Department of Environment, Land and Infrastructure Engineering

Master of Science in Petroleum Engineering

Structural Health Monitoring of Jacket Offshore Structures Under Different Operational Conditions Using a Cointegration Approach

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Abstract

Many efforts were done by the oil Industry to develop damage detection methods for offshore platforms since the offshore structures are widely used for different functions and in a variety of environments across the globe mainly in the petroleum industry for offshore drilling, exploration and production activities. Platforms faces many practical problems and difficulties occurred in harsh environment, in addition to other problems including mass variation and varying fluid storage that usually occurs on the deck of the platform. These problems affect the dynamic response of the structure and cause higher vibrational modes. Also, damage detection in offshore platforms considered very difficult in some parts of the structure that is covered by sea water especially in deep sea-beds. In addition, damages caused by environmental and operational conditions can affects health, environment, and economics. Structural health monitoring is implemented to check the health of the structure and how the structure is responding to various loading conditions and determine whether it is susceptible to failure. The Vibrational based techniques developed for damage detection are based on the natural frequency and dynamic response variations but are not capable to distinguish between environmental and operational condition and structural damage.

In this study the non-linear Co-integration method is presented with the aim of an early stage damage detection in offshore platform structures. This based method has advantage over other techniques that it is capable to deal with structures subjected to different operational conditions and differentiate effectively between the normal operating conditions due to difference in oil storage and damage conditions. Moreover, the Co-integration is a technique used to analyze non-stationary time series where its variables are co-integrated, and the linear combination of the time series must be stationary. The difference between the real data and the estimated ones is the stationary residual, where

this residual that is created from co-integration is used as a damage-sensitive that is independent of environmental and operational conditions. In Chapter 1, an introduction to structural health monitoring is presented followed by introduction to the damage detection and different techniques available are outlined. Chapter 2 consists of a comprehensive Data normalisation and a definition of the Co-integration technique. To apply this method, a case study (Chapter 3) is performed by developing a general finite element model of an offshore platform structure on the software ANSYS and simulated for 21 different normal operational conditions due to change in the oil storage mass and for damage conditions due to stiffness reduction. The dynamic response of the structure in terms of frequency is monitored for each normal condition and levels of damage in first normal condition and inserted in a non-stationary dataset of 500 observations with different normal conditions and level of damage where implemented and presented in chapter 4. Finally, Co-integration were applied through multiple regression techniques, Support Vector Machine(SVM) and Relevance Vector Machine(RVM), are generated on MATLAB for analysis and discussion for damage detection of the structure presented in Chapter 5.

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Chapter 1: Introduction

Offshore Platforms are widely spread all over the world and plays a very important role in the petroleum industry with its variety of the function in drilling, production and upstream activities. Mainly, these structures due to its position are designed to sustain the stresses that can be exerted on it due to the harsh environments with different environmental and operational conditions such as wind, tides, and variation of masses on structure that can affect the environment, health, and economics. Offshore platforms are manufactured from steel or concrete structures used for exploration or extraction of petroleum products from the earth's crust. There are many types of offshore structures, depending on their use or on the water depth on which they will work. Oil and gas are produced, separated, stored on the platform, and then transported through pipelines or by tankers. [1]

Damage detection occurs in offshore structures is fundamentally different from other structures due to such environment where the damage location cannot be detected by eye especially in the parts covered by the sea-water. Many very practical problems were encountered including measurement difficulties caused by platform machine noise, difficulties faced in hostile environments, changing mass caused by marine growth and varying fluid storage levels(tanks), temporal variability of foundation conditions and the inability of wave motion to excite higher vibration modes [2]. The Structural Health Monitoring become an important component to structural engineering practices. The need to monitor the health of our infrastructure and maintain it has never been more necessary than now with most of the infrastructure being structurally deficient. Structural health monitoring is essential for safe operations. These techniques make measurements locally, where the damage of the whole structure is extremely time-consuming, expensive, and prone to human loss. The main objectives of the SHM are to monitor the loading conditions of a structure, to assess its performance under various service loads, to verify or update the rules used in its design stage, to detect its damage or deterioration, and to guide its inspection and maintenance. [3]

Structural health monitoring research for offshore oil platforms has been widely spread due to economic, life-safety and environmental issues. As an example, deep water platforms can represent over a billion US dollar capital investment before any revenues are generated from the platform. In addition, these structures can have many people working and living on the platform at any time. There have been numerous cases where damage of these platforms has resulted in the loss of life of all those on the platform as can be seen in figure 1.

Figure 1: BP Offshore Drilling Platform in Gulf of Mexico damaged by Hurricane Dennis.

There are many damage detection techniques where used in the recent years, but many of these existing methods neglect the important effects of the Environmental and/or operational variations(EOVs) on the structures. Data normalisation procedure, as it is applied to SHM, is defined as the operation that separates the changes of the features derived from sensors that caused by damages from those caused from EOVs. Many methods where used to apply data normalisation will be discussed later while in this paper I will be focusing on non-linear co-integration approach where evidence of the damage is not projected out. Recently this method has been developed, based on a concept derived from the world of econometrics. Cointegration is used to remove common trends in SHM data, the purpose is to detect a feature that can provide information on the health of the structure.

Chapter 2: Structural Health Monitoring

This chapter present a general review on Structural Health Monitoring (SHM). To do this, a brief introduction on SHM is presented, description of damage detection, damage definition, damage detection approaches, review for damage detection techniques where recently used and finally environmental effects on SHM are described.

2.1 Introduction:

The health of the structure in terms of failure is determined by structural health monitoring, and in this project an offshore platform. It is known that the failure of such structure, cause a very high loss in economics, where the failure of offshore structures will lead to the interruption of the operations done on platform (drilling, production, transportation, etc.). SHM is used in order to reduce the cost invented for the inspection of such structures. Also, the use of SHM sensors will help understand the state of a structure after a certain damage. To determine whether a structure was safe minutes after a natural disaster occurred would be very beneficial not only to the structure but also could save lives, in case of offshore structures as an example. The localization and severity of the damage occurred on a structure is determined by measuring the model parameters like acceleration, curvature, temperature and natural frequencies. This method is based on historical cases measurements such as average failure and damage rates of a similar structures.

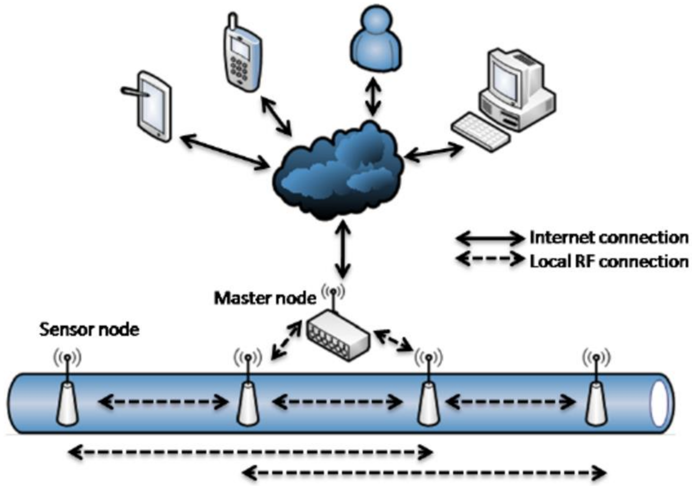

Figure 2: Structural Health Monitoring System

Therefore, there is a vital need to monitor the health of the offshore structures and the reliability. However, the local tests occurred on offshore structures are very costly due to the size of the structure, difficulties of replacement of sensor and the depth of the structure. These damages usually effects the dynamic response of the structure, therefore structural health monitoring is introduced and the dynamic responses are measured through different techniques. Researchers focused on many ways to identify damage location or damage intensity on the element structure. One of the most used method is finite element model, applying it on different civil infrastructures. This method is used as an optimization method which aims to correlate the measured modal properties extracted from sensors and the outputs from the finite element model in order to minimize the error between them. [4]

2.2 Loads Acting on Offshore Platforms

Many loads usually acts on offshore platforms that affect the dynamic response of the structure. The loads that may be applied on the platform are necessary to be studied for the design of the structure. These loads can be classified into several categories such as permanent loads (dead), operating loads (live), environmental loads, construction – installation loads and accidental loads.

Starting with permanent loads are the loads including the weight of the structure in air, weight of equipment or structures permanently mounted on the platform, and the hydrostatic forces on the various members below the waterline. While operating loads, the live loads, arise from the operations such as the weight of all non-permanent equipment (e.g. workover rig), consumable supplies, and liquids, ori t can be forces generated during operations, e.g. drilling, vessel mooring, helicopter-landing and crane operation.

Environmental issues are very important in offshore structures that plays an major role in influencing the structure and can lead to the damage of it. The environmental loads can be classified into wind, waves, current tides, earthquakes, tempreture, ice, sea bed movement, and marine growth. Figure 3 shows some examples of the damage of the offshore platforms due to environmental loads. [5]

Figure 3: Examples of environmental loads acting on offshore structures

2.3 Damage Detection

2.2.1 Damages

There are several definitions for "damage" in structures depending on the case. Pawar [6] defines damage as "a deficiency or deterioration in the strength of a structure, caused by external loads, environmental conditions, or human errors". Worden [7] defines damage as "when the structure is no longer operating in it sideal condition but can still function satisfactorily". Farrar [8] defines damage as "changes to the material and/or geometric properties of these systems, including changes to the boundary conditions and system connectivity, which adversely affect the system's performance". Crossetal. [9] consider any gradual or sudden change in structure as a damage. And generally speaking, damage can be defined as "changes introduced into a system that adversely affect its current or future performance". The term damage does not necessarily imply a total loss of system functionality, but rather that the system is no longer operating in its optimal manner. Physically, damages may be visible as a crack, de-lamination, de-bonding, reduction in thickness/cross section, or exfoliation.

The majority of offshore oil-production platforms are jacket type, welded, steel tubular, space frames. In these structures periodic inspections are mandatory, because offshore structures during their service life continually accumulate damage as a result of the action of various environmental forces and operating conditions. For instance fatigue and corrosion damage, collisions with supply ships and objects dropped from the platform decks, member overload during intense storms, and Installation and maintenance activities. [2]

2.2.2 Damage Detection Approach

According to Pawar [6], damage detection is defined as "the identification of existence of an anomalous condition in a system". Most damage detection and localization methods that have been proposed are based upon comparing signals damaged and undamaged structures [7]. Detection can be defined passing through these main 4 steps that are subdevided also to other procedures [13]:

1. Operational evaluation,

2. Data acquisition,

3. Feature selection

4. Statistical modelling for feature discrimination.

Operational evaluation

Mainly, operational evaluation can be sammurized by answering 4 questions:

A) Economical and safety benefits of applying SHM?

B) Type of damage, or multiple damages available, which cases are most concern?

C)The operational and environmental conditions while structure is monitored?

D)Limitations on acquiring data of the operational environment?

By setting these questions it will be clear how the system will be monitored.

Data acquisition

The data acquisition process is related to the selection of the excitation method, types, number and location of sensors used, and type of the data transmitted. In damage identification techniques, data normalisation is considered an important issue due to the measurement of the data under several environmental and operational conditions. Data normalisation is the process used in SHM to separate the data extracted from the sensors that are affected from the EOVs from those affected by damage occurred on structures. The main procedure used is to normalize the measured outputs from the measured inputs data, it will be discussed briefly in the next chapter. Data cleansing is a selective process used to check if the data can pass or it must be rejected from this feature selection process. The data cleansing process is dependent on the commands selected by individuals based on their knowledge and directly connected to data acquisition.

Feature selection

Feature selection technique is used for the data condensation and selection of the feature that allows to distinguish between damaged and undamaged structures. Most of the damage detection studies that were done previously on cites, offshore oil platforms examine changes in basic modal properties (resonance frequencies and mode shapes) that are extracted from measured acceleration response time histories. In many cases numerical modelling approaches were used, comparing the changes in the predicted modal properties simulated within the finite element approach and the estimated modal properties from measured system response. In theory, this approach allows one to detect, locate and estimate the extent of damage.

