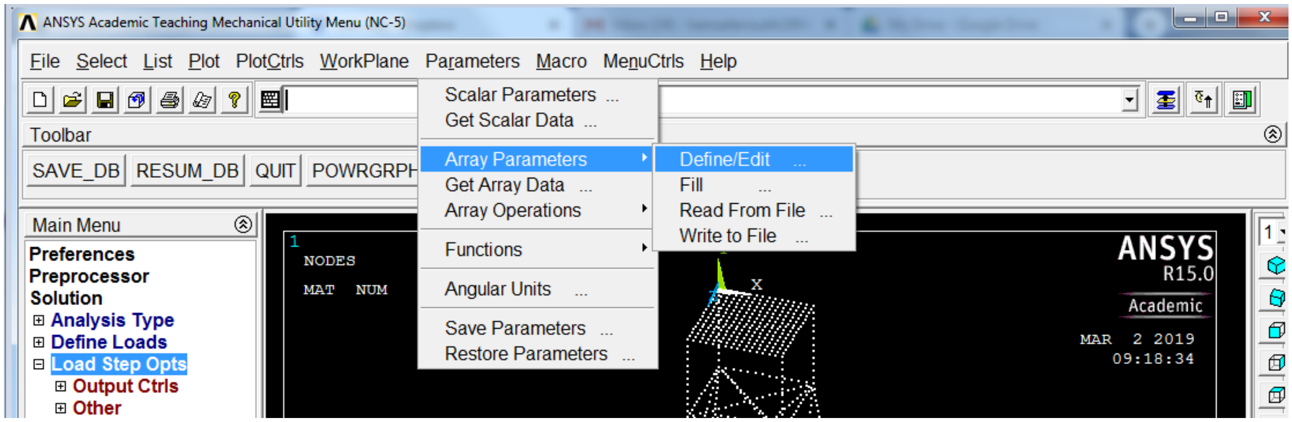

Fig.7(a) load impulse generation on ANSYS.

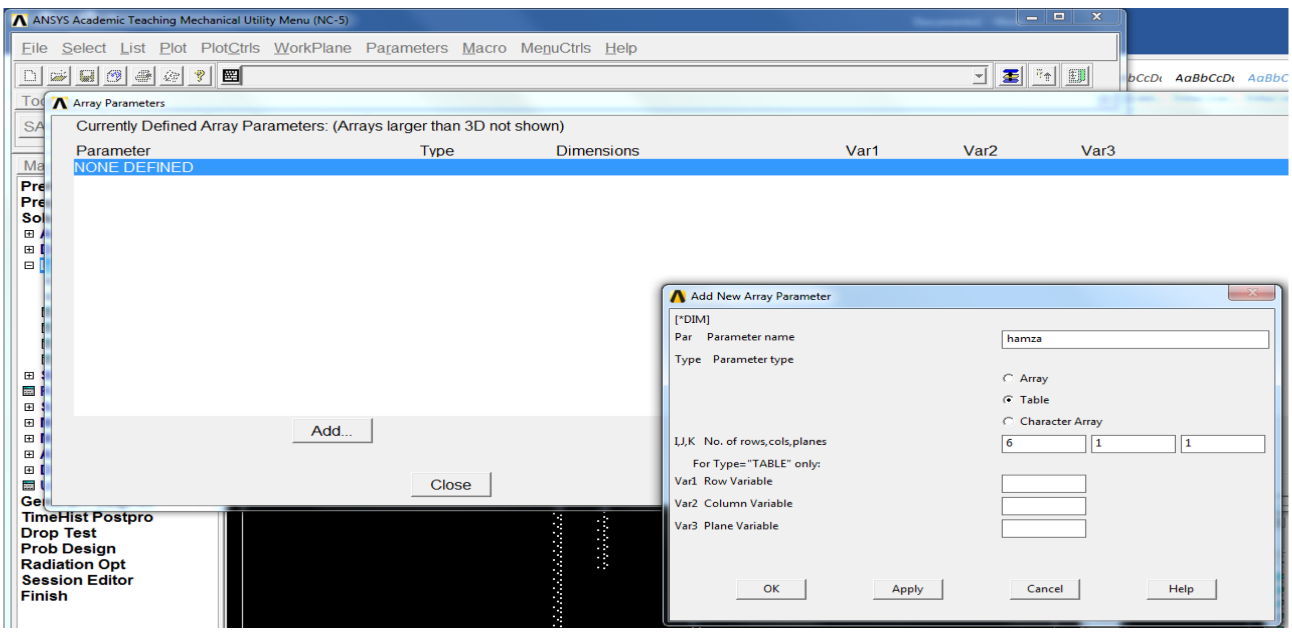

Fig.7(b) load impulse generation on ANSYS.

Insert the values of the impulse load, APPLY/QUIT.

