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GUIDED ULTRASONIC WAVE FOR MONITORING STRESS LEVELS IN PIPELINES

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Summary: *In this article, the pattern variation of the wave propagation in a pipeline is studied by means of Principal Component Analysis (PCA) and some extensions to indirectly evaluate the tensile stress in a pipeline. This method can be potentially used in-situ and real time for continuous condition monitoring. The test bench utilized in this research represents a mimic of an actual installation. A 1" sch 40 A-106 pipeline is supported at the free ends by fixed support. Then, a variable load is applied in the half of the length emulating the stress condition produced by a fault in the foundation. The mechanical and geometrical characteristics of the pipeline were considered to optimize the experiment configuration and the selection of the guided ultrasonic mode at a suitable frequency. A Picoscope® is used for signal generation (Gaussian pulse signal of nine cycles) and acquisition of the guided wave. A dedicated Matlab® software is implemented to perform processing of this signal. Data captured by the piezoelectric sensor for each load condition are projected into the PCA model-based. Results of each load scenario are presented and discussed demonstrating the feasibility of using this formulation in the evaluation of the tensile stress in pipelines.*

1 INTRODUCTION

Health monitoring of pipeline in service is an important research topic and a challenging task. Pipeline systems in service are continuously affected by different factors: corrosion, erosion, chemical attack, stress, extreme climate conditions, among others. Stresses in the pipeline have great influence in the performance during the operation, affecting its strength, expected operational life and dimensional stability.

Some stresses in the pipeline are developed in service, which are difficult to diagnose and identify; they can unexpectedly appear and turn into invisible due to the apparent absence of an external load, such as the associated to the differential settlement in the foundation of the pipeline supports.

The stress or strain in a structural element can be determined using either non-destructive or destructive methods. Several destructive methods exist for measuring absolute stress and a deep explanations are found in [1]. Destructive methods are based on measuring the strain relaxation (change of length), when a part of an element in service is removed.

On the other hand, the use of strain gauges is one of the most common non-destructive methods to measure relative surface stress. However, its uses are limited to determine the stress after the sensor is attached to the element. It cannot be directly used to measure, for example, residual stresses introduced in manufacture or the stress state of a previously un-instrumented structure. Additionally, the use of the strain gage is limited to determine the strain in a specific position, which is a disadvantage when the specimen is subjected to variable stress in magnitude and position, as the case of a pipeline with differential settlement in the foundation.

Various physical properties are directly related to the state of stress or strain in a structure and can potentially be exploited for measuring absolute stress. Some of this properties are displacement, capacitance, inductance and electrical resistance, which can be used in a strain gage, with the previously mentioned limitations. Additionally, some other NDT techniques are also used for measuring stress, such as eddy current, thermoelectric, ultrasonic [2]. All of these exhibit measurably high sensitivity to strain, but they are also affected by other variables such as grain structure and magnetic properties.

Among the available techniques for monitoring stress, some of them present limitations such as: low level of penetration, only relative stress measurement, high sensitivity to other variables, and restricted use in field due to the nature of the equipment required. Thus, a suitable alternative is the use of low-frequency ultrasonic guided waves.

The guided waves propagating under a stress medium present changes in the wave pattern, which are subjected to be monitored. Variations in the wave travelling under stress could be traced under two monitoring approaches. The first one, based on the Acoustoelastic Effect, involves the evaluation of the change of ultrasonic bulk wave velocities. The second one, relies on particular features in the waveform attributed to the propagation in a medium under stress. Changes in the wave pattern can be followed using statistics tools, such as PCA and time and frequency indicators. PCA is exploited in this work to evaluate the stress condition in a pipeline.

The acoustoelastic effect has been widely studied for stress monitoring since the second half of the 20th century. Some recent works are focused on the evaluation of the changes in the velocity using signal processing. In [3] the Wigner-Ville transform technique is used to determinate the Time Of Flight (TOF) of each frequency component in the group velocity of a guided waves propagating under stress. In [4], changes in wave group velocity of longitudinal waves as a function of stress are determined by measuring the arrival time delays of the signals with respect to the stress-free case. The cross-correlation technique is employed for the accurate determination of time delays.

2 THEORICAL FRAMEWORK

2.1 Acoutoelastic effect

In 1937 Murnaghan [5] published “Finite Deformations of an Elastic Solid “. In this work Murnaghan presented a model of the linear elastic theory, including finite deformation in elastic isotropic materials, describing the variation of the bulk velocities whilst the waveguide is subjected to an initial static stress field (Acoustoelastic Effect). The Acoustoelastic Effect is a non-linear effect of the constitutive relation between mechanical stress and finite strain in a material of continuous mass. It includes higher order expansion of the constitutive relation between the applied stress and resulting strain, which yields bulk velocities dependent of the stress state of the material. This new model includes three Third-Order Elastic Constants (TOEC), the acoustoelastic constants.