Statistical modelling for feature discrimination

Statistical model development is used with the implementation of the algorithms that are used to check the damage state of the structure based on the extracted data feature. These algorithms used in statistical model development are classified into two categories, supervised and unsupervised learning machines. Supervised learning machine, is illustrated by the availability of the data from both damaged and undamaged structure, group classification and regression analysis are categories of supervised learning algorithms. However, when the algorithms are applied to data that does not contain examples from damage structure, this referred to as unsupervised learning. Outlier or novelty detection algorithms applied in unsupervised learning applications. [25]

2.2.3 Comprehensive Review of Damage Identification Methods

A comprehensive review on the modal parameter-based damage identification methods of structures is necessary and presented in this section. Damage identification methods are widely used by engineers to predict the failure of the structure that may cause catastrophic, economic, and loss of lives especially in offshore platforms. The main idea behind the vibration-based damage identification is the influence on the structure in the physical properties (mass, damping, and stiffness) due to environmental and operational parameters. Damage can be detected by analyzing the changes in the vibration features of the structure. The vibration- based damage detection methods can be divided into four categories: natural frequency-based methods, mode shape-based methods, curvature mode shape-based methods, and methods using both mode shapes and frequencies.

Natural frequency-based methods are effective because it requires just a few points on the structure that are measured compared to other methods. The change of the natural frequency is important for damage detection due to some parameters that influence the structure. Damage location and severity are determined by the natural frequencies changes. Usually, the determination of damage is done using the forward problem or the inverse problem. In our study, the natural frequency-based method is used and discussed briefly for damage detection and localization. However, this method still has several common limitations. One of the main limitations is that this method is applicable only for beam-structures with small cracks, and modelling of crack as rotational spring based in fracture mechanics will lose its credibility in high frequency modes or deep crack cases.

Mode shape-based methods is more effective compared to the natural frequency-based methods because it is more sensitive to local damages and more useful in case of multiple damages. However, it is less sensitive to the environmental parameters such as temperature, that is difficult to be measured. Furthermore, mode shape-based method requires a series of sensors and mode shape measurements are more prone to noise contamination compared to natural frequency-based method.

Mode shape-method, based on many researches, is known that it is not sensitive to small damages. Curvature/strain mode shape-based method is used instead to enhance the sensitivity for smaller damage identification. This method is classified into two categories, the traditional modal curvature change method that is summarized by the localization of the damage by the difference of curvature mode shapes from intact and damaged structure, and the modern signal processing methods using modal curvature by measuring the difference of strain mode shape of different points.

To locate and size precisely the damage occurred on the structure other methods are used based on modal parameters by measuring the natural frequencies and mode shapes of the damaged structure. [12]

Chapter 3: Data Normalisation

3.1 Introduction

As mentioned before, many structural damage techniques have been used for monitoring the health of the structures. Some of these techniques are based on the change of the dynamic response recorded due to external loads exerted. However, many of these structures are exposed to environmental and operational conditions apart from the forces that leads to the damage of the structure. Even though, such EOVs can significantly affect the structure in terms of its dynamic response such as acceleration and natural frequencies. For a better development of SHM techniques where the EOVs are result in changing the dynamic response as function of time-varying, data normalisation must be introduced.

Data normalisation, is a process applied to SHM data extracted from the sensors separating the data changes caused by EOVs from those changes due to the damage. This chapter will focus on the data normalisation, its approaches, with a brief explanation of an approach to data normalisation that is used in this paper, non-linear co-integration.

In some cases, data normalisation can be achieved without measuring the parameters causes the changes, it is applicable when the damage produces the changes in the dynamic response data are in some way orthogonal to changes produced by EOVs. However, it is difficult to know the influence of the EOVs on the structure when there is available initially only the data of the undamaged conditions, as most cases in SHM. [13]

3.2 Approaches to Data Normalisation

This chapter presents six approaches that provides the way of separating the changes of the measured dynamic response caused by EOVs from the changes caused by damages. [13]

1. Experimental approaches
2. Regression Modelling
3. Look-up Tables
4. Machine Learning approaches
5. Intelligent feature selection
6. Co-integration

Starting with the experimental approaches, many environmental conditions can affect the model structure response due to hydrodynamic loadings, varying temperature, varying wind conditions, humidity and moisture. Usually, all structures are subjected to more than one EOV and the influence of the environmental conditions must be assessed. Many structures were studied carefully, and measurements were extracted from different types of sensors to check the changes of the dynamic response due to the variability of the environmental conditions. The main reason behind this is to apply the data normalisation and minimize the effect of EOVs on the dynamic response of the structure by separating the experimental data of the damage conditions from the environmental one.

When all the environmental and operational conditions measurements are available, many methods can be used to predict the influence of the measured parameters on the dynamics response of the model. Firstly, regression technique is used to link the environmental and operational parameters with the associated damage-features. Linear regression is considered the simplest method that can be used to predict the relationship between the measured environmental and operational parameters, ti (e.g.

loads, temperature) on a vector of damage-sensitive features, {f}i. This model is described by linear function of the form:

$$\{f\}_i=\{a\} + \{b\}t_i \quad (1)$$

This equation is used for one feature vectors and the corresponding EOV parameters, and the coefficient {a} and {b} can be estimated through a linear least-squares process. While this equation can be extended to the more general polynomial relationship. The model can increase in complexity, more coefficients are needed and therefore more data must be collected in order to extract the coefficients accurately.

When all the measurements of the influence of EOVs on the damage-sensitive features are not available, look-up tables may be considered a simple approach to data normalisation to monitor the structure under EOVs when it is undamaged and create a table of feature vectors that were acquired under these varying conditions. When data is available from a damage condition structure, the damage-feature vector is extracted from these new data is compared to the one in the look-up tables that is closest to it in terms of Euclidean distance metric. Figure 3 illustrates the look-up table approach to data normalisation where the test data feature vector acquired under unknown EOV is found to be closest to the undamaged data acquired under EOV T3.

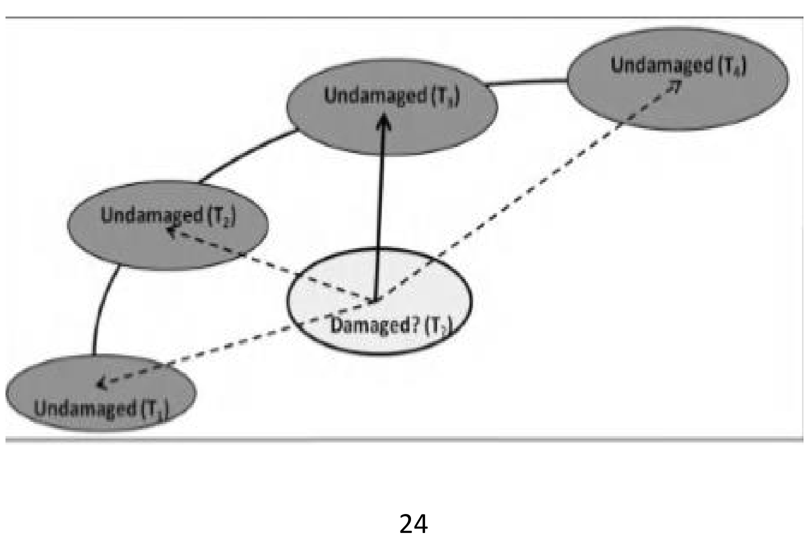

Figure 4: Look-up table approach to data normalisation

Machine learning algorithms can be used for data normalisation, and the algorithms are implemented in a manner that allows for direct comparison of their relative data normalisation performance. Firstly, each algorithm is trained using the same feature vectors extracted from time series data acquired from undamaged structure. Secondly, in the test phase all the machine learning algorithms will transform each input feature vector into a scalar feature referred to as a damage index DI, and then perform the damage classification using a novelty detection approach applied to the damage index. If adequate data normalisation has been achieved, the DIs should be nearly invariant when calculated from feature vectors corresponding to the undamaged condition when EOVs are present. Additionally, robust data normalisation will allow the DIs to be classified as outliers when the features correspond to the damaged condition even with EOV present. The four main machine learning algorithms that are used for data normalisation are listed below.

a) Auto-Associative Neural Networks
b) Factor Analysis
c) Mahalanobis Squared-Distance (MSD)
d) Singular Value Decomposition

Intelligent feature selection is summarized by selecting the damage-sensitive features that are insensitive to the EOVs while retaining their sensitivity to damage. The measured data of the features related to the damaged state can be used as an index to the damage presence compared to the undamaged one. [13]

Finally, Co-integration is the method used in our study for data normalisation and is discussed briefly in the following chapters.

3.3 Non-Linear Co-integration

3.3.1 Definition

Co-integration has become an important property in time-series analysis. Co-integration is used usually in econometrics, useful for non-stationary data in long term-scales. This method is considered very important in data normalisation and especially in SHM since EOVs are often applied on a structure in a long time-scale more than the dynamic response due to damage.

Co-integration is a non-stationary time series property. A time series is considered co-integrated only when the combination of two or more time series that are non-stationary is stationary. Time series in econometrics is usually linear, however, passing to engineering structures the time series become more complex and non-linear. Moreover, the EOVs occurred on a structure are known to be non-linear with respect to the dynamic response sensitive to damage. In this case, the linear combination of the time series is no longer useful, and therefore non-linear co-integration is introduced. This section provides a brief introduction to non-linear co-integration used in engineering structures as a damage detection technique. [16][17]

In general, in econometrics, it is considered more interesting to know if a relationship among different time series exists, and to estimate its parameters. However, for SHM purposes, engineers are interested to find a relationship between dynamic variables of a system, which is sensitive to damage presence but is not disturbed by environmental and operational variations; the residual error of the relationship can be used as health indicator [16]. In this project, the main idea is passing from the non-linear co-integration to non-linear multiple regression on a time series generating a residual that can be used later as a damage indicator.

For a better understanding of the non-linear co-integration, integration order phenomena must be introduced.

3.3.1 Integration Order

Time series a(t) that is non-stationary is said to be integrated of order x (i.e. I(x)), when the x-th difference is stationary. For instance, a time series a(t) integrated of order 1 (e.g. a(t)~I(1)), the difference is only once to get a stationary trend, which will be later I(0). While, two or more time series are co0integrated when the combination of these time series is stationary. More specifically, an example is introduced to clarify the process, given {a}i, a non-stationary time series, they are co-integrated when the vector {β} is introduced where ui is stationary, the form is:

$$ui=\{\beta\}T\{a\}I \tag{2}$$

The vector {β} is called the cointegrating vector. This case is used in linear combination while the case where the non-linear stationary combination exists will be addressed later. At this point, in order to apply the concepts just analyzed, ADF test is introduced in order to apply the integration of a time series. [16][17]

3.3.2 Augmented Dickey Fuller (ADF) Test

The first step in co-integration is checking the integration order of the variables needed in the analysis. The process is achieved in econometrics by checking each for a corresponding unit root, if the unit root is present in the equation of the time series, then the time series is stationary. This unit root used is called ADF test and the steps are described in this section.

Augmented dickey fuller (ADF) test is a statistical test used to determine if a time series is stationary or not and, in this last case, how many times one must difference a time series to make it stationary [16]. The ADF test used to fit each variable to a model type of the following form:

$$\Delta yi = \rho y_{i-1} + \sum_{j-1}^{\rho-1} bj\Delta y_{i-j} + \varepsilon_i \tag{3}$$

Where the difference operator Is defined as yi−j = yi−j − yi−j−1. A suitable number of lags p should be included to ensure that εi becomes a white noise process (Anderson, 1971). In Equation (3.3.2.1), the value ρ determines the stationarity of the model, if this value is close to the null value the process will be non-stationary and integrated of order 1, I(1). this form, the stability (and therefore stationarity) of the model in Equation (3) is determined by the value of ρ; if it is statistically close to zero the process will be nonstationary and integrated order 1, I(1). The concept behind the ADF test is to check the null of ρ =0 by comparing the statistic of the test according to this formula:

$$t_\rho = \frac{\rho'}{\sigma_\rho} \tag{4}$$

Where ρ' is the least-squares estimate of ρ and σ_ρ is the variance of the parameter, with the critical values that can be found in Fuller (1996) [19], in much the same way one would when conducting a t-test. The hypothesis is can be rejected or accepted, it is rejected when tρ < ta. However the hypothesis is accepted, if the time series has a unit root and integrated of the first order I(1). When the hypothesis is accepted yi is I(2) non-stationary sequence, while If the when it is rejected, the test should be repeated for yi. This process is continued until the integrated order of the time series is found. Other hypotheses and tests are necessary in case of a complex model that include shifts or deterministic. [20] [21]

3.3.3 Multiple Regression

To define the relationship among several variables, Regression is a process that is used for this purpose. The relation between the dependent and one or more independent variables are analyzed using many techniques in regression analysis. Usually in the system the flaws are categorized into inputs and outputs, the inputs are considered as dependent variables, while the independent variables (predictors) are the outputs that have been studied previously.