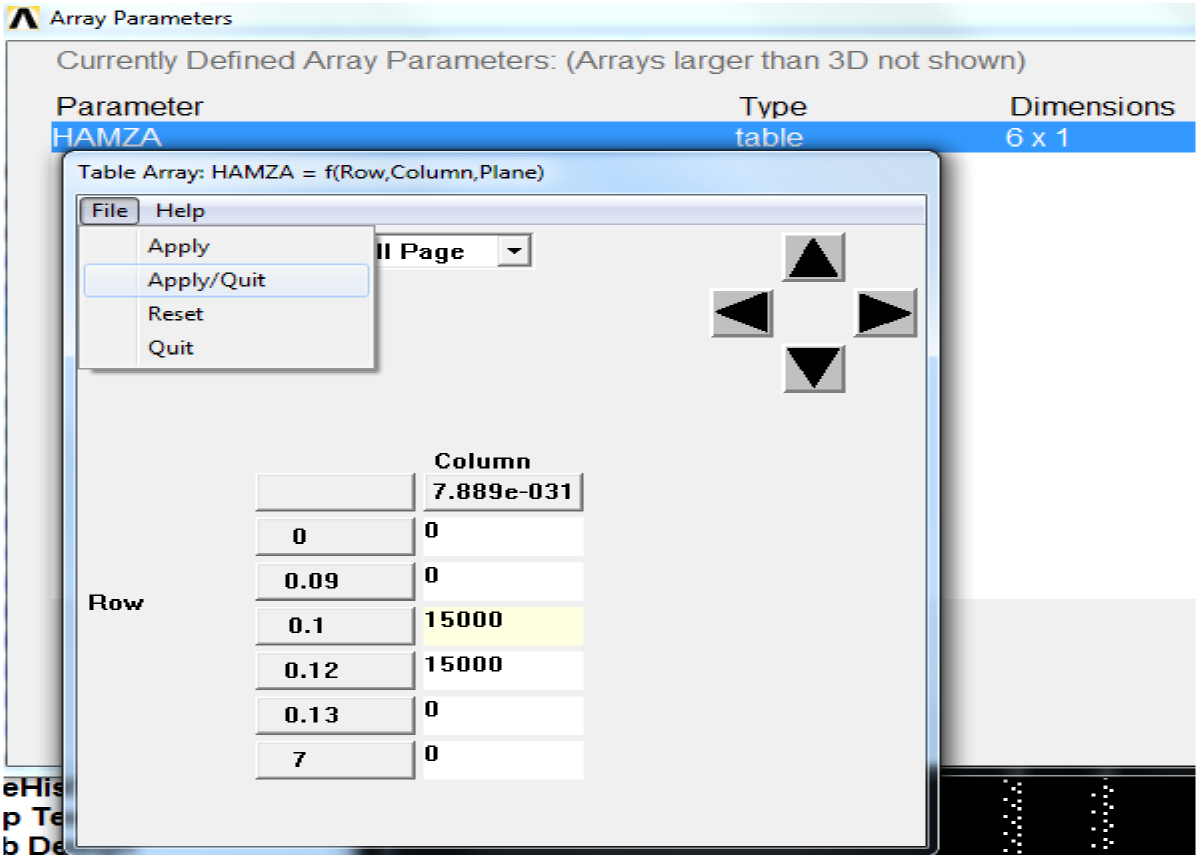

Fig 7(c) generation of load impulse.

5. After definig the array parameters, Go to main menu , select Define loads, Apply Structural Force/Moment on Nodes, choose Box , selecting the area of application the load ,setting the direction of load along X-axis ,apply as existing Table array we have initially defined. Repeat the same procedure along z-axis.

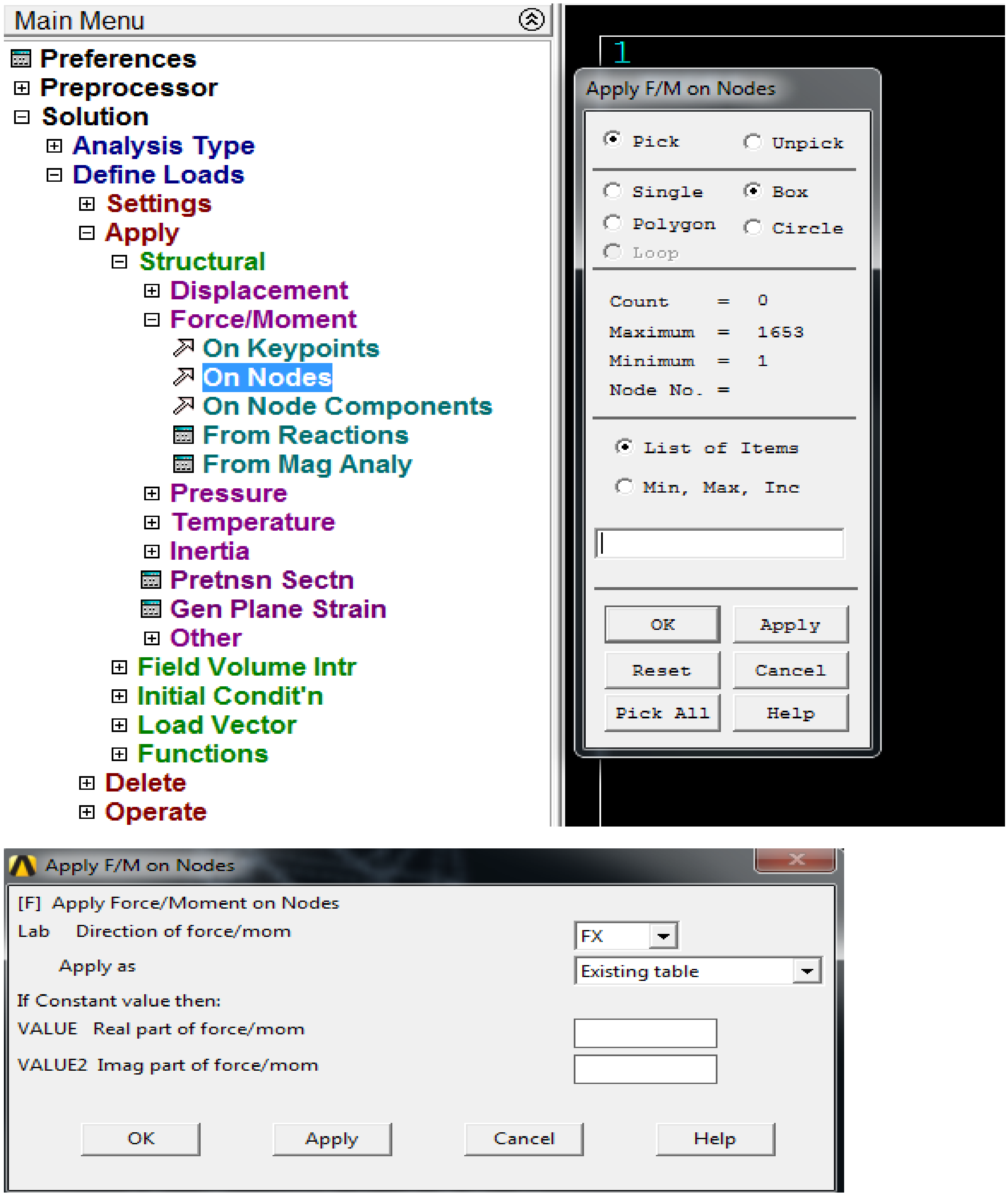

Fig.7(d) applying the impulse load

6.After Go to main menu, solve current LS. The software will automatically analyze the model behavior under the defined impulse load respecting the assigned constraints.

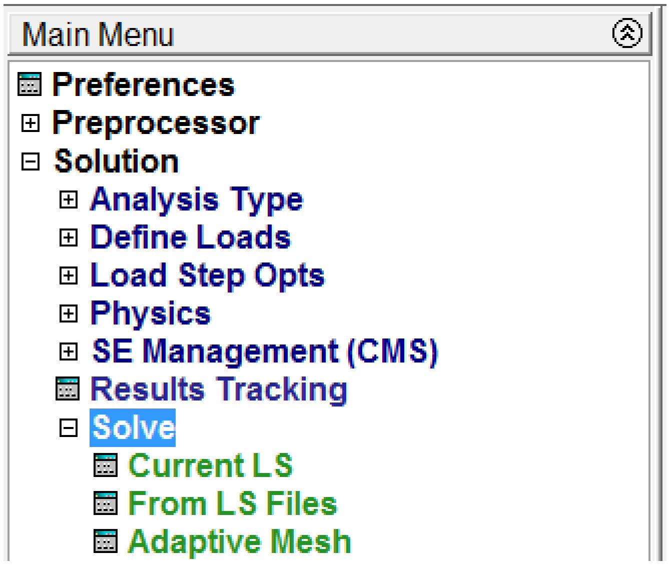

Fig.8 solving the current LS

7. After solving the model, go to main menu, select time History postpro, select displacement response,show the results on each node.