The modern theory of acoustoelasticity was developed in 1953 by Hughes and Kelly [6]. They were interested in calculating the (TOEC) in crystals using third order energy terms in their constitutive equations and Murnaghan's theory of finite displacements. Hughes and Kelly determined that in addition to the two Lamé constants, λ and μ, three additional constants, l, m, n are required to describe the wave propagation in isotropic materials subject to uniaxial stress. Once the values of l, m, n of a particular material specimen are determined, any experimental measure of one of the bulk velocities reveals the stress at which the specimen is subjected to.

These constants are determined experimentally by measuring acoustic phase velocities and solving a system composed by a set of 5 equations. Each equation describes a particular bulk velocity in a predefined direction and polarization as a stress function. Hughes and Kelly experimentally determined the TOEC of polystyrene, iron, and Pyrex glass.

TOEC highly depend on the material processing, such as casting, rolling, or drawing. This dependence on processing was traced to the presence of residual, or internal, stresses. The degree, depth, and location of residual stresses influence the acoustoelastic properties. So, a new stage of applications started using acoustoelastic to estimate the residual stress [7].

The most current researches in the Acoustoelastic Effect, have been oriented to the measuring of residual stress. Three major difficulties are impeding the advancement of this technology [8]. First, the Acoustoelastic Effect is small, typically about of 0.001% per MPa of applied stress, for metals. These small variations impose high precision in experimentation. Second, the inherent or induced preferred orientation of crystalline grains affects acoustoelasticity. This orientation, called texture, causes an anisotropic effect in the material properties. The third major problem is the unknown influence of localized plastic deformation. This problem is also caused by material processing and is closely related to residual stresses. The plastically deformed lattices will not have the same acoustoelastic properties as the elastic lattices and hence must be accommodated for.

Therefore, Acoustoelasticity is not the only cause for variations in acoustic velocity. Processing anisotropy and residual stress can cause variations in acoustic velocity comparable to those caused by material nonlinearity. In addition, changes in microstructure with service life also cause changes in acoustic velocity. These additional sources of nonlinearity complicate experimentation and physical interpretation.

Although, the model of the acoustoelasticity predicts the change of ultrasonic bulk velocities. Some recent works have shown the extension of this behavior to the guided waves. Therefore, a new subject of research has been gaining the attention, the disperse behavior of the guided waves propagating under stress. In this approach, the velocity is no longer only frequency dependent but also stress dependent. Some recent works have been using this behavior, such as [9,10], where the longitudinal mode L(0,1) is used to track the variations of the phase velocity in a rod waveguide exposed to stress. In [11] a finite element technique for modelling the dispersion characteristics of guided waves in a waveguide of arbitrary cross section subjected to axial load is presented. A dimensionless quantity of the sensitivity of phase and group velocity to load is defined. The sensitivity to strain levels term shows that the change in velocity is proportional to the strain and decreases as the frequency increases. In [12], the dispersion curves for a plate are obtained considering initially the material isotropic, but later the dispersion curves are determined assuming that the specimen under uniaxial stress becomes unstressed anisotropic. This problem is similar to the lamb wave propagation in an anisotropic plate, except for the fourth order tensor in the resulting wave equation, which has not the same symmetry as the unstressed anisotropic plate. Thus, the constitutive equation relating incremental stress to incremental strain is more complicated.

An experimental approach simplifies the acoustoelastic analysis by introducing a lineal model of velocity change with the stress, Ec. (1). The coefficient K is obtained by achieving an acoustoelastic calibration test in laboratory.

$$\frac{V_\sigma - V_0}{V_0} = \epsilon - \frac{l_0}{l_{so}}\frac{\Delta t}{t_0} = K\sigma \quad (1)$$

where V_0 and V_σ are the velocities at unstressed and stressed states, respectively, ϵ is the strain, l_0 is the initial length, l_{so} is the grip length at σ = 0, Δt is the difference between the total Time Of Flight (TOF) under stress and the TOF in the specimen before loading t_0, σ is the stress applied axially to the waveguide and K is a constant . It should be noted that the K value depends on material properties, on waveguide diameter and on the probing frequency.

2.2 PCA

PCA is a statistical tool with a wide variety of uses i.e. data dimensional reduction, pattern recognition, data compression and extraction. The goal of PCA is to discern among a set of data which are significant for the system, which are redundant and which are just noise. This is achieved by determining a new space (coordinates) to re-express the original data, filtering noise and redundancies, based on the variance–covariance structure of the original data. The aim of PCA is to re-express the original data in a new basis where the data are arranged along directions of maximal variance and minimal redundancy.

In Structural Health Monitoring (SHM), PCA has been extensively applied for extracting structural damage features [13-14] and to discriminate features from damaged and undamaged structures [15-16], among others applications. In the above references just the principal components or theirs projections were studied, however, PCA provides additional statistical features that can be considered as indices.

For SHM PCA-based the data can be arranged in a matrix **X** as follows in Eq. (2)

$$\mathrm{X} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1j} \\ \cdots & \cdots & \cdots & \cdots \\ x_{i1} & x_{i2} & \cdots & x_{ij} \\ \cdots & \cdots & \cdots & \cdots \\ x_{ni} & x_{n2} & \ldots & x_{nj} \end{bmatrix} = \left[\vartheta_1 | \vartheta_2 | \ldots | \vartheta_j \right| \ldots \vartheta_n] \quad (2)$$

This **X** matrix contains information from the measurement j and n experimental trials. Each row vector (x_i) represents measurements from the sensors attached to the structure for a specific experiment trial. In the same way, each column vector (ϑ_j) represents samples from sensors (one variable) in the whole set of experiment trials. Usually, each sensor vector ϑ_j is re-scaled to have zero mean and unity variance.