In order to estimate the independent variables corresponding to only one dependent variable, multiple regression must be taken into consideration. Multiple regression is a technique used to evaluate the predictors from the response variables, for instance supposed that the predictor variable is {ai} and the dependent variable is {bi}. Furthermore, this technique can check the relationship between both variables and dependency of {bi} on {ai} [16].

Damage indicator is necessary for data normalisation approach, that is considered as error residual, can be detected by finding out the difference between the predicted data and the measured ones. Multiple regression is used to predict the predictors according to the measured data, in order to achieve the co-integration approach by estimating the residuals between both data

3.3.3.1 Support Vector Machine

Support vector machine is a very successful approach to supervised learning, usually applied for classification problems and regression. A set of input vectors (e.g. $\{x_i\}_{i=1}^{N}$) are given in supervised learning with corresponding targets (e.g. $\{t_i\}_{i=1}^{N}$) that can be real values in regression or class labels in classification. The main objective is to make accurate predictions of t for previously hidden values of x, to build a model from the dependency of the targets on the input values. For real data, the it is necessary to avoid over-fitting of the training set due to the presence of noise in regression and class overlap in classification.

Support vector Machine makes predictions based on a function summarized by this form:

$$y(x) = \sum_{i=1}^{N} w_i K(x, x_i) + w_0 \qquad (5)$$

where {wi} are the weights and K(x,xi) is a kernel function. The main target function in SVM is to minimize the number of errors done on the training set and maximizing the “margin” between the classes in case of classification (in feature space defined as kernel). The advantages behind SVM is that avoiding over-fitting leads to generalization, and results in sparse model depends only on subset of kernel functions. [18]

In case of regression, minimizing the functional risk can be done using several types of risk function such as the least-squares empirical risk that works when the errors have a Gaussian distribution, or risk error in other cases. Risk is assumed to be ε-insensitive function,

$$R_{emp}^{\varepsilon}(\{w\}) = \frac{1}{N}\sum_{i=1}^{N}|t_i - y(x)|_{\varepsilon} \tag{6}$$

Where,

$$|t_i - y(x)|_{\varepsilon} = \begin{Bmatrix} |t_i - y(x)|\,, if\ |t_i - y(x)| > \varepsilon \\ \varepsilon, \text{else} \end{Bmatrix} \tag{7}$$

Minimizing R_{emp}^{ε} with respect to the weight {w} is linked to the minimization of the function of the slack variables that replaces the inequality constraints with equality constraints pointed out. The support vectors are later defined as the limited numbers that will be different from zero. [17]

Support vector machine suffers from different disadvantages:

- Not probabilistic predictions and estimation of SVM outputs in regression.
- SVM requires numbers of kernel functions which grows with the size of training set
- Necessary the estimation of the error, ε-insensitive function in case of regression, which considered a waste of data and computation.
- Kernel function K(x,xi) must satisfy Mercer’s condition.

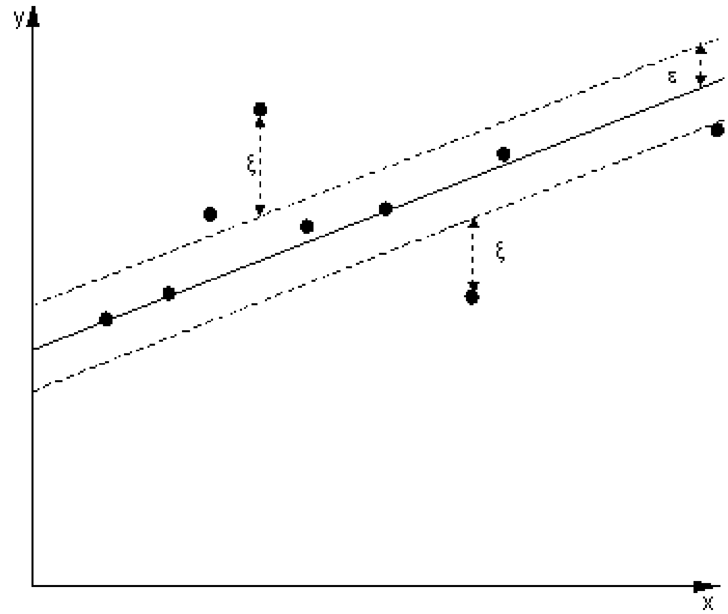

Figure 5: One-dimensional linear regression with epsilon intensive band

Figure 6 shows similar situation but for non-linear regression.

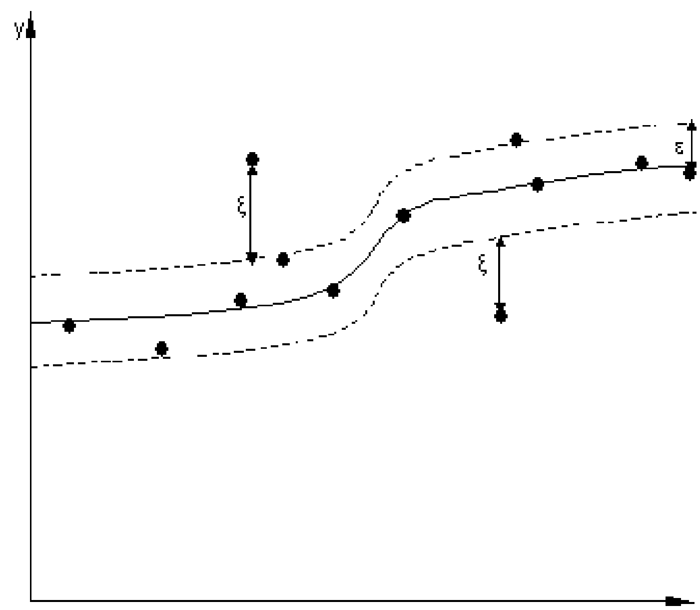

Figure 6: One-dimensional non-linear regression with epsilon intensive band

3.3.3.2 Relevance Vector Machine

Relevance vector machine (RVM) is another kernel model approach that is similar to SVM in terms of the functional form and based on probabilistic sparsity. In this method, a Bayesian approach is adopted, where hyperparameters are introduced, one corresponding to each weight, whose most values are estimated from the data. RVM is capable for generalisation compared to SVM and it requires fewer kernel functions. Furthermore, RVM does not suffer from the limitations that SVM suffers from.

Given an example with data set of inputs and targets, {xi} and {ti} respectively, by following the standard formulation we assume that $p(t|x)$ is Gaussian $N(t|y,x',\sigma^2)$. As defined previously in equation (5), the x is modelled by y(x). the likelihood of the dataset is written as:

$$p(t|w,\sigma^2) = (2\Pi\sigma^2)^{-N/2}\exp\{-\frac{1}{2\sigma^2}\|t-\phi w\|^2\}, \quad (8)$$

where t is the N target, {w} is weight and ϕ is a matrix of dimension N*(n+1) that is called the "design matrix" with $\phi_{nm} = k(x_n, x_{m-1})$ and $\phi_{n1} = 1$. The estimation of w and σ^2will lead to overfitting, so we define a Gaussian prior over the weights:

$$p(w|\alpha) = \prod_{i=0}^{N} N(w_i|0,\alpha_i^{-1}), \quad (9)$$

with α a vector of N+1 hyperparameters. Therefore, there is a hyperparameter corresponding for each weight and is the key feature of the model and is responsible for its sparsity properties. Then, the prior over the weight is given by Bayes's rule:

$$p(\{w\}|\{t\},\{\alpha\},\sigma^2) = (2\pi)^{-\frac{(N+1)}{2}}|\Sigma|^{-\frac{1}{2}}\exp\{\frac{-1}{2}(\{w\}-\{\mu\})^T\Sigma^{-1}(\{w\}-\{\mu\})\}, \quad (10)$$

where,

$$\Sigma = (\phi B\phi^T + A)^{-1} \quad (11)$$

$$\{\mu\} = \Sigma \phi^T B\{t\} \quad (12)$$

A is matrix of N α on the diagonal and B=$\sigma^{-2} I_N$. Moreover, σ^2 is hyperparameter that must be estimated as well from dataset. By integrating the weights out, the evidence for the hyperparameters can be achieved:

$$p(\{t\}|\{\alpha\},\sigma^2) = (2\pi)^{-\frac{N}{2}} |B^{-1} + \phi A^{-1} \phi^T|^{-\frac{1}{2}} \exp\{\frac{-1}{2}\{t\}^T (B^{-1} + \phi A^{-1} \phi^T)^{-1} \{t\}\} \quad (13)$$

The predictors are sparse and contain few non-zero wi parameters while the others are set to zero during the learning process. Therefore, this approach is extremely effective at discerning the basis functions which are relevant for making better predictions. [17][18]

Chapter 4: Case Study: Jacket Offshore Structure

4.1 Introduction

After the explanation of the methodology of non-linear co-integration, a case study is presented to demonstrate this method. As described in the previous chapter, this method is applicable for an offshore platform structure designed with different normal conditions and different damage conditions. The normal conditions related to the storage of oil tank on the deck of the platform, while the damage conditions are presented by a force applied on the structure and the damage occurs on two different elements by reducing the stiffness of the material. The system undergoes the variation of normal conditions as a function of time, then the damage is introduced later.

4.2 ANSYS: Finite Element

4.2.1 Modeling Procedure

Using the software ANSYS the geometry of the structure and the element type are selected together. In a large structure, shell elements are used where the thickness is negligible with respect to the width and height. For the analysis of the structure, meshing is required after selecting material type, element type and the mesh type. Therefore, the modelling procedure consist of seven steps presented in the figure below.

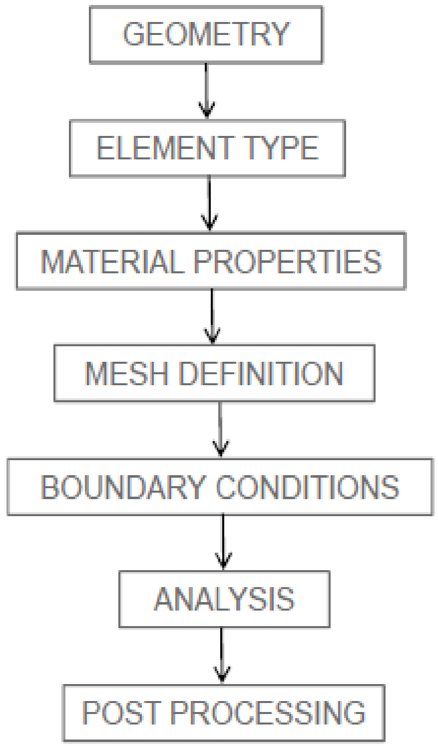

Figure 7: Modeling Procedure

4.2.1 Model Geometry

The geometrical model developed has the following configuration:

Deck: 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.

Foundation: the foundation is 30 meters long under the soil consisting on the four legs which support the platform.

Connection: a small connection having a height of 2.5 meters connects the foundation with the first steel layer.

Elevation: the elevations from the deck till the first steel layer are 50 meters, 38 meters, 30 meters, 21.7 meters, 12.5 meters and finally the connection of 2.5-meter height. [23] [24]

The design example of the structure and the assumptions where taken from [23] and [24]. Based on the model properties i.e.., degree of freedom, nodes, beams, pipes, spring, dashpots, and all the details, following the modeling procedure listed above, the finite element model of the offshore platform is modeled.

4.3 Structure Analysis

The static and dynamic analysis of the finite element are performed on the software and the results are reported separately.