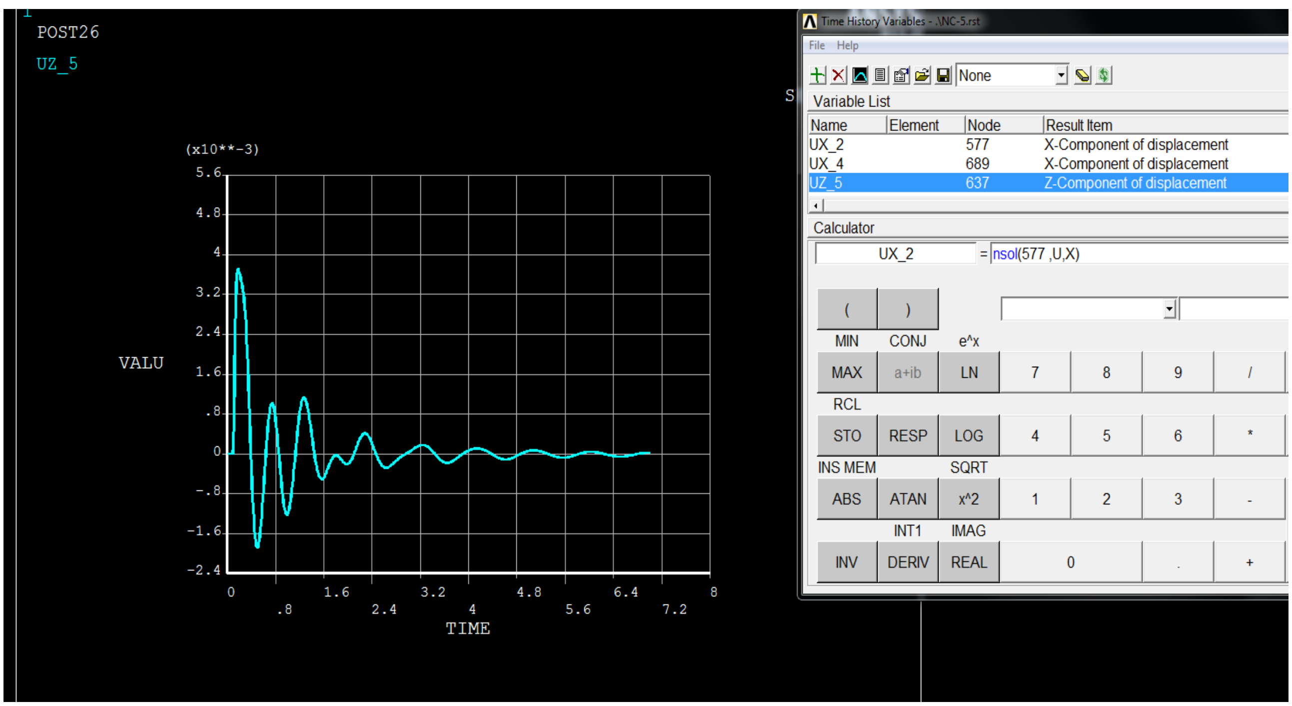

Fig.9 the results obtained after performing transient analysis

8.Repeat the same procedure in making transient analysis for Damage 1 and Damage in order to get the dynamic displacement response of the system

9. The output results from ansys can be defined as dynamic response of the system whch then introduced to Matlab software to perform signal decomposition.

4.6 Wavelet Decomposition Using MATLAB(2017a)

After performing the transient analysis of the given model under the impact of the defined impulse load using ANSYS(2015), the dynamic signal has been obtained for each node of the given 32 nodes at different operational condition (for undamaged and damaged 1 and 2).

The next step is to introduce the obtained signals to matlab in order to make wavelet decomposition of the signals by importing the signals to matlab workspace as array. Using the 1-D wavelet packet decomposition function which already defined on the software.first we load the input signal, then we assign the wavelet mother wavelet choosing duabachies and its level in addition to selecting a certain level of decomposition and setting the entropy type. We have choose the level of decomposition by performing trial and error method and we got 4th level is well enough providing the needed data. For the entropy, we have chosen Shannon type. In addition, the mother wavelet is assumed to be duabachies since it performs better in terms of damage detection in marine platforms, we did the decomposition for both db4 and db5 to see the difference in mother wavelets level.