Given a data matrix **X** in (2), which has been previously scaled, the covariance matrix is defined in Eq. (3).

$$C_X = \frac{1}{n-1}\chi^T\chi \quad (3)$$

The diagonal terms of C_X are the variances σ_{vj}^2 of the corresponding variables, Eq. (4):

$$\sigma_{vj}^2 = \frac{1}{n-1}\vartheta_j^T\vartheta_j = \frac{1}{n-1}\sum_{i=1}^{n} x_{ij}^2 \tag{4}$$

The off-diagonal terms $\sigma_{vj,vk}^2$ are the covariance between pairs of variables, Eq. (5)

$$\sigma_{vj,vk}^2 = \frac{1}{n-1}\vartheta_j^T\vartheta_k = \frac{1}{n-1}\sum_{i=1}^{n} x_{ij}x_{ik} \tag{5}$$

Large covariance values correspond to high redundancy and small values to low redundancy.

Consider a jxn linear transformation matrix **P**, which is used to transform the original data matrix **X** into the form expressed by Eq. (6):

$$T = XP \tag{6}$$

To achieve the minimal redundancy goal, a transformation matrix P is determined such that the covariance of the new data matrix **T** is diagonal, Eq. (7):

$$C_T = \frac{1}{n-1}T^T T = \frac{1}{n-1}P^T X^T XP = P^T C_X P \tag{7}$$

Consequently, the row vectors of the transformed data matrix **T** are uncorrelated and their respective variances are given by the eigenvalues of the covariance matrix C_X of the original data. C_X has *j* real eigenvalues, λ_j (variances) and *j* orthonormal eigenvectors p_j, which form a basis in the *j*-dimensional space. Then, the transformation matrix is chosen having the eigenvectors in their columns, that is:

$$p = \left[p_1|p_2|\dots|p_j|\dots p_n\right] \tag{8}$$

With this matrix the following property is satisfied by Eq. (9):

$$C_X P = P\Lambda \tag{9}$$

With $\Lambda = \text{diag}(\lambda_1, \lambda_2, \dots., \lambda_m)$ so, Eq (10) is satisfied

$$C_T = P^T P\Lambda = \Lambda \tag{10}$$

Usually, the eigenvectors p_j forming the transformation matrix **P** are sorted according to the eigenvalues by descending order and they are called *the Principal Components* of the data set. The eigenvector with the highest eigenvalue is the most representative value for the data with the largest quantity of information. Geometrically, the j^{th}-column vector t_j of the transformed data matrix **T** is the projection of the original data over the direction of vector p_j (j^{th} principal component). The projection of the data in the new frame is characterized by being uncorrelated and have the maximal data variance, thus with best potential to exhibit process features.

Since eigenvectors are ordered according to the amount of information, it is possible to reduce the dimensionality of the data set **X** by choosing only a reduced number r of principal components, those corresponding to the first eigenvalues.

Two statistics scores associated to the PCA are the Hotteling T^2 statistics and the Q statistics. The first one is based on analyzing the residual data matrix $\tilde{X}$ to represent the variability of the data projection in the residual subspace. It only detects variation in the subspace of the first r principal components, which are greater than what can be explained by the common-cause variations. In other words, T^2-statistic is a measure of the variation of each sample within the PCA model. The T^2-statistic of the i^{th} sample (or experiment) is defined in the form of Eq.(11) .

$$T_i^2 = \sum_{j=1}^{r} \frac{t_{sij}^2}{\lambda_j} = t_{si}\Lambda^{-1}t_{si}^T = x_i P \Lambda^{-1} P^T x_i^T \tag{11}$$

Besides, Q-statistic denotes the change of the events that are not explained by the model of principal components. It is a measure of the difference, or residual between a sample and its projection into the model. The Q-statistic of the i^{th} sample (or experiment) vector x_i is defined as follows by Eq. (12):

$$Q_i = \tilde{x}_i \tilde{x}_i^{\,T} = x_i (I - PP^T) x_i^{\,T} \tag{12}$$

where $\tilde{x}_i$ is its projection into the residual subspace. Normally, Q-statistic is much more sensitive than T^2-statistic. This is because Q is very small and therefore any minor change in the system characteristics will be observable. T^2 has great variance and therefore requires a great change in the system characteristic to be detectable.

Information about the experiments can also be obtained directly from plotting the scores T^2 and Q for the relevant principal components. The scores present different values in presence of a new dynamic providing information to detect changes. In this way, the plots of Q and T^2 are hypothesis tests that clearly distinguish experiments with abnormal behavior, whereas the inspection of the scores plot is a qualitative tool.