4.3.1 Static Analysis

The static analysis is performed on the structure choosing two elements of the structure and the damage occurs by reducing the stiffness of the material. The reduction of the stiffness is illustrated by four values, 25%, 50%, 75% and 100% which is considered as total removal of the element. Usually, the mass on the deck of the offshore platform increases as a function of storage of oil tanks. In our case study, the mass of the deck is 135 tons when the tank is empty and considered as uniformly distributed loads on the deck with 800 kg/m2. Due to the production of oil, the level of oil storage may vary. The normal conditions in this case were 21 normal conditions between 800kg/m2 when the tank is considered empty and 900 kg/m2 when the tank is full of an increment of 5 kg/m2.

In the static analysis, the model is run for the first operational condition when the tank is totally empty with a load of 800 kg/m2 and without any external forces that can affect the structure. The deformed and undeformed shape of the structure is represented in figure 8.

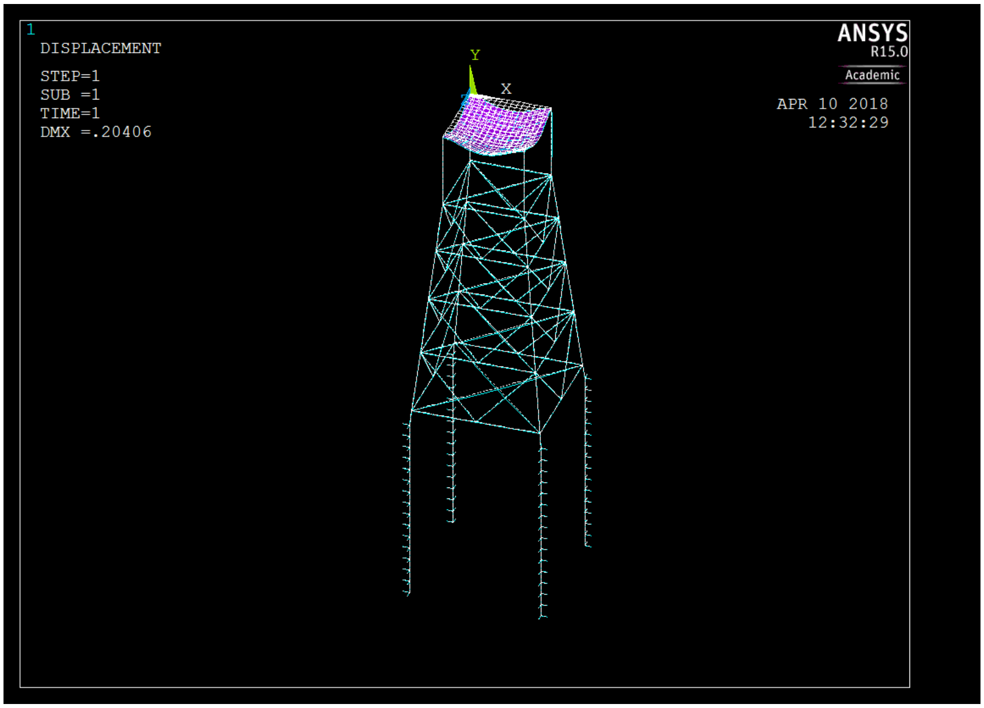

Figure 8: Deformed and undeformed shape in static conditions

4.3.2 Modal Analysis

The modal analysis is performed in the next step on finite element model. In our case, due to the variation of the oil tank storage due to the production and transportation of the fluid, all the dynamic response of the structure must be extracted that is useful to our study. In the modal analysis, the natural frequencies were extracted for different normal conditions and different damage conditions. As we mentioned before, the normal conditions are related to the different distributed loads on the deck of the platform due to the storage of the tank between empty and full storage. While the damage conditions are reducing the stiffness of the element after introducing a force of 12000 N on node 709. The Tables 1 and 2 presents both normal conditions(NC) and damage conditions(DC) respectively.

Normal Conditions	Distributed loads [kg/m2]
NC1	800
NC2	805
NC3	810
NC4	815
NC5	820
NC6	825
NC7	830
NC8	835
NC9	840
NC10	845
NC11	850
NC12	855
NC13	860
NC14	865
NC15	870
NC16	875
NC17	880
NC18	885
NC19	890
NC20	895
NC21	900

Table 1: Normal Conditions

Damage Conditions	Stiffness Reduction [%]
DC1	25
DC2	50
DC3	75

Table 2: Damage Conditions

All the steps were done via ANSYS software and the natural frequencies were extracted for all the normal conditions mentioned above with and without damage conditions. The first four frequencies and the model shape were obtained for all the conditions.

The natural frequencies for the first normal condition while the oil tank is empty and the model shape is reported below.

NC1 800kg/m2		INDEX OF DATA SETS ON RESULTS FILE		
SET	TIME/FREQ	LOAD STEP	SUBSTEP	CUMULATIVE
1	1.0911	1	1	1
2	1.0911	1	2	2
3	1.3378	1	3	3
4	1.9481	1	4	4

Table 3: Natural Frequencies for NC1

All the model shape of the structure changes corresponding to the natural frequencies. The deformed and undeformed model for each frequency are presented below.