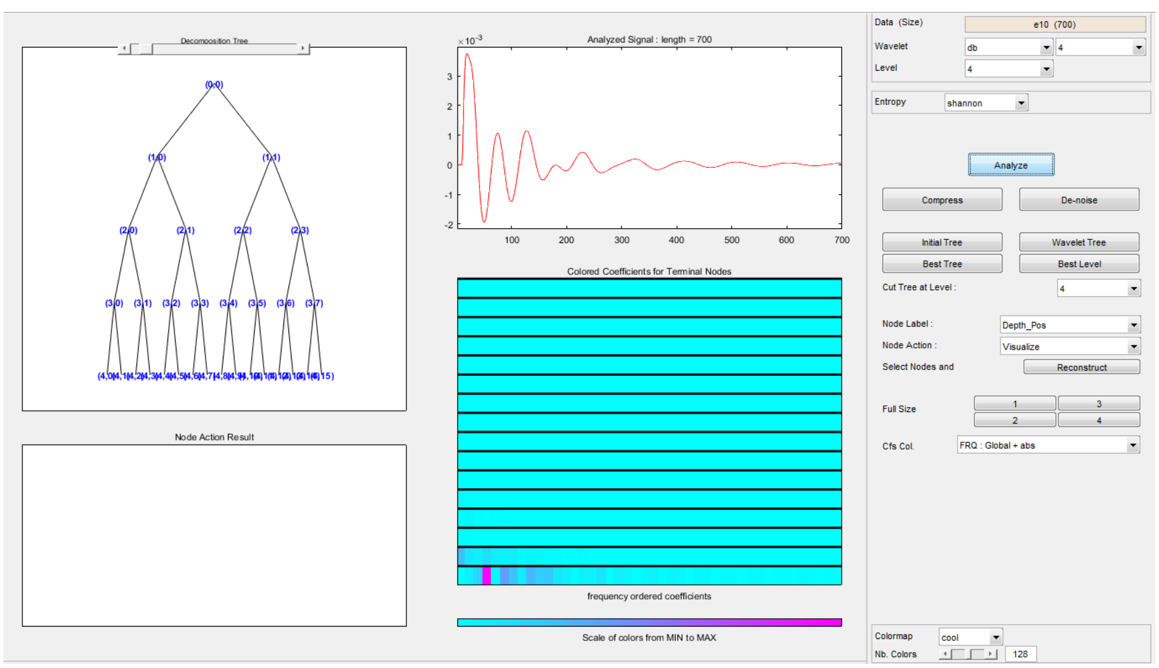

Fig.10(a) wavelet packet decomposition 4th level by db4

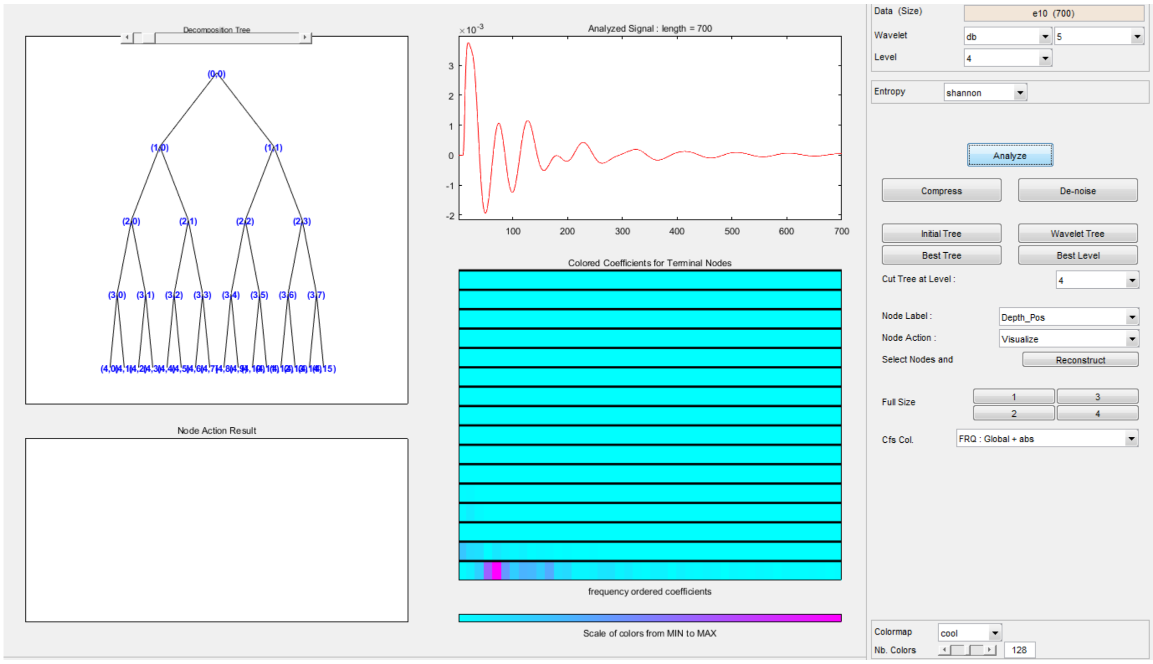

Fig.10(b) wavelet packet decomposition of 4th level by db5.

Repeat the same procedure of wavelet packet decompositon on all nodes and with different operation conditions for each damage scenario.

4.7 Matlab code for calculating component energies and energy rate index

After introducing all the dynamic signals into the matlab(2017a), Ing. Marco Civera and I worked on creating a code in which the signal decomposed and component energies can be calculated in order to apply the eq.(18) to obtain the wavelet packet energy rate index at each node for damage 1 and damage 2.

```
close all
clear all
[u,F,uF]=xlsread('damaged 1 along x.xlsx');
[u1,F1,uF1]=xlsread('normal conditions along X.xlsx');
for i=10:30
dam=u(1:700,i);
norm=u1(1:700,i);

% Damaged Energy

T(i)=wpdec(dam(i),4,'db4' ,'shannon' );

% UnDamaged Energy

W(i)=wpdec(norm(i),4,'db4' ,'shannon'  );

end
E_dam=zeros(1,16);
E_undam=zeros(1,16);

for j=1:30

E_dam =[E_dam wenergy(T(j))];

E_undam = [E_undam wenergy(W(j))];

deltaN(j)= sum (abs(E_undam(j) -E_dam(j) )/E_undam(j));
end
```

Fig.11 matlab code applied

Chapter 5: Results and interpretations

5.1 graphical representation of obtained results

After running the matlab code, the wavelet packet energy rate index at each node for damage 1 and damage 2 are represented in these histograms:

The damage location can be intuitively shown in histograms where high wavelet packet energy rate index at a certain node indicates the existence of abnormality.