2 STRESS MONITORING PCA BASED APPROACH

In this work a relative stress monitoring approach for a piezo-actuated pipeline, based on the ultrasonic guided wave pattern recognition, is proposed. Information of the wave propagated along pipeline in its nominal stage is statistically processed by means of PCA, in order to obtain a baseline model represented by the principal components. The stress conditions diagnosis stage is executed by projecting the sensed ultrasonic wave data onto the baseline model, and, scores and T^2 and *Q-Statistics* indices are computed to distinguish a new experiment respect to the baseline case.

Data organization and preprocessing

In the proposed methodology, the actuated and sensed signals are coupled by using cross-correlation, before implementing the PCA model, Eq. (13).

$$x_i(k) \stackrel{\text{def}}{=} \sum_{m=-\infty}^{\infty} f^*[m]g[m+k] \tag{13}$$

where f^* denotes the complex conjugate of f (actuated signal) and g is the sensed signal. In the proposed PCA model, the cross-correlation is arranged in the matrix **X**, Eq. (2). The multivariate data is acquired from a set of signals or experiments (*I* experiments *x K* samples per experiment). The matrix **X** represents the cross-correlation between actuated and sensed signal for all the measurements in one sensor. So, the matrix **X** is *I x 2K-1*, since the cross-correlation doubles the size of each vector. As explained previously, before applying PCA it is necessary to normalize the data matrix **X** since PCA is scale variant. Each sensor vector is re-scaled to have zero mean and unity variance.

The baseline is built by applying PCA to the matrix that contains received guide wave of the pipeline without deflection (normal condition) as illustrated in Figure 1. Applying PCA to build a baseline means to calculate the projection matrix **P**, which offers a better and dimensionally reduced representation and a greater capture of the relevant dynamics of the original data **X**.

In the diagnosis phase, the current structure is subjected to a number of experiments to determine its stress states and a new matrix **X** is arranged with the captured data. The number of collected samples (data-points) must be the same that the used in the modelling phase. This matrix is projected into the PCA model using Eq. (6). Projections onto some of the first components are obtained and the stress indices (T^2-statistic and *Q-statistic*) are calculated and compared with the baseline values. The general procedure for detecting and distinguishing stresses on structures based on PCA can be summarized in Figure 1.

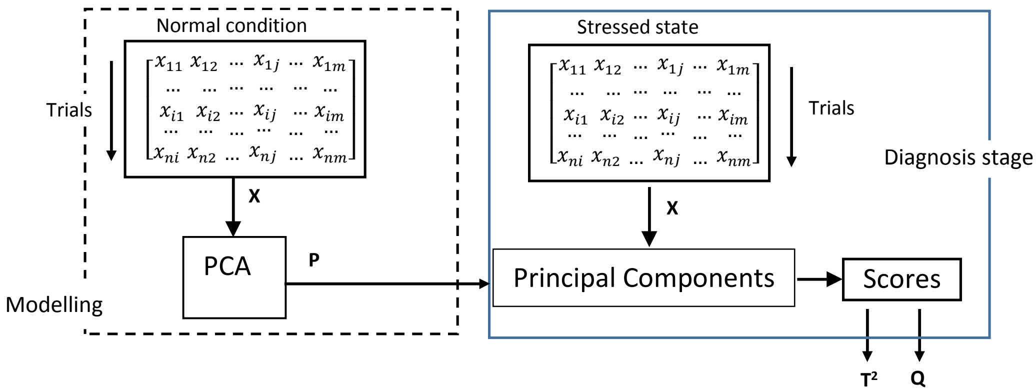

Figure 1: General scheme based on PCA for detecting and distinguishing stress in structures.

3 EXPERIMENTAL SETUP

The test bench used in this research represents a scaled mimic of an actual installation. A 1" 6 m of length sch 40 A-106 pipeline supported at the free ends by fixed support is used and a variable load is applied on the half of the length emulating the stress produced for a fault in the foundation. The different stress conditions are either produced by changing the magnitude of the reaction in the variable support located in the middle of the pipeline (L/2) or by adding a concentrated force at the middle part of the pipeline, as shown in the Figure 2.

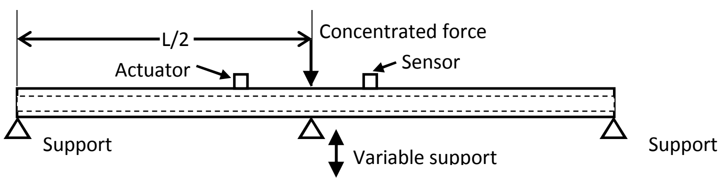

Figure 2: Schematic representation of the test bench

The pipeline is excited with a 9 cycles Gaussian-modulated sinusoidal pulse via PZT. The modulated signal is defined by Eq. (14).