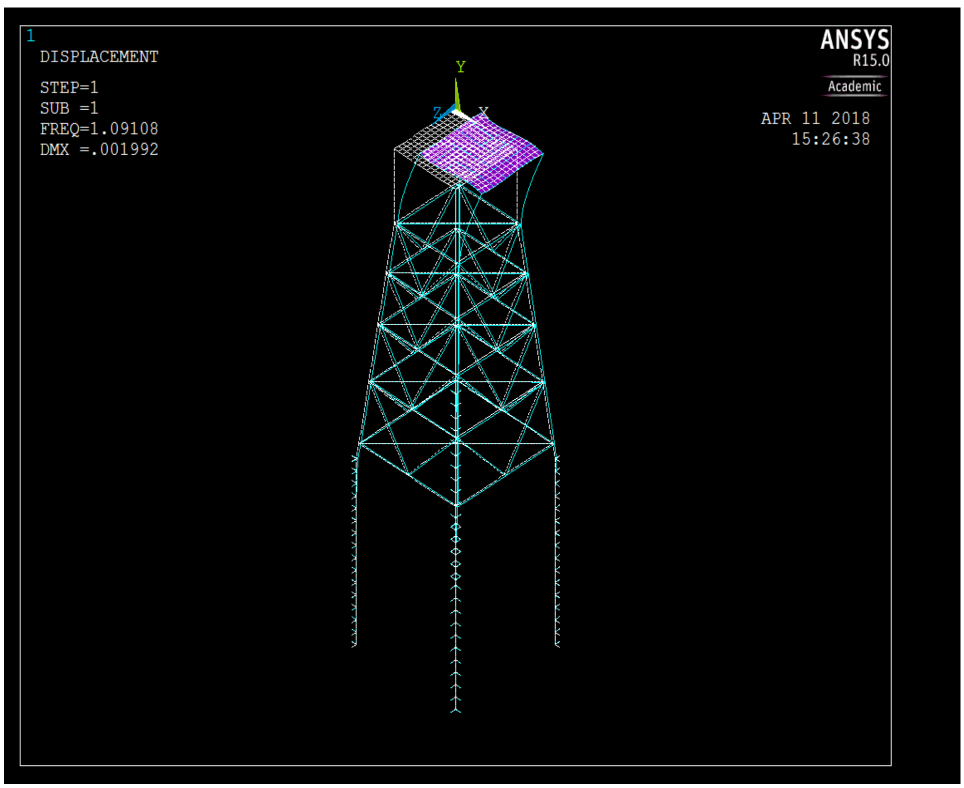

Figure 9: First Deformed and undeformed model shape for NC1

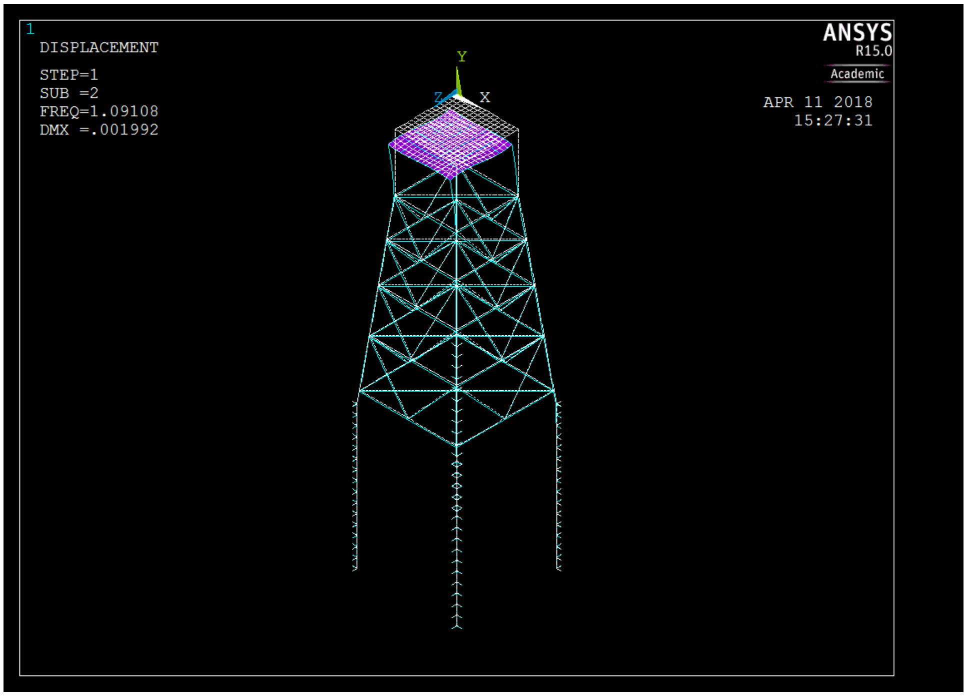

Figure 10: Second Deformed and undeformed model shape for NC1

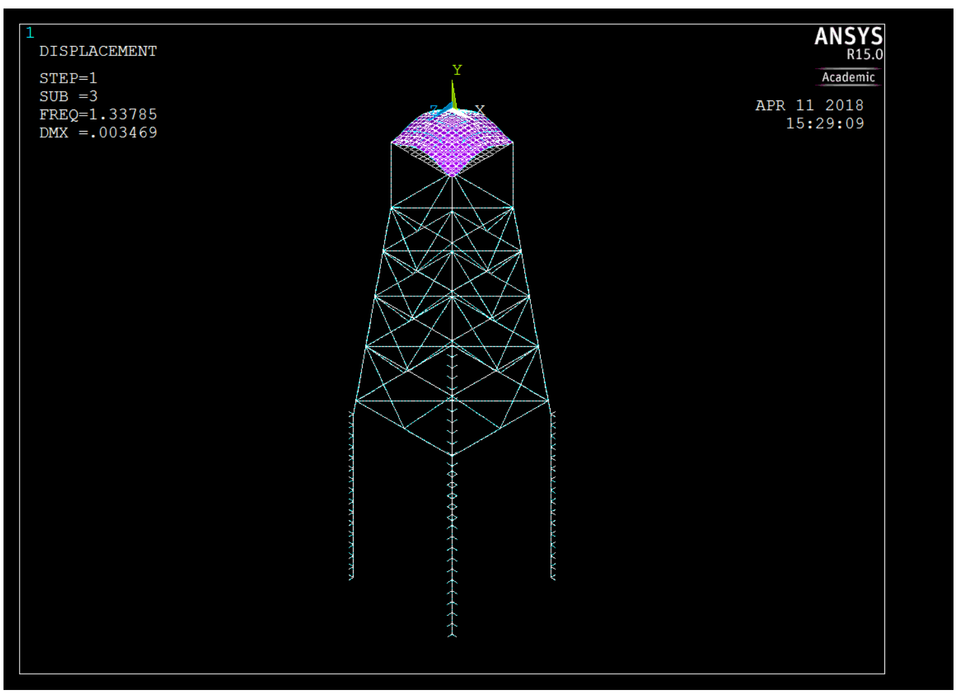

Figure 11: Third Deformed and undeformed model shape for NC1

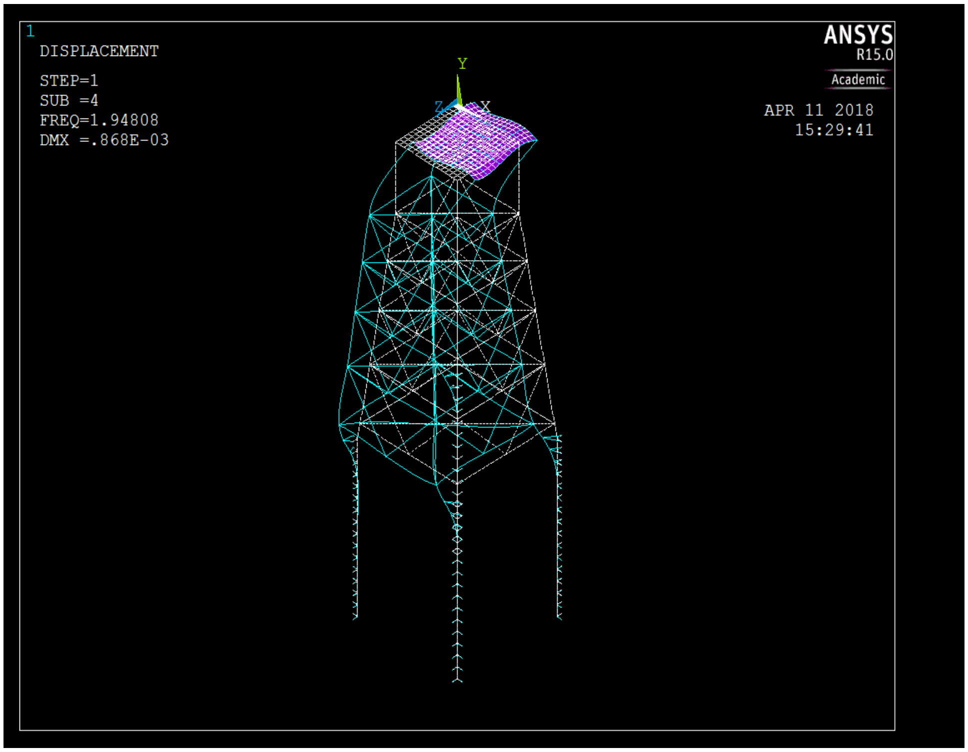

Figure 12: fourth Deformed and undeformed model shape for NC1

As listed above, the analysis were done for all the conditions but only the first normal condition was presented above. Similarly, the model analysis for the model for all the damage conditions at different normal operational conditions were done as well. The natural frequencies for the first damage condition while the oil tank is empty and the model shape are reported in table 4.

DC1 E=1.8E+11Pa INDEX OF DATA SETS ON RESULTS FILE *****

SET	TIME/FREQ	LOAD STEP	SUBSTEP	CUMULATIVE
1	1.0910	1	1	1
2	1.0911	1	2	2
3	1.3378	1	3	3
4	1.9479	1	4	4

Table 4: Natural Frequencies for DC1

All the model shape of the structure changes corresponding to the natural frequencies. The deformed and undeformed model for each frequency with damage conditions are presented below.

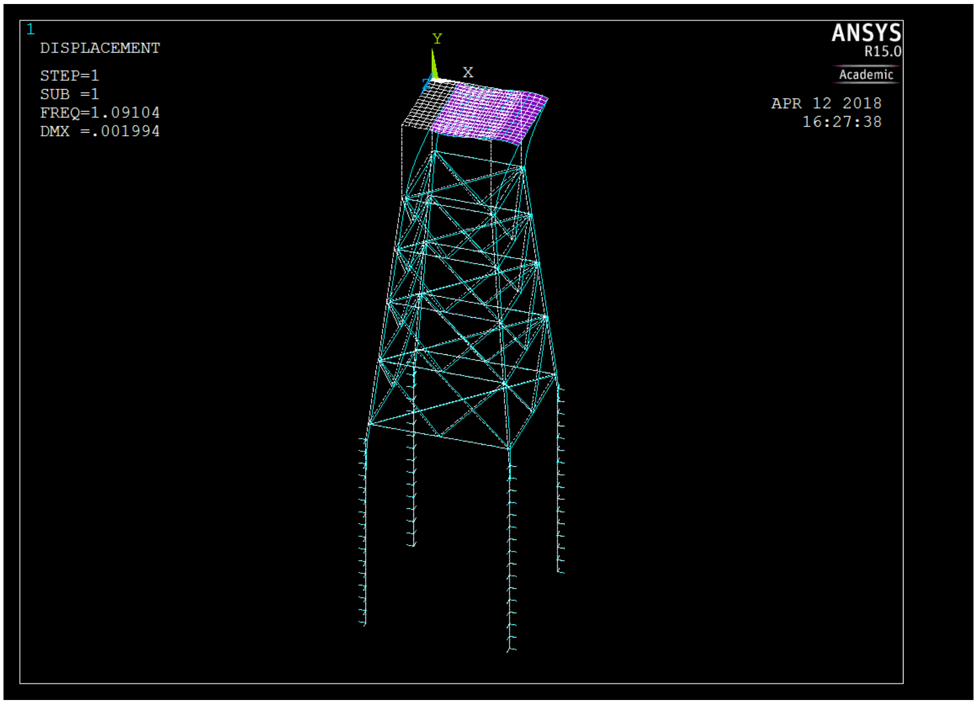

Figure 13: first Deformed and undeformed model shape for DC1

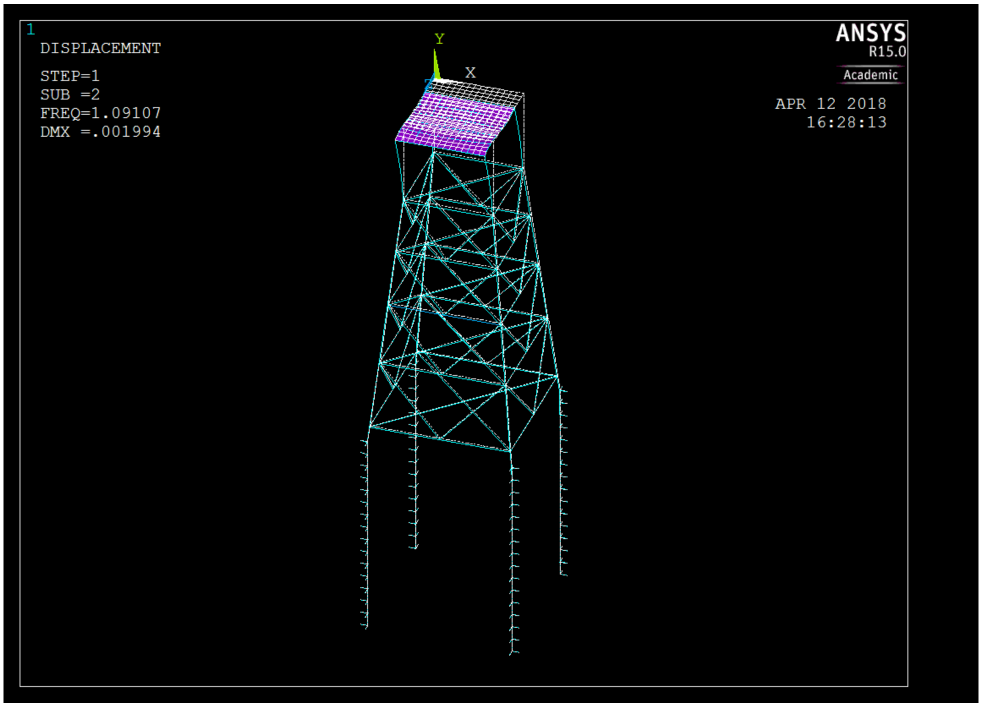

Figure 14: Second Deformed and undeformed model shape for DC1

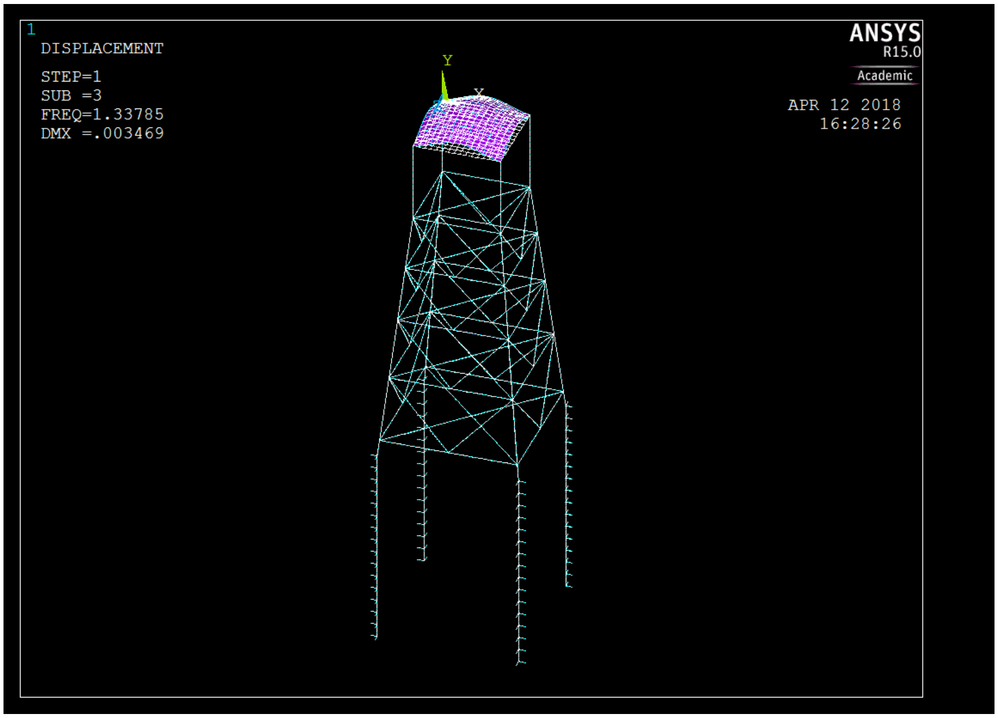

Figure 15: Third Deformed and undeformed model shape for DC1

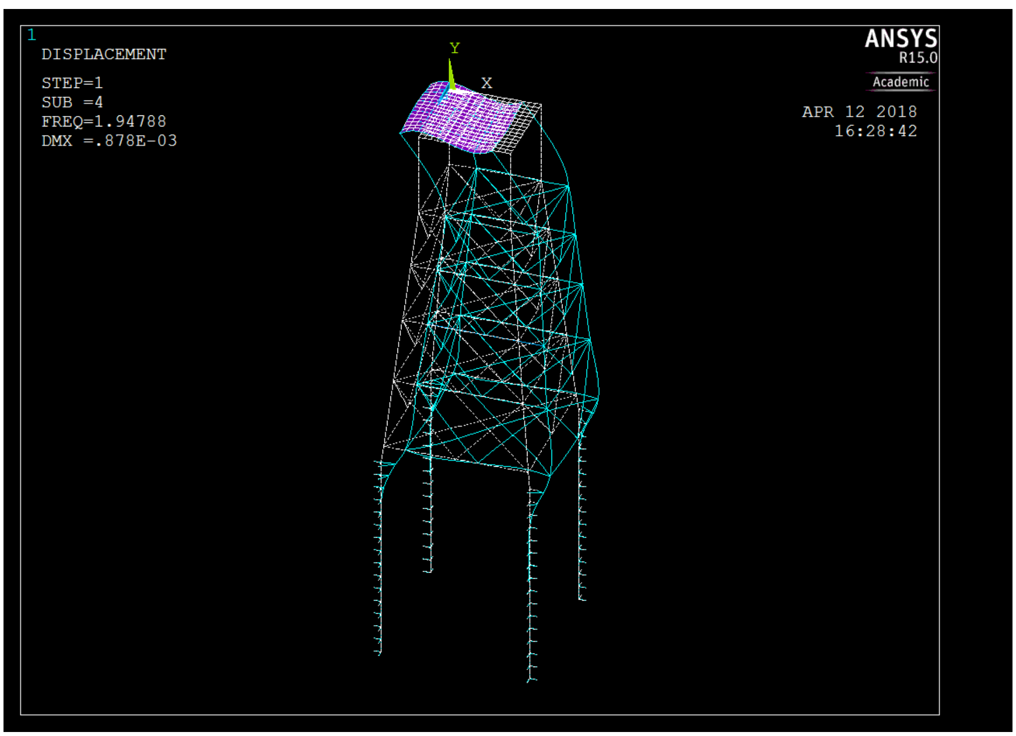

Figure 16: Fourth Deformed and undeformed model shape for DC1

Chapter 5: Co-Integration: Application and Results

5.1 Study Case Explanation

As Described in chapter 4, the operational and normal conditions applied on the deck of the offshore platform as distributed loads varies between 800 kg/m2 and 900 kg/m2 for empty and full tank respectively. An increment of 5 kg/m2 was taken to study the response of the structure with different oil storage level. These 21 conditions were implemented as an example of oil storage during a certain interval of time where production and delivering of produced oil are occurring. The samples were taken for 542 observations and level of storage was pointed down. In some observations fluctuations of data were obvious due to the low rate of production and high demand of transferring stored oil. The implemented example of oil tank storage as distributed loads in kg/m2 as a function of 542 observations is presented below.