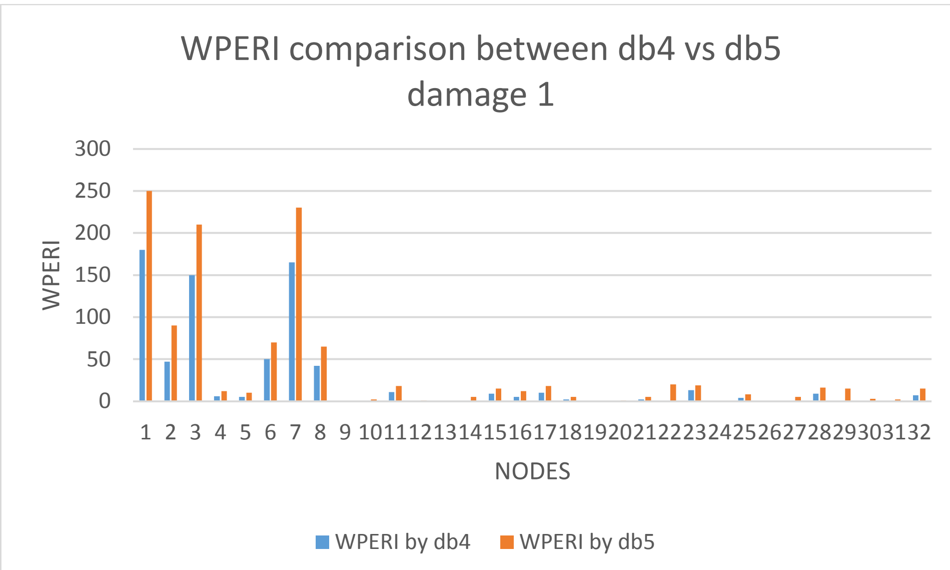

Fig.12(a) WPERI for damage 1 as function of db4 and db5

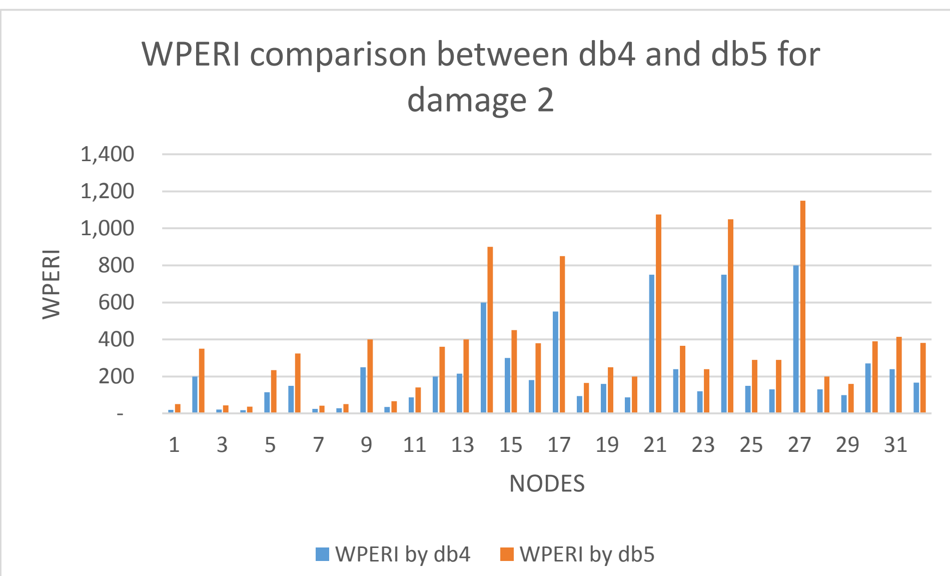

Fig.12(b) WPERI for damage 2 as function of db4 and db5

Histogram representation of wavelet packet enrgy rate index (WPERI) of damage one by daubachies mother wavlet considering 4th level type at each node :

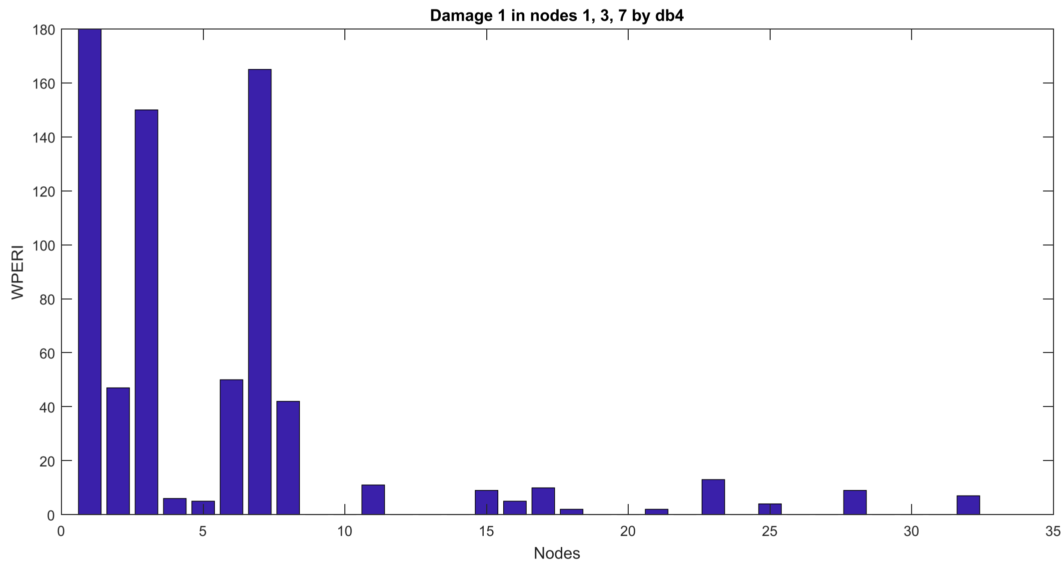

Fig.13(a) WPERI of damage one by db4 as function of nodes number

It can be observed that the wavelet packet energy rate indices appeared in nodes number 1, 3 and 7 are greater than other nodes, then we can conclude that these nodes are damaged.

ULWPERI α value is subtracted from the WPERI values :

Applying the technique of statistical process control (SPC) for the computation of threshold values for the damage indicators. The X-bar control chart gives a statistical framework for checking future estimations and for recognizing anomaly in the new data by building up the lower and upper control limits. These limits encase the variety of the extracted damage indicator. If any indicator fall outside the threshold values, illustrates an abnormality occurrence. In the case of multiple damage existence, the proposed method can still work efficiently.

A total of thirty-two WPERIs is the result of wavelet packet decomposition of the dynamic signal response on the given thirty two nodes.

Ang and Tang described the one-side (1-α) upper confidence level by the following formula :

$$UL_{WPERI}^{\alpha} = \mu_{WPERI} + Z_{\alpha}\left(\frac{\sigma_{WPERI}}{\sqrt{n}}\right) \quad (19)$$

Where Z_α is the value of a standard normal distribution with zero mean and unit variance such that the cumulative probability is 100(1- α)%.

The statistical analysis is then implemented within those 32 WPERI values. The mean value μWPERI and the standard deviation σWPERI can be evaluated. Assuming that α = 0.02, the one-sided 98% confidence upper limit UL α WPERI for the WPERI. For every damaged structure, the histogram can be drawn the WPERI ULα value is subtracted from the WPERI values.

The histogram showing the WPERI-UL of damage one by daubachies mother wavlet at level four with decomposition to 4th level ensures the damage existence in nodes number 1,3 and 7

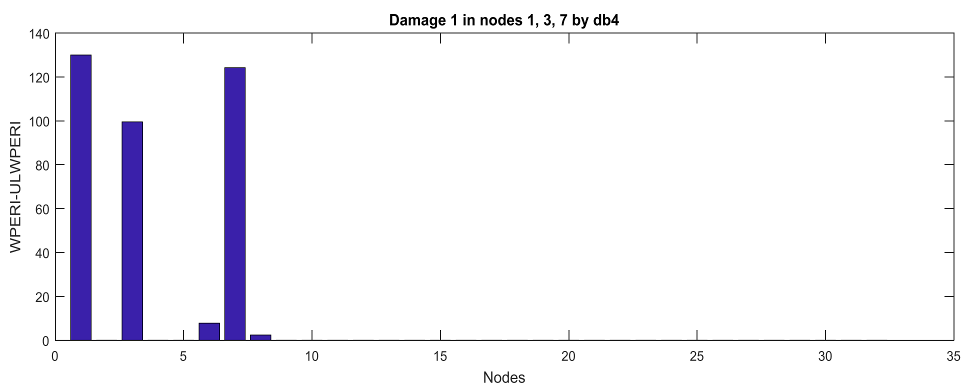

Fig13.(b) WPERI-ULWPERI of damage 1 by db4 as function of nodes number

These following histograms represent the wavelet packet energy rate index at both damage condition 1 and 2. A small comparison showing the difference in WPERI by using different duabachies mother wavelet basis. We considered in our analysis, duabachies 4 and duabachies 5.