$$m(t) = sin(2\pi f_0 t) \tag{14}$$

where $f_0 = 1/\tau_0$ and τ_0 is the period of the modulated signal $m(t)$. A Gaussian window centered at t_c is defined by Eq. (15)

$$g(t) = e^{-(t-t_c)^2/2\sigma^2} \tag{15}$$

Let $t_c = 9\tau/2$ so the Gaussian pulse is centered at half of the total 9 cycles of the modulated signal. σ is determined by requiring that t_c be confined within the Full Width at Half Maximum (FWHM) of the Gaussian pulse or

$$\sigma = \frac{t_c}{FWHM} = \frac{t_c}{2\sqrt{2\ln 2}} \tag{16}$$

Multiplication of (14) with (15) produces the continuous modulated Gaussian source, Eq. (17).

$$E_x(t) = sin(2\pi f_0 t)e^{-(t-t_c)^2/2\sigma^2} \tag{17}$$

The power spectral density of the resulting modulated signal with a central frequency of 80 kHz is shown in Figure 3. This value of central frequency guarantees a low dispersive behavior in the longitudinal modes of the guided wave for the pipeline under test, as shown in the disperse curves in Figure 4. The dispersion curves are obtained using the freeware PCDISP [17].

The baseline (normal condition) of the PCA model is determined considering the absence of deflection in the middle variable support. Under this condition the middle part (L/2) is experimenting a negative bending moment and the pipeline develops an internal stress of 5% of the yield strength. The stress was measured by using a strain gage model CEA-13-125UN-350 of Vishay micro-measuments located in the middle point of the pipeline and it is also calculated analytically. Now, the magnitude of the variable support is decreasing while the pipeline deflection is increasing in steps of 5 mm down of the original axis position (baseline). Every 5 mm, deflection constitutes a different stress scenario, denominated D1 for a 5 mm of deflection, D2 for a deflection of 10 mm and so on consecutively until D9 with 45 mm of deflection (37.5% of the yield strength). The variation of the deflection yields an increase in the magnitude of the bending moment in the middle part of the pipeline from negative in the initial condition (-27.31 N-m) to positive upward the 15 mm of deflection, see table 1.

Additionally, in Table 1 it can be observed the variation of the maximum positive bending moment along the pipeline and its location for each studied scenario. The distance can be indifferently measured from any end, due to the symmetric of the loads in the pipeline.