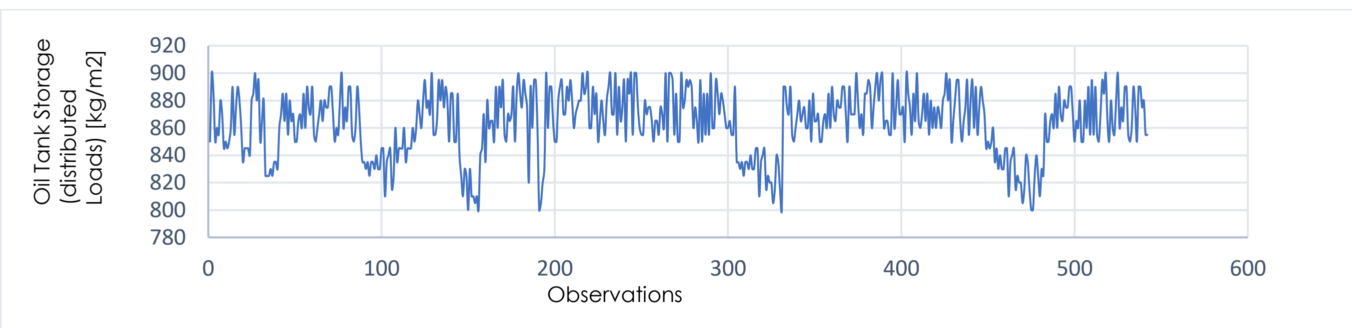

Figure 17: Variation of Oil Tank Storage [kg/m2] as Function of 542 Observations

Furthermore, four natural frequencies extracted from the modal analysis of the structure on ANSYS was set according to each corresponding normal condition without a reduction of stiffness for the first 457 observations. At the observation 458 damage was exerted, so different four natural frequencies with reduction of stiffness of 25%, 50% and 75% was inserted for each corresponding normal condition from the 21 samples.

Finally, 3 examples were implemented for the same element 1 with different levels of damage 25%,50% and 75%. Moreover, 2 examples for element 2 for studying the sensitivity analysis with reduction of stiffness 25% and 20%.

After the distribution of the data for all observations, by using the MATLAB a code is generated and the non-linear co-integration is applied to distinguish the normal conditions from the damage conditions of offshore platform structure. Two approaches were applied on MATLAB, The RVM regression and the SVM regression. The code consisted of different steps initiated by checking the ADF test, SVM & RVM functions, small rate of Gaussian noise has also been added, and finally the risk-error and the residual model was plotted out. The process was repeated many times for different normal conditions and damage conditions, also for different training data to find the best solution. All the results are presented in the following part.

5.2 Final Results: Plots and Interpretations

After applying both techniques SVM and RVM by MATLAB code, the results of our observations with different operational conditions applied as distributed loads due to tank storage between 800 kg/m2 when its empty and 900 kg/m2 when its full, and with different damage conditions for different elements represented by reduction of stiffness with 25%, 50%, and 75% are presented in this chapter. However, the sensitivity of both methods on different damage conditions and different damage locations will be discussed as well.

5.2.1 ADF Test Results

ADF test was performed on four natural frequencies, and by referring to the results obtained by MATLAB it is possible to state that these frequencies are nonstationary at confidence level of 95%. As a result, all the four frequencies have an integration order equal to 1 and their first differences are stationary equal to 0, and these values where reached by repeating the test after having the difference operator. Results of the ADF test are represented below on the four different frequencies of the structure.

Time Series	ADF Test	Integration order
f1	Non-stationary	f1 ~ I(1)
Δf1	Stationary	
f2	Non-stationary	f2 ~ I(1)
Δf2	Stationary	
f3	Non-stationary	f3 ~ I(1)
Δf3	Stationary	
f4	Non-stationary	f4 ~ I(1)
Δf4	Stationary	

Table 5: Results of ADF test on the first four frequencies of the Offshore Platform

5.2.2 SVM & RVM Plots

The Application of the cointegration technique is represented with the two-regression method explained previously: SVM & RVM. The trend of the four frequencies exampled from the offshore structure are extracted for different damage conditions where these frequencies where obtained along 542 observations. Then, the plot of the residual ε was created. The training data were taken in the nonlinear behavior of the natural frequencies to widen the scattering points between 80 and 145. After testing all the frequencies, the results were obtained for the fourth frequency because it was considered more sensitive to damage. From ADF test, it can be stated that the residuals ε in all the cases are stationary. Before starting with the application, it is important to mention that the difference between the predicted data and the real one is considered the residual error. When the residual error exceeds the 3 times standard deviation of the measured data, it means the damage starts to occur.

Firstly, both regression methods where applied on Element 1 far a little bit from the 12000 N force applied on the node 709. Element 1 is presented below in figure 18.

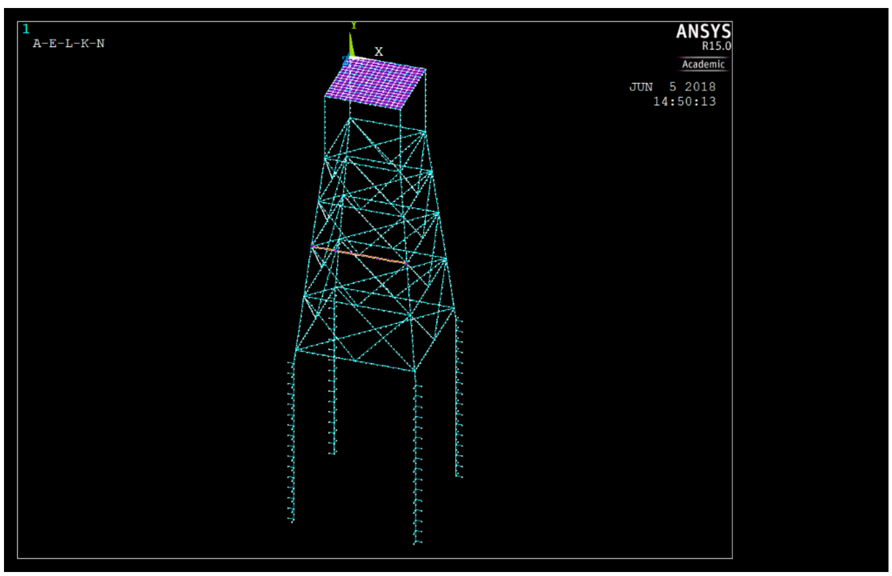

Figure 18: Element 1 in Offshore Platform

Both the SVM and RVM approximate the data set very well; the model residual series are plotted for frequency f2 which considered more sensitive when damage occurs and shows a small decrease. Starting with reduction of stiffness of 25 %, both SVM and RVM regression models are represented in figures 19 and 20 respectively. As can be seen from figure 19, a small decrease in the residual errors from the zero-mean line after introducing the damage without exceeding the limits. While in the RVM regression model the residual error decreases more than SVM until it crosses the limits.

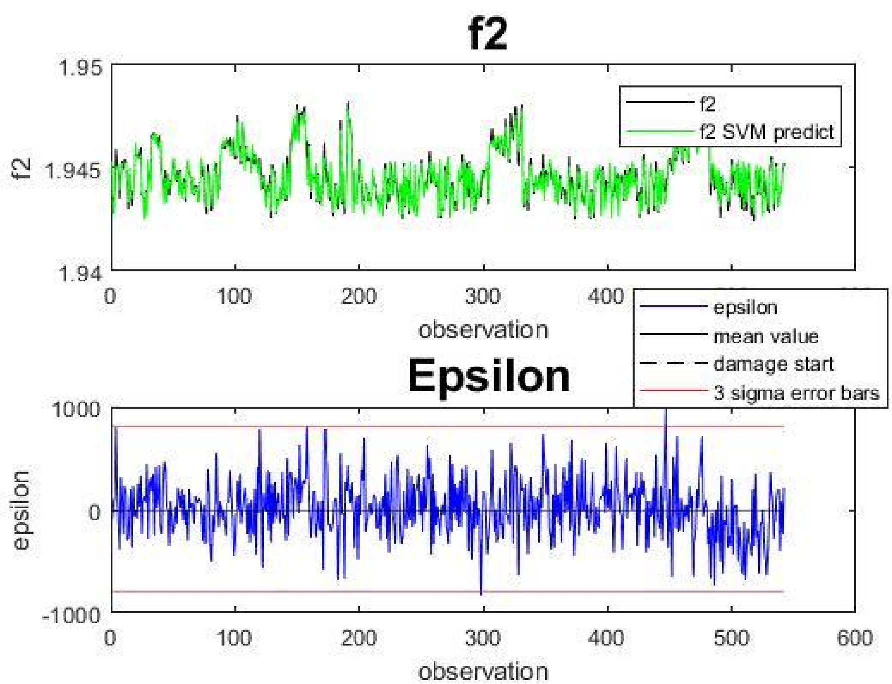

Figure 19: SVM regression model and model residual for 25% reduction of stiffness

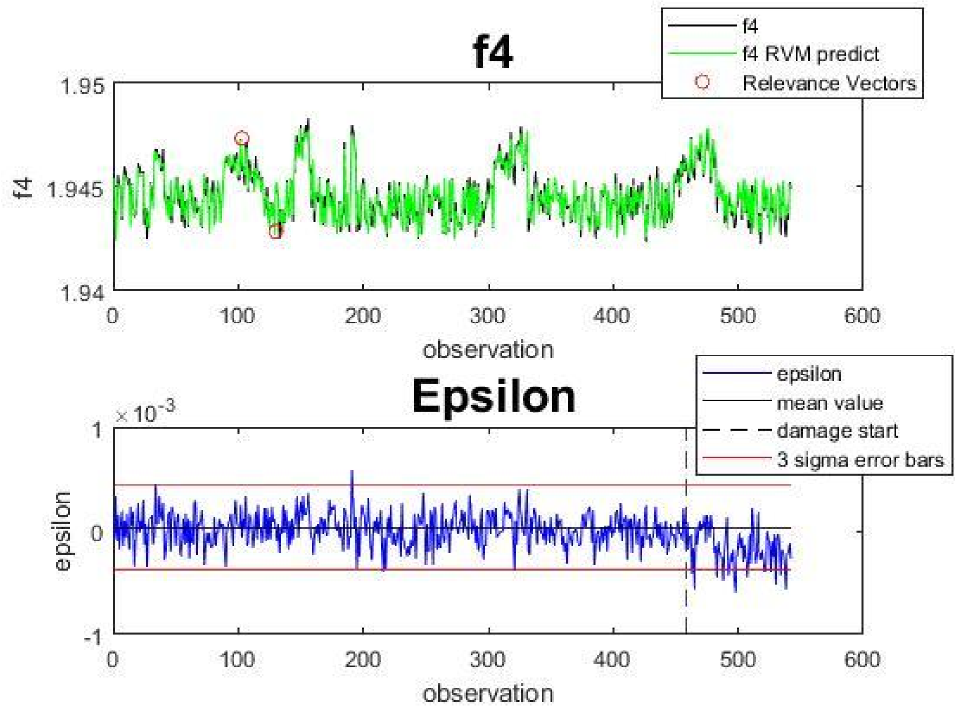

Figure 20: RVM regression model and model residual for 25% reduction of stiffness

The results, in figures 21 and 22, correlated to the both SVM and RVM regression models at reduction of stiffness of 50%. It is significant that in both models the ε crosses the limits while it is clearer in the RVM model, where it is a strong evidence of the damage occurrence.