Using duabachies mother wavelet level 5, the results shown in the histograms

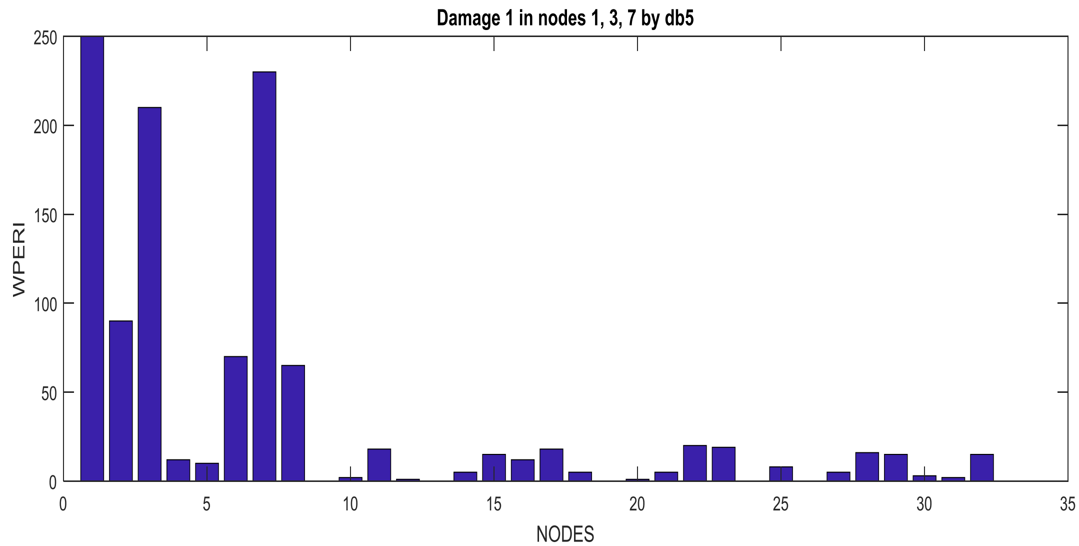

Fig.14(a) WPERI of damage 1 by db5 as function of nodes number

It can be seen that the wavelet packet energy rate indices appeared in nodes number 1, 3 and 7 are larger than another nodes then we can conclude that this nodes are damaged.

Then we apply UL-WPERI to the retrieved results:

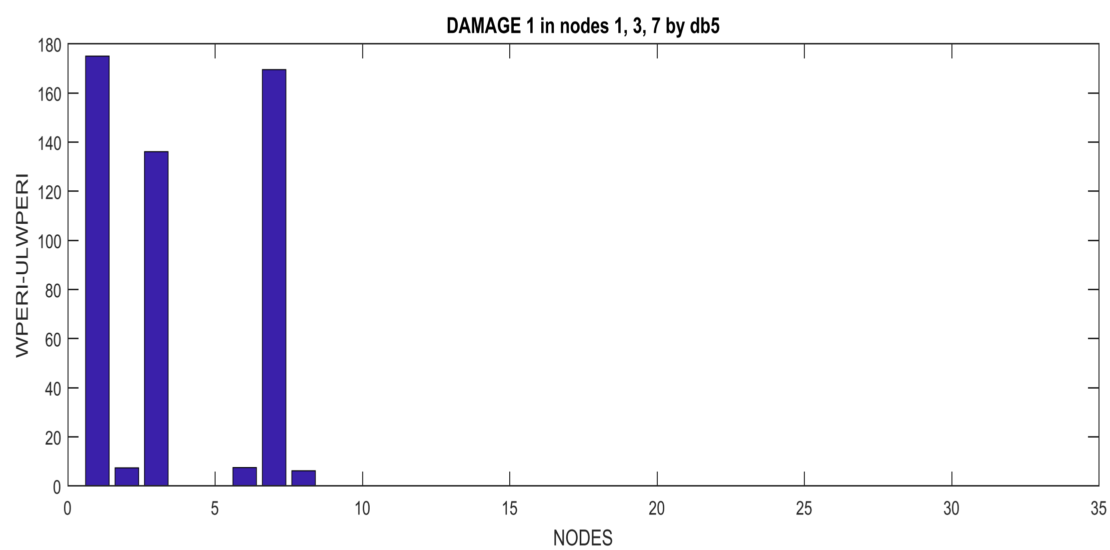

Fig.14(b) WPERI-ULWPERI OF damage 1 by db5 as function of nodes number

The histogram of WPERI as function of node number by damage two using duabachies at level four are well presented in the following histogram

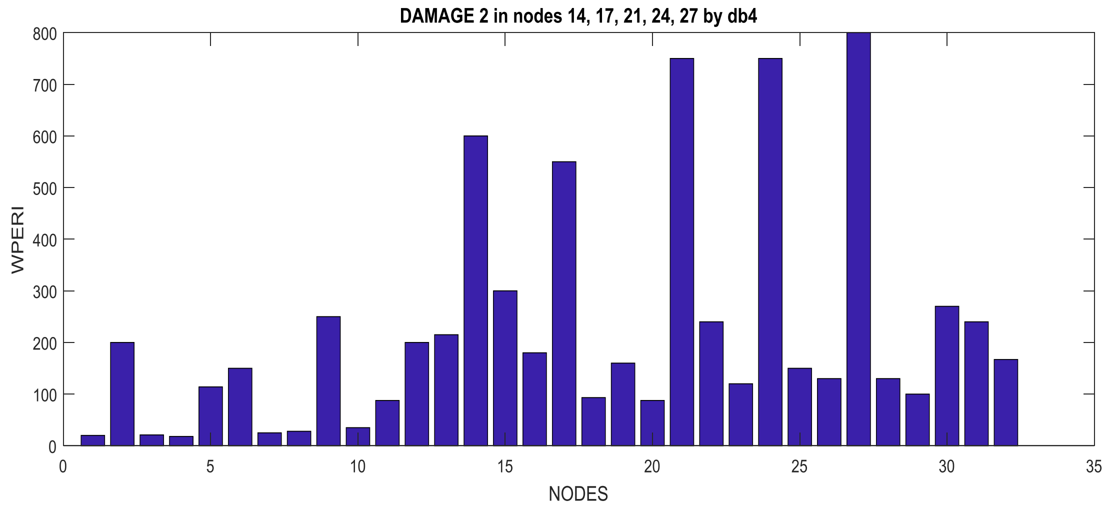

Fig.15(a) WPERI of damage 2 by db4 as function of nodes number

it can be obvios that the wavelet packet energy rate indices appeared in nodes number 14,17,21,24 and 27 are larger than another nodes, then we can suspected that this nodes are damaged.