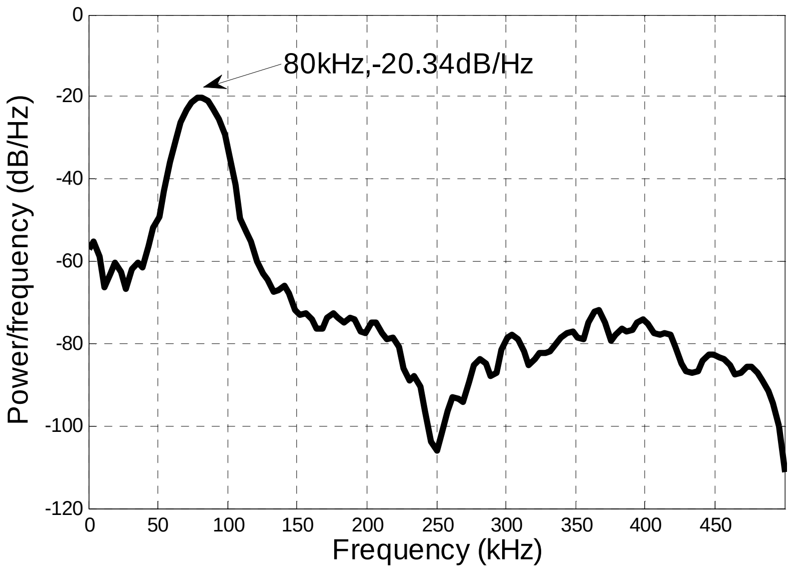

Figure 3: Power spectral density of the Gaussian-modulated sinusoidal pulse

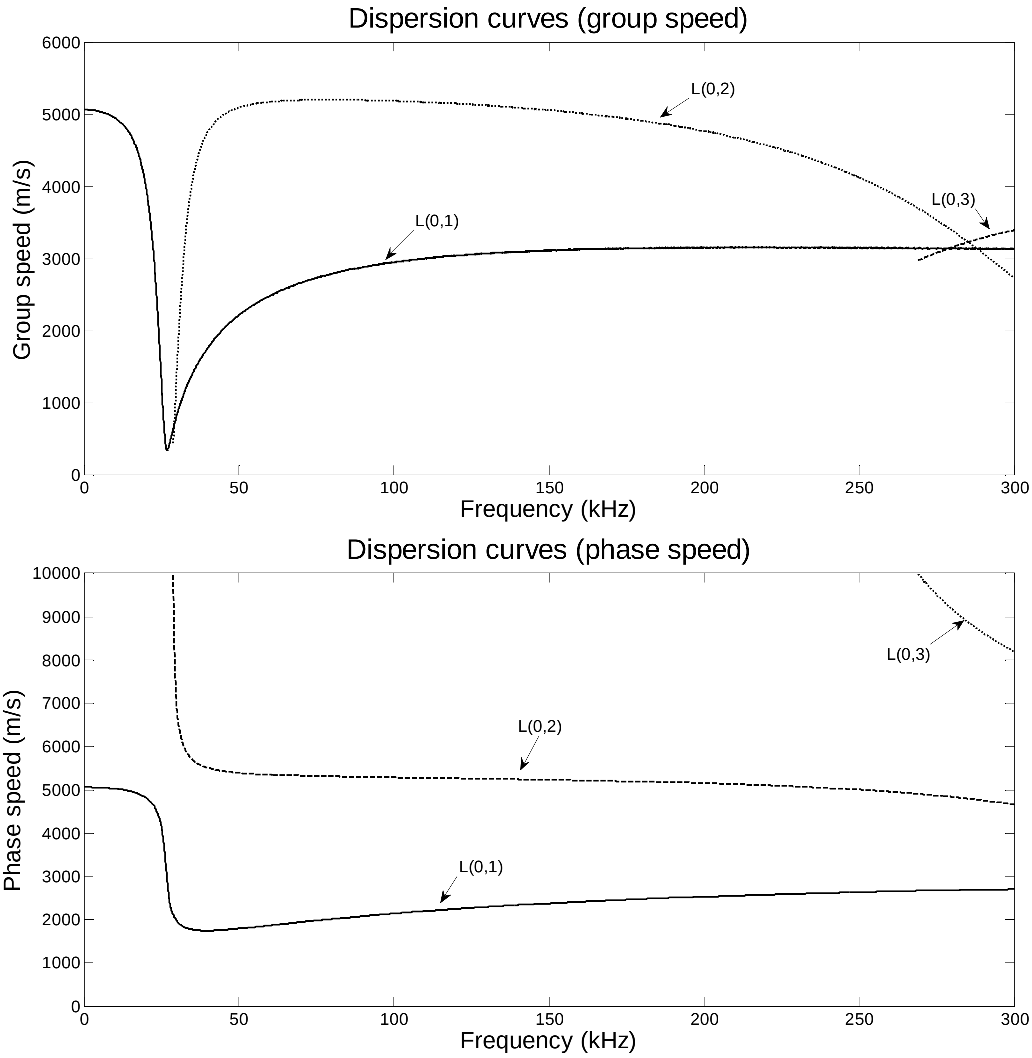

Figure 4: Phase speed and group speed dispersion curves for a 1” Sch. 40 A-106 pipeline

Although, only for the baseline the bending moment in the middle is greater than the maximum positive bending moment in the pipeline, the difference between the bending moments in all the consecutive deflection is greater in the middle part of the pipeline. This difference will be more sensible for a suitable feature used to track the changes in the stress whether a monitoring system is implemented.

Scenarios	Deflection in the middle of the pipeline (m)	Bending moment in the middle of the pipeline (N-m)	% of yield strength in the middle	Maximum positive bending moment (N-m)	Position of the maximum positive bending moment (m)
Normal	0	-27.31	5	15.25	1.1
D1	0.005	-14.31	2.6	20.49	1.28
D2	0.01	-1.39	0.25	26.5	1.45
D3	0.015	11.56	2.12	33.2	1.63
D4	0.02	24.53	4.5	40.84	1.8
D5	0.025	37.49	6.8	49.17	1.98
D6	0.03	50.45	9.2	58.27	2.16
D7	0.035	63.41	11.6	68.14	2.33
D8	0.04	76.37	14	78.79	2.51
D9	0.045	89.34	16.41	90.2	2.68

Table 1: Bending moment and yield percentage for deflection in the pipeline

Based on the previous considerations, the piezoelectric transducers location is defined. The actuator and the sensor are located at 0.63 m equidistant from the middle, aligned with the pipeline axis, as shown in Figure 2.

A number of 100 experiments have been performed and recorded for each scenario of stress condition. Every experiment is composed by 1000 samples and after the cross-correlation the number of samples is increased by 2000. The baseline is obtained using only 70 experiments and the rest are used to validate the model. The principal components are determined using the data of the baseline. PCA analysis provides the variability retained for each component, where 99.8% of the variability is presented in the first 60 components out of 2000, as shown in Figure 5. Then, every new study case is projected onto the selected components.

In the diagnosis step, nine different scenarios D1 to D9, as shown in Table 1, are projected onto the model. Once the projections are obtained, the indices T^2 and Q-*Statistics* are determined for each experiment. The results of the indices for each stress scenario studied are shown in Figures 6-8. In Figures 6 and 7, the damage detection indices (T^2-statistic and Q-statistic) were plotted for each experiment, shapes and colors represent different conditions of the specimen. In Figure 8, Q-statistic against T^2-statistic are plotted. In Figure 8 is shown the phase shift produced in the captured wavepacket signal for the PZT in time domain attributed to the acuostoelasticity.