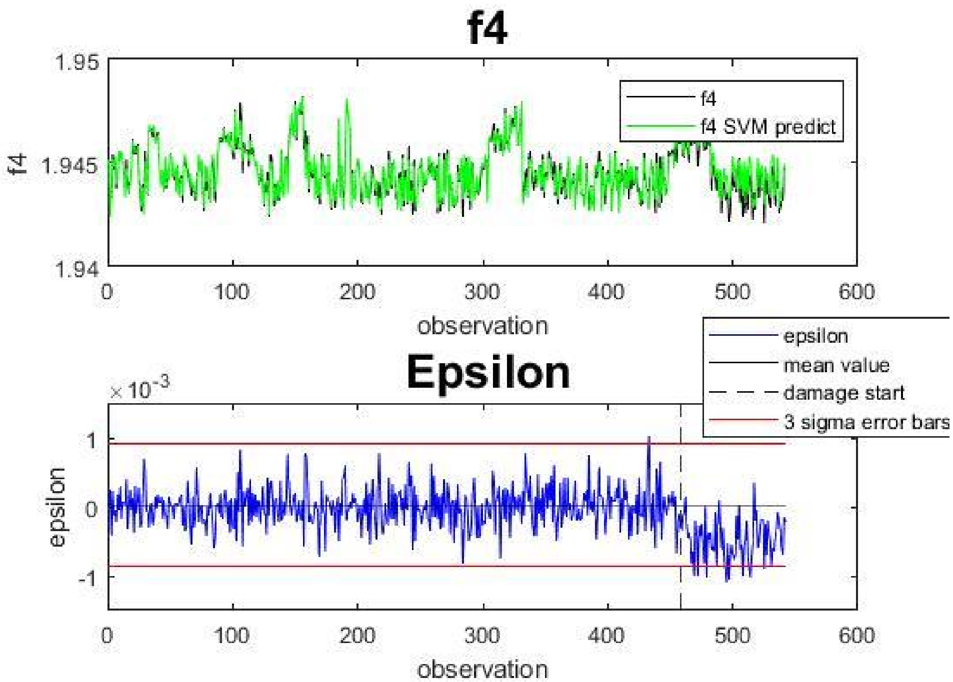

Figure 21: SVM regression model and model residual for 50% reduction of stiffness

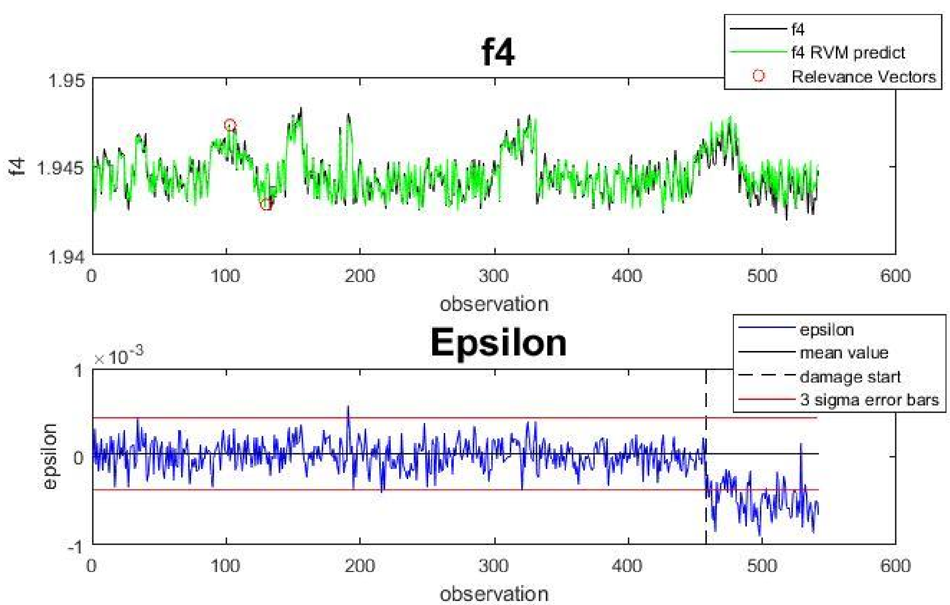

Figure 22: RVM regression model and model residual for 50% reduction of stiffness

The Figures 23 and 24 presents the results of the both models at reduction of stiffness at 75%. In both models, it is apparent that damage occurs after observation 458.

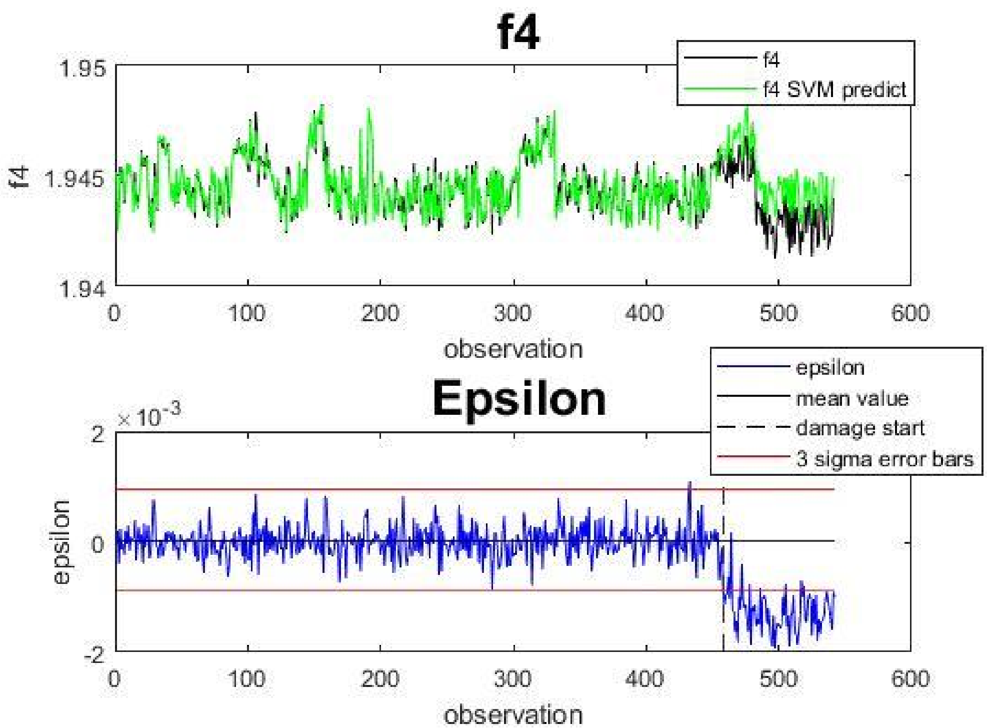

Figure 23: SVM regression model and model residual for 75% reduction of stiffness

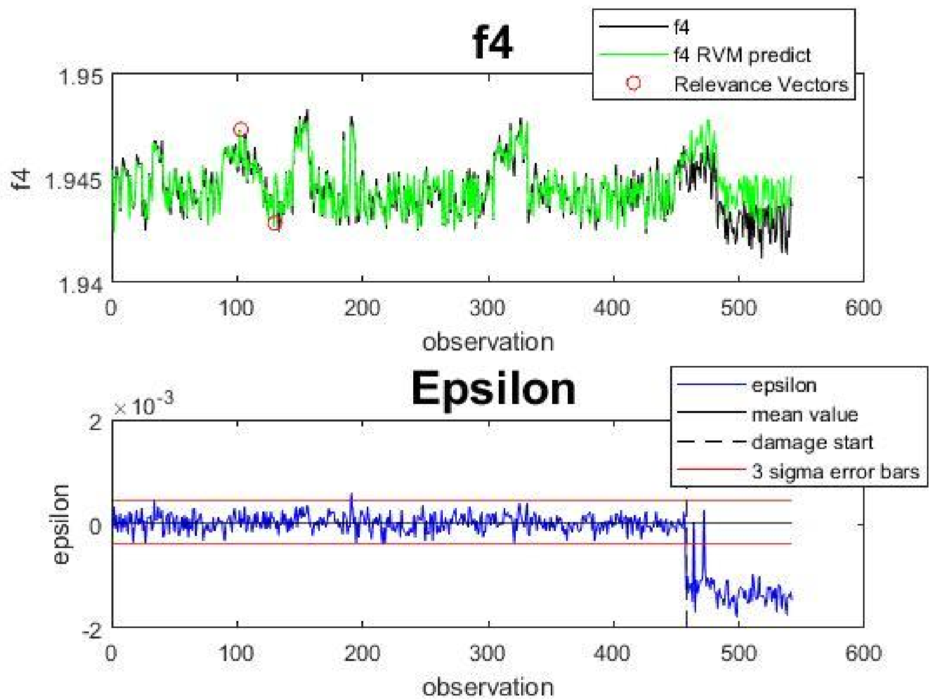

Figure 24: RVM regression model and model residual for 75% reduction of stiffness

Moreover, the regression method has different sensitivity for different damage level and different location of damage. Element 2 was tested similarly to check the sensitivity of the methods with 25% reduction of stiffness, then different damage levels were tested for the two techniques obtaining the minimum damage level sensitive for SVM and RVM are 20% for both. All the results of the regression model and residual model of frequency 4 for Element 2 are presented below.

Element 2 was chosen very close to the node 709 where the damage force was applied on it to check the sensitivity of the method in location of damage. Figure 25 shows the location of element 2 on the offshore structure.

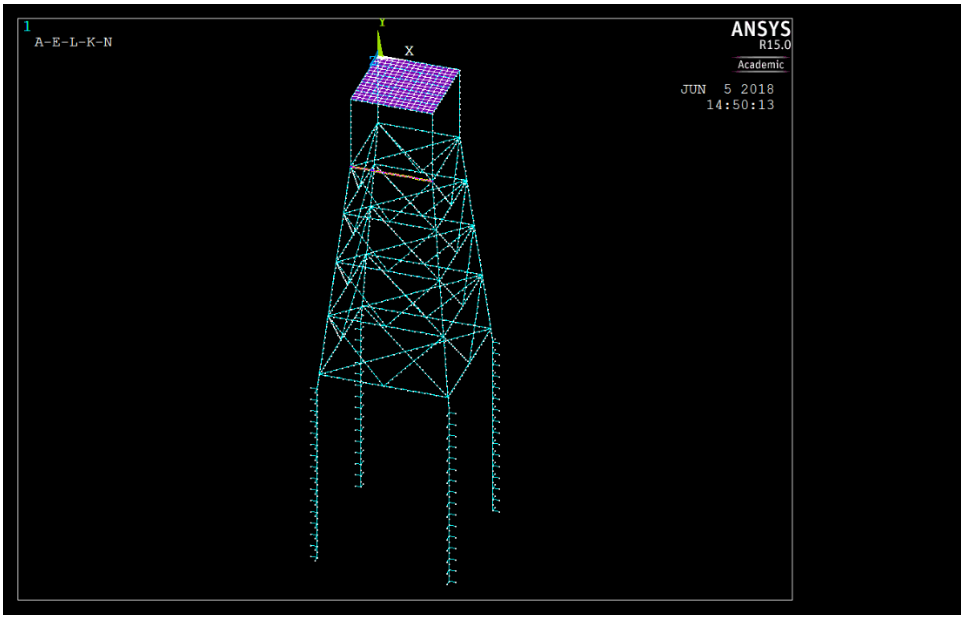

Figure 25: Element 2 in Offshore Platform

The results obtained on element 2 shows a sudden decrease in residual error ε at small reduction of stiffness 25%. The regression models, SVM and RVM, are represented below in figures 26 and 27 respectively.