The histogram of representing the result after applying threshold method confirms the same indication of damage occurrence at the same nodes.

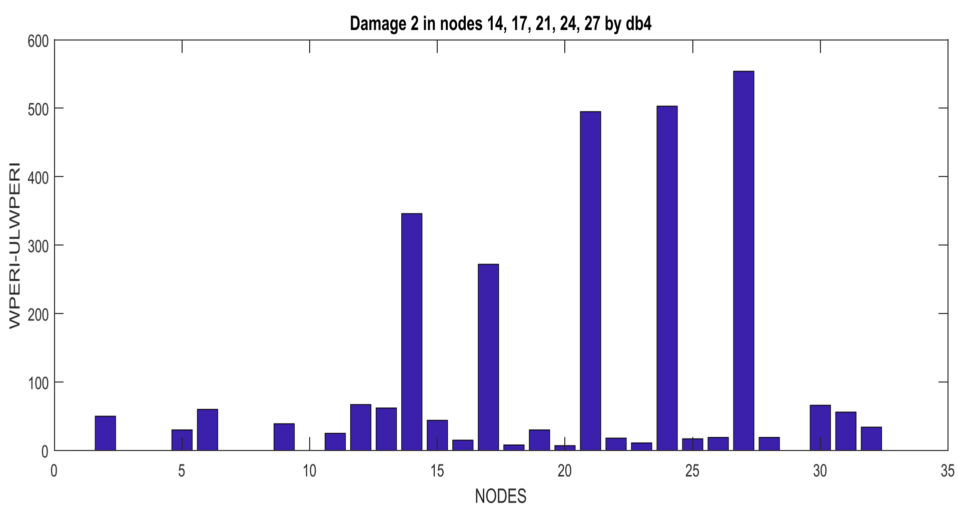

Fig.15(b) WPERI-ULWPERI of damage 2 by db4 as function of nodes number

The same procedure of comparison of WPERI by using daubachies at level 5

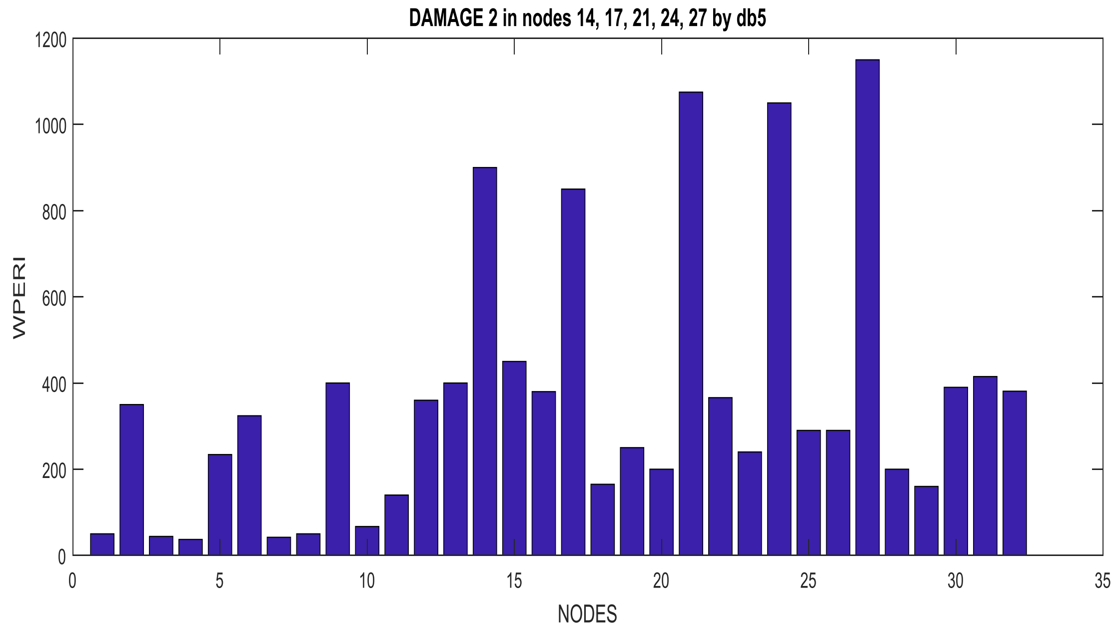

Fig.16(a) WPERI of damage 2 by db5 as function of nodes number

It can be clear that the wavelet packet energy rate indices appeared in nodes number 14,17,21,24 and 27 are higher than other nodes then we can notice that these nodes are damaged.

After evaluation of the subtraction of upper limit values to WPERI values :

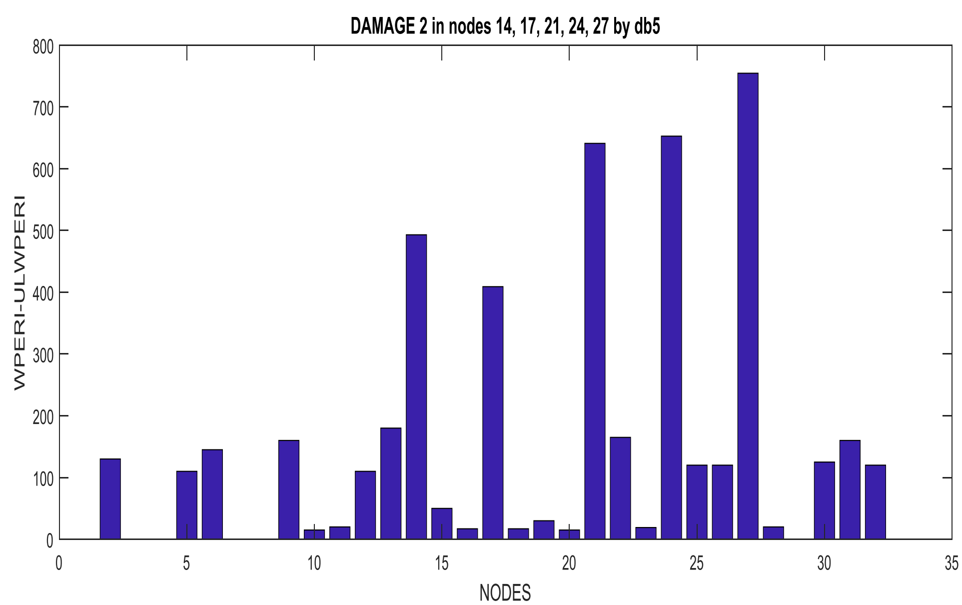

Fig.16(b) WPERI-ULWPERI of damage 2 by db5 as function of nodes number

6.2 Damage description and Results interpretation

For damage one scenario which represents 40% stiffness reduction in a vertical and horizontal element located at the upper side of the platform. The dynamic response due to physical property changes has been solved by the finite element software ANSYS.these outcomes went into wavelet decomposition using MATLAB and component energies calculations are done. Fig12(a) represents the WPERI of damage one in both vertical and horizontal elements. It is evident that WPERI is higher in nodes number 1,3 and 5 which are located at extremes of our induced stiffness reduction damage, which can provide an initial success of the introduced method to detect the damage location based on wavelet packet energy index. The WPERI in the nodes near to zone of induced damaged is higher than that of other nodes. The other WPERI's of the faraway damage nodes is shown to be small and limited which may relate to the effect of the damage on whole structure.