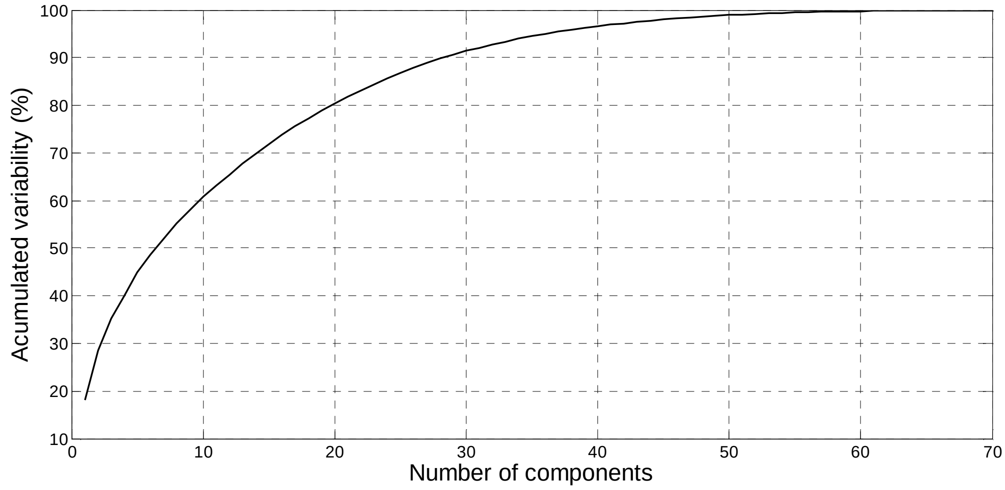

Figure 5: Accumulated variability versus number of components of PCA

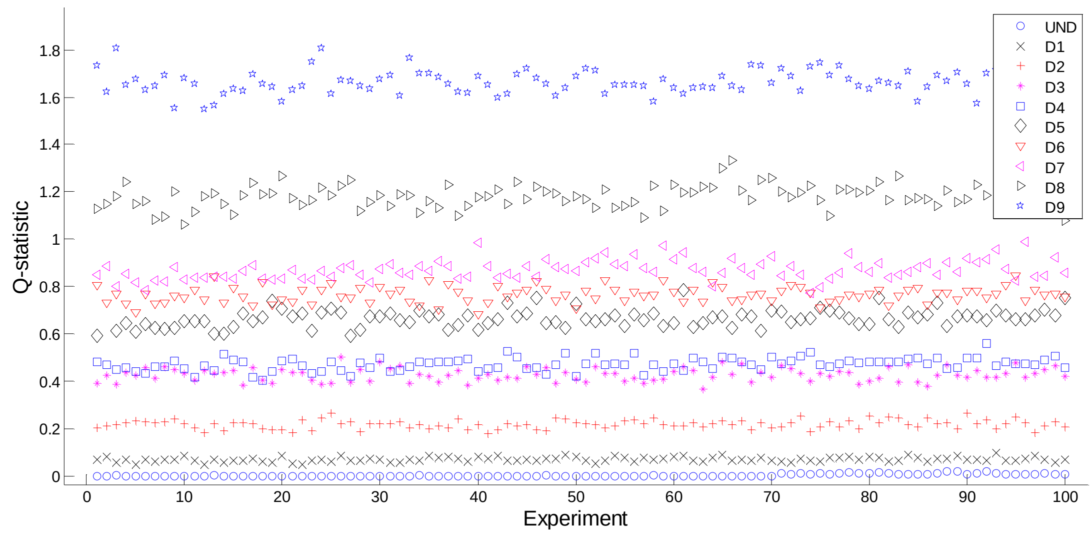

Figure 6. Q-Statistics versus Experiments for all scenarios studied

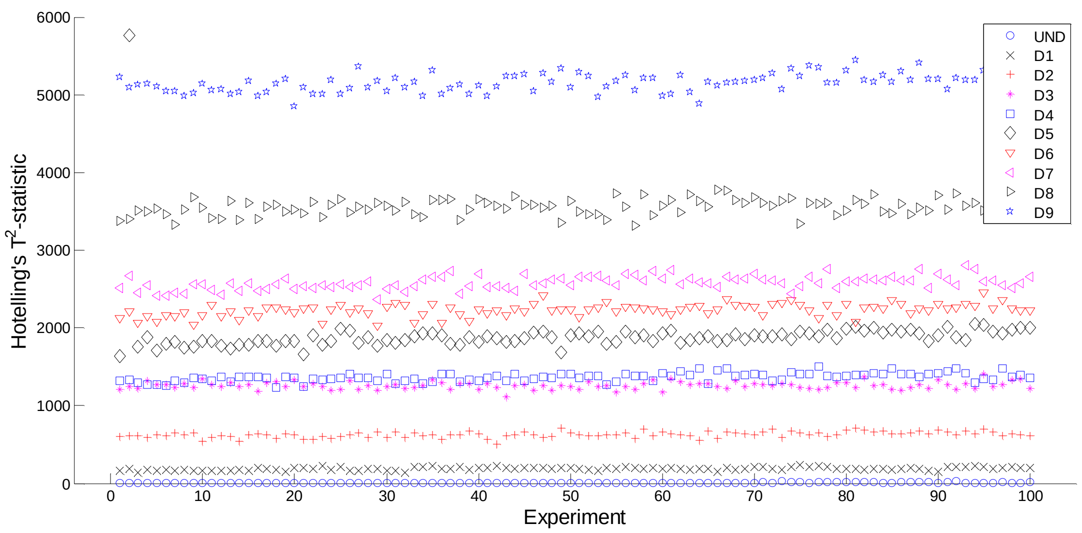

Figure 7. T^2 versus experiments for all scenarios studied

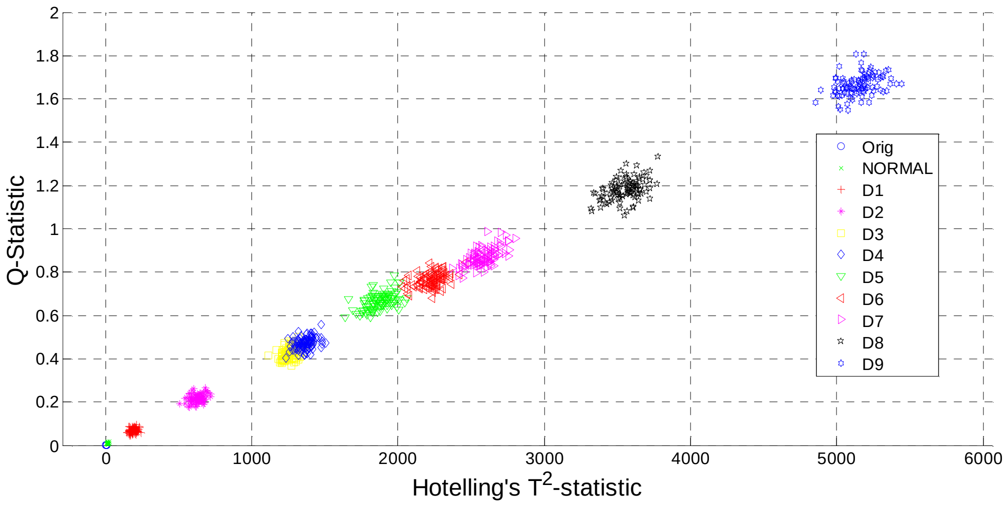

Figure 8. Q-Statistics versus T^2 for all scenarios studied

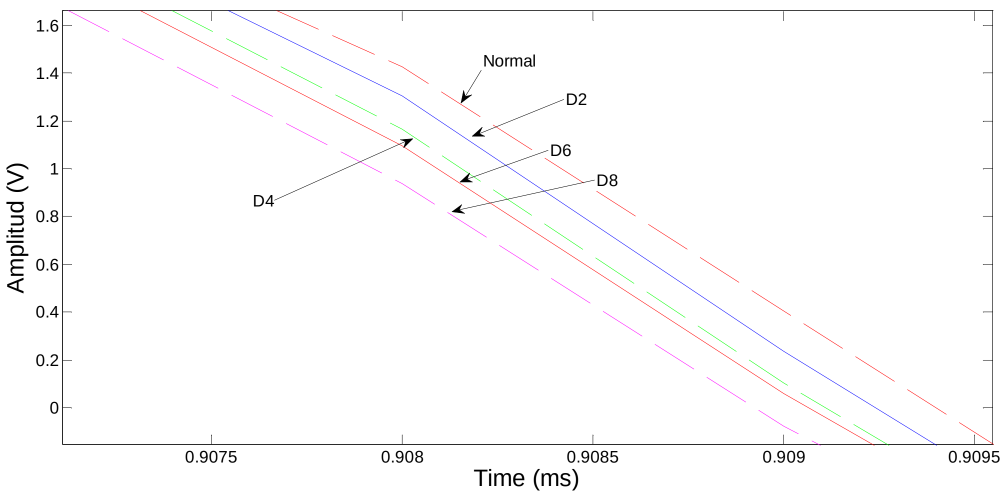

Figure 9. Phase shift in time domain due to Acoustoelasticity Effect for some scenarios

4 RESULTS AND ANALYSIS

In Figures 6-8 can be observed that the values of the indices T^2-statistic and Q-statistic for each stress scenario are around some value and differ among the different stress scenarios; however in some experiments the indices are slightly overlapping, mainly in the D3 and D4 scenarios, as shown in Figures 6-8. Based on the previous results, it can be concluded that the indices T^2 and *Q-staticstics* of the PCA model provide capabilities for distinguishing among the different stress scenarios. Additionally, in Figure 8, it is observed a linear relationship between the indices, when the specimen is subject to a different stress condition. Nevertheless, although exists a linear relation between the values of the indices, this relation is not proportional with the stress magnitude.

5 CONCLUSIONS

The experimental results of the proposed algorithm based on PCA model shows a reliable and suitable capabilities for discriminate every stress condition scenario for a 1” sch 40 A-106 pipeline under the experimental conditions. PCA technique, in particular the T^2 and Q-

staticstics indices, is a tool for detecting the presence of different stress conditions, comparing the values of the indices to the values of the baseline via a threshold.

The implemented methodology is able to detect any stress condition, but the evaluation of the magnitude of the stress applied to the specimen requires a more extent experimentation in order to determine the statistically appropriate threshold to define the magnitude of the stress applied. For instance, by means of multivariate statistical inference.
Therefore, the studied indices constitute a base for implementing a classifier algorithm allowing to discern among different deflections or stresses of the pipeline.

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