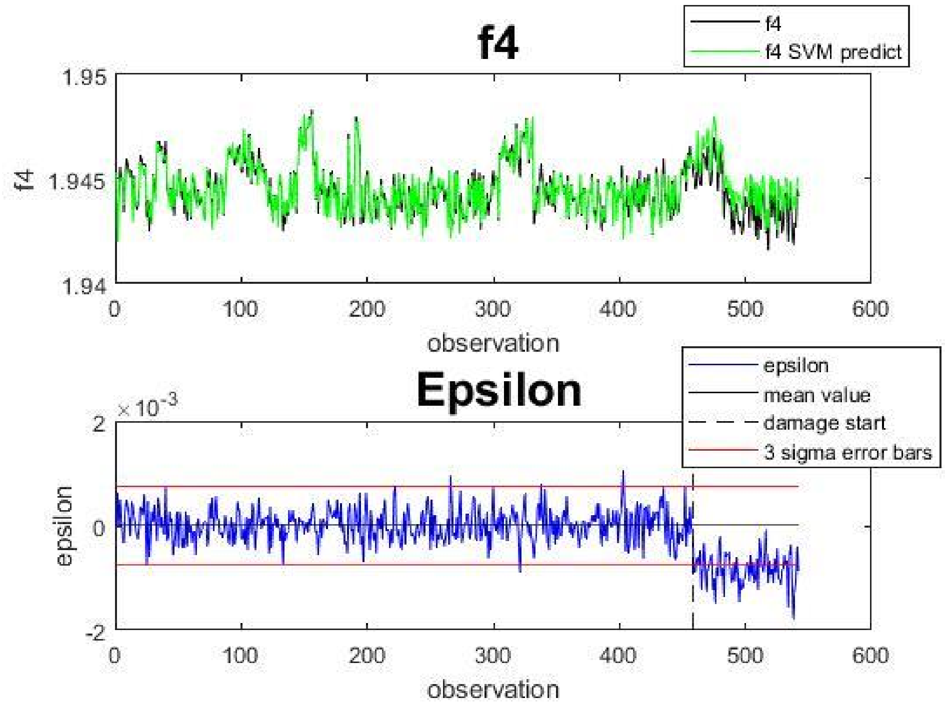

Figure 26: SVM regression model and model residual for 25% reduction of stiffness(Element 2)

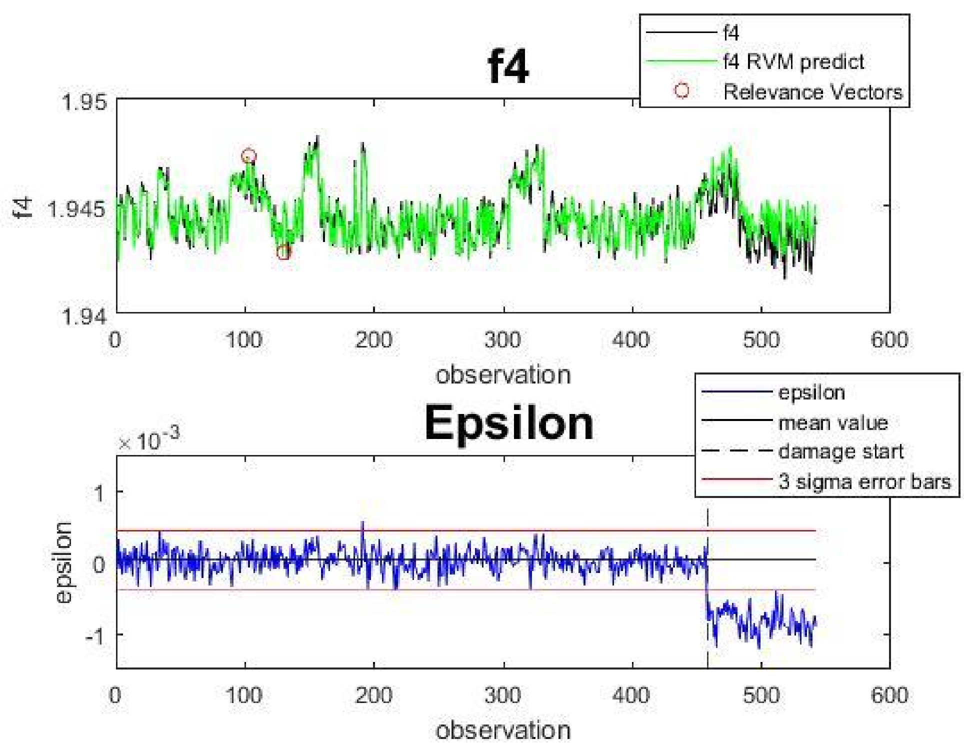

Figure 27: RVM regression model and model residual for 25% reduction of stiffness(Element 2)

Then many trials were done to reach the minimum damage level that the method is sensitive to, reaching reduction of stiffness at 20%. From figure 28, it is significant that residual error is in the minimum point before crossing the limits that clarify that the method as sensitive to a minimum damage level at 20%.

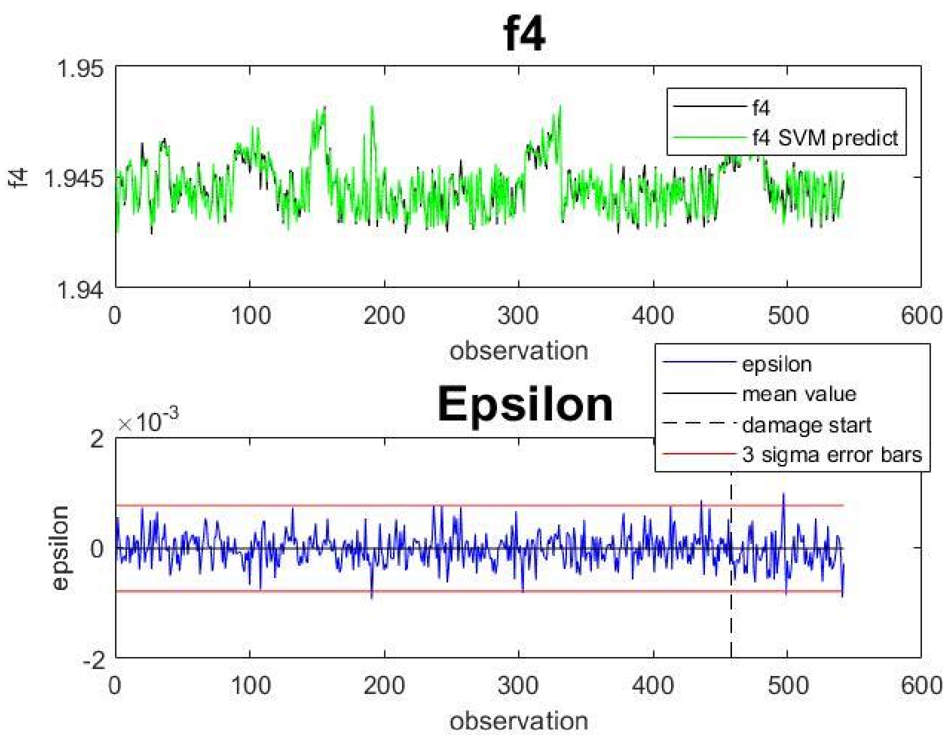

Figure 28: SVM regression model and model residual for 20% reduction of stiffness(Element 2)

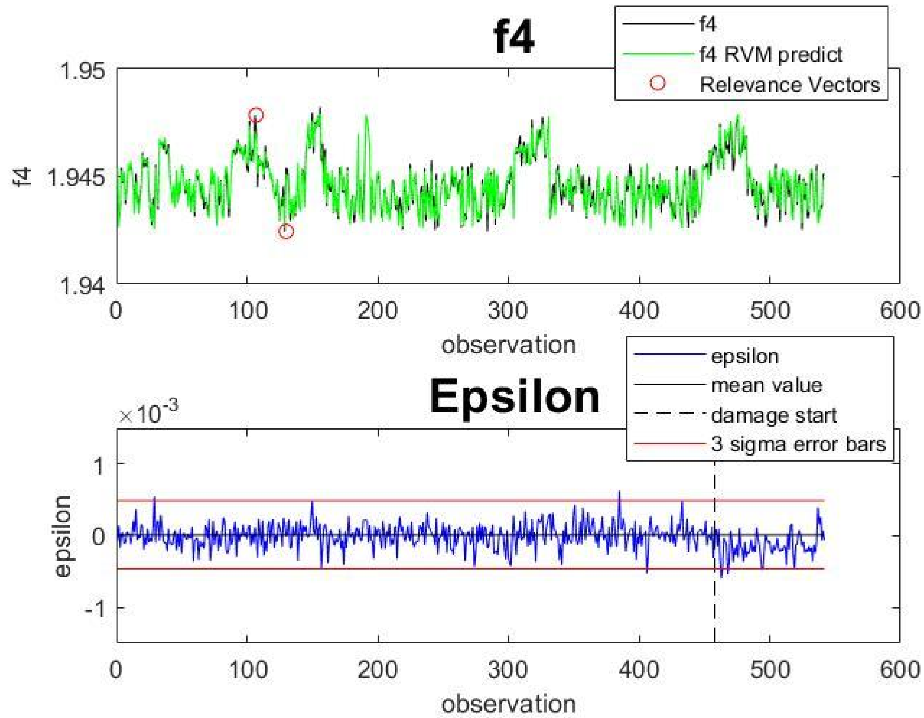

Figure 29: SVM regression model and model residual for 20% reduction of stiffness(Element 2)

5.2.3 Interpretations of Results

From the final results and plots presented previously it's clear that in both method SVM & RVM for different normal conditions the residual model varies along a zero-mean value while it shows an obvious change when the system is damaged. The residual was found to be stationary when computed for normal conditions, and nonstationary when the damage is present, this means that ε is sensitive to damage while the environmental and operational effects are efficiently eliminated. When the ε exceeds ±3σ, it can be stated that the damage has been occurred. Firstly, by comparing both approaches we can conclude that RVM for this study case can be considered more efficient and faster in detecting the damage for same element and same training data, for instance comparing both regression models for reduction of stiffness by 50%, detection of damage is more clear in RVM regression approach than SVM and the residual model justify that. From the above results, it's evident that as the damage in a function of reduction of stiffness increases, the residual model crosses the limits more.

The sensitivity of the two regression approaches was checked in terms of damage level and damage location where another element was tested called element 2 which is closer to the damage force with a reduction of stiffness of 25% and by comparing the regression models and residual models of both elements summarizes that damage in element 2 was clearly visible than element 1 for same damage level. However, to detect the sensitivity to the damage level, different damage levels where tested on element 2, and the 2 approaches are sensitive to minimum value of reduction of stiffness 20%, so any damage level less than this percentage will not be visible in terms of residual model and the regression methods will not distinguish between environmental and operational conditions, and the damage conditions.

Chapter 6: Conclusion

Structural health monitoring is used to monitor the health of the structure and determine how the structure is responding in case of failure due to several loads applied on the structure. All the previous techniques and efforts were developed, such as the vibrational based techniques, used for damage detection based on the natural frequency and dynamic response variations but are not capable to distinguish between environmental and operational condition and structural damage.

Data normalisation has not received as much attention from the research community as other parts of SHM processes. Furthermore, almost all the detection techniques are used to investigate the effect of one or two EOV parameters applied on a structure. Whereas, in real-world cases there are many EOV sources that are applied on the same structure at the same time which can influence the damage feature of a structure. For instance, offshore platforms are required to several EOVs that effect the platform such as waves, tides, equipment installations, and other that can be detected at the same time. The methods listed in chapter 3 must be extended for such situations.

One of the approaches to data normalisation was presented in this study, non-linear co-integration, and it is applied to offshore platform with a case study to check the ability in detecting the damage. The method was applied on a designed structure based on modeling and simulation using the natural frequency, after applying several normal conditions with four different damage conditions. Two regression method were used to differentiate the effect of the damage on the structure from the normal conditions and results were plotted for both methods. The results extracted from this situation, can state several drawbacks:

The sensitivity of the non-linear co-integration is demonstrated by the results of our case, using the variation of different damage conditions. The minimum damage condition detected by this method is reducing the stiffness by 20%, this result indicate that a smaller damage conditions cannot be detected by this method.

Further analysis showed that the sensitivity of the method is linked to the location of the damaged material. the results are a strong evidence that this method is not sensitive to the response of all materials location selected and cannot easily detect the damage.

Many parameters can affect the format of the data measured from sensors located on the structure in a real-case, such as temperature, where this method does not require these parameters. While having only one parameter (frequency) available, any wrong choice of the training data will lead to wrong results.

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