In both situations of assuming mother wavelets as duabachies 4 and duabachies 5, the WPERI's are still higher in the damaged nodes, giving the same results and providing a good understanding of the health of the structure and the ability of detection of any harm existence in the system. The quality of representing the results could be better using daubachies 4 mother wavelet. The results are well comparative and represented of damage occurrence. Hence, the decomposition level of the dynamic signal is enough. It is always better taking the lowest level of decomposition which can give the wanted results which facilitates the calculation procedures.

In Fig.12(b) which is referred to WPERI's of the damage two as the effect of the induced damage on the nodes and other surrounding elements. To record, the damage assumption in second scenario is higher than the damage assumption in the first one. Also, the location of damage is different in second scenario from that of first one, where the damage is applied to more elements and below the damaged 1 which is in the upper side of the platform. It is good to know the effect of this damage position and its impacts over all elements of the system. It is obvious that in this case, more dependence of the other elements of the structure on this part, as we can see from WPERI's which is very high in the position of induced damage. But also evident that WPERI's in the other elements are high relatively to that of case one . The situation of the structure in damaged two is worser on the system and affects most parts.

The same results can be recognized by using duabachies four or duabachies five. Hence, a small difference in quality representation of damage detection gives better resolution of results using db4. Moreover, both db4 and db5 are good choices for marine structures damage detection.

The damage assessment which is directly applied on the results obtained, upper-limit subtracted from WPERI's, a more robust signal feature for classification. There is limit value of WPERI can show the limit in which the decomposed signal energy component control to check the existence of the abnormaility in the system. As shown in figures,WPERI-UL is better represented than WPERI's. It is high effective if there is a small intense of damage in the structure. In these figures,WPERI-UL histograms shows and confirms the results we have analyzed and conclude that in damage one , the higher the UL-WPERI in the given elements confirming the damage existence in that element.

Chapter 6: Conclusion

The major importance of offshore platforms in oil and gas exploration and exploitation in the seaside, oil and gas industries provide a huge investment on developing this technology. Lot of challenges face the existence of offshore platforms which are subjected to harsh environmental conditions threatens the health behavior of the structure. A degradation of its initial physical properties can lead to complete failure of the structure. The universe trend of increasing the reliability and safety supported by governmental policies concerning these large structures and after experiencing several failure behavior of past structures and their catastrophic effects on the environment and man health. The high necessity of structural health monitoring due to its efficient analyzing of the dynamic responses of the structure leading to online monitoring with low cost and high reliability.

Damage detection is a local phenomena.SHM using wavelet packet energy rate index shows a powerful technique in detecting any abnormality occurance. Its concept based on the changes in the dynamic properties of the structure, which can be recognized by high frequency signals.

WPERI can be considered as an effective indicator of damage by highlighting damage location. The higher the index of energy of given element represents the occurrence of a damage. In order to perform the wavelet packet energy rate method ,a smart sensing system is required to measure the dynamic signals at the expected damage positions. By analyzing the dynamic response of the structure,it provides good signs of structure's integrity and operatibilty. Starting by decomposing the dynamic signals using wavelet packet decomposition function followed by good calculation of the energy components and their usage for damage assessment.WPERI is a promising tool to recognize any harm with short time evaluation procedure. Online implementation of this technique provides efficient results in avoiding any failure of the structure.

Bibliography and Sitography

Asgarian Behrouz , Vahid Aghaeidoost , Hamed Rahman Shokrgozar, 2015, Damage detection of jacket type offshore platforms using rate of signal energy using wavelet packet transform, © 2015 Elsevier Ltd. All rights reserved.

BALAGEAS, Daniel.2005. Introduction to Structural Health Monitoring

Charles R. Farrar, Keith Worden. 2013. STRUCTURAL HEALTH MONITORING,A MACHINE LEARNING PERSPECTIVE,Thisedition first published 2013 C 2013 John Wiley & Sons, Lt

Civera M.,C. M. Filosi, N. M. Pugno, M. Silvestrini, C. Surace and K.Worden. 2018. Using Wavelet Level Variance and the Discrete Wavelet Transform to Monitor Postoperative Healing of Vocal Cords,in: 9thEuropean Workshop on Structural Health MonitoringJuly 10-13, 2018, Manchester, United Kingdom.

Gokhale M. Y., Daljeet Kaur Khanduja. 2010. Time Domain Signal Analysis Using Wavelet Packet Decomposition Approach, Int. J. Communications, Network and System Sciences, 2010, 3, 321–329 doi:10.4236/ijcns.2010.33041 published Online March 2010 (http://www.SciRP.org/journal/ijcns/).

Han Jian-Gang , Wei-Xin Ren , Zeng-Shou Sun. 2005. Wavelet packet based damage identification of beam structures, International Journal of Solids and Structures 42 (2005) 6610–6627

Harish N,Sukomal Mandal, Shanthala ,Subba Rao, 2010, ANALYSIS OF OFFSHORE JACKET PLATFORM, Proceedings of SWaRM

Lotfollahi-Yaghin Mohamad Ali,Sajad Shahverdi,Reza Tarinejad,Behrouz Asgarian.2011. STRUCTURAL HEALTH MONITORING (SHM) OF OFFSHORE JACKET PLATFORMS , Proceedings of the ASME 2011 30th International Conference on Ocean, Offshore and Arctic Engineering

RUOTOLO R. and C. SURACE. 1997. Proceedings PACAM 197 Puerto Rico. A statistical approach to damage detection through vibration monitoring. “Damage detection for a system with time- varying parameters”

Sadeghi Kabir. 2007. An Overview of Design, Analysis, Construction and Installation of Offshore Petroleum Platforms Suitable for Cyprus Oil/Gas Fields , K. Sadeghi, GAU J. Soc. & Appl. Sci., 2(4), 1-16

Surace Cecilia, Romualdo Ruotolo, Keith Worden. 1999. Application of two damage detection techniques to an offshore platform, In: 17th International Conference of Modal Analysis (IMAC XVII), Orlando, USA Feb. 1999, ISSN: 10466770