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Health Monitoring of Welded Pipelines with Mechanical Waves and Fuzzy Inference Systems

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Abstract

This research presents a cost effective vibration-based pipeline integrity identification method for welded pipes using mechanical waves and fuzzy inference systems. At the moment, in terms of instrumentation, there are two approaches towards integrity identification of pipelines: (i) measurement throughout the pipeline (ii) measurement at a limited number of points along the pipeline. The second approach is normally much less expensive. Use of ultrasonic waves is the only widely used method of this approach. This paper introduces an alternative, in the second approach: use of mechanical waves. That is, the pipeline is mechanically excited at a point, and the mechanical response (e.g. acceleration) is measured at another point. Advantageously, mechanical waves are inexpensive to generate and measure. In addition, it is well known that any change in pipe structure affects the measured mechanical response. However, this effect is very complex, so that it is practically impossible for human beings to interpret information of such tests. This research focuses on fault isolation (location) on welded pipelines and employs Fourier series, statistical analysis and fuzzy inference systems to interpret the recorded responses. Preliminary results are promising and show a standard deviation of 3.8 meters. These results can improve significantly with increase of the tests used for data analysis.

1. Introduction

Two main categories of methods are employed to tackle fault diagnosis of pipelines. In the first category, the whole pipe should be examined; that is, the fault detection device needs to be moved or installed along the entire pipe. Instances are the use of optical or acoustic sensors to find leaks [1].. Other examples are the injection of flammable chemicals and use of a flame detector along the pipeline [2] and simultaneous use of electromagnetic sources and sensors [3]. This latter method is performed manually or by special robots namely “pigs” [4] in which their use requires the pipeline to be out of service. Another example is the installation of optical fibres along the pipe [5]. All these methods are time-consuming and/or expensive.

The second category includes the methods that need measurement at a limited number of points along the pipeline. There are two methods in this category, (i) fault diagnosis based on monitoring the change of fluid characteristics (i.e. flow rate and pressure) [6, 7] and (ii) use of ultrasonic waves [8]. In the first method, a set of nonlinear equations which describe the flow dynamics are solved (e.g. through linearization [9] or discretisation [10]) and used to predict the flow rate or pressure in the presence/absence of faults. This method still suffers from inaccuracies inherited by complex dynamics of natural gas and uncertainties in parameters of governing equations. In opposite, ultrasonic waves have been successfully used to detect leaks of gas pipelines. The main shortcoming of this method is its limited range of operations (tens of metres) and high expense of generators and detectors of ultrasonic waves.

This paper suggests a new approach: the use of mechanical waves, which are much less expensive to generate/detect than ultrasonic waves and can progress much further along the pipeline due to their lower frequency.

2.Problem Statement

This research aims to investigate whether meaningful information can be extracted from mechanical waves to identify changes in pipeline structure. For this purpose, fault isolation (location) capability is examined with use of fuzzy inference systems. Figure 1 shows the case study: a 50m 2" carbon steel pipe welded and vertically supported every 5 meters. The pipe is first assumed to be fault less, and then a 300N force is applied for 0.001 s and the resultant acceleration is recorded in Abaqus finite element software. Sampling frequency of 6Hz is used for frequency; that is sinusoidal waves with natural frequencies up to 3kHz can be captured. In the end, the acceleration data was transferred to frequency domain with fast Fourier transform. Afterwards, this simulation is repeated 15 more times with a whole through hole with 2mm diameter located on 90º position (top) of the cross section with the distances of 3,6,9,12,15.5, 18,21,24,27,30.5,33,36,39,42,45.5 meters from left end of the pipeline, one fault location per simulation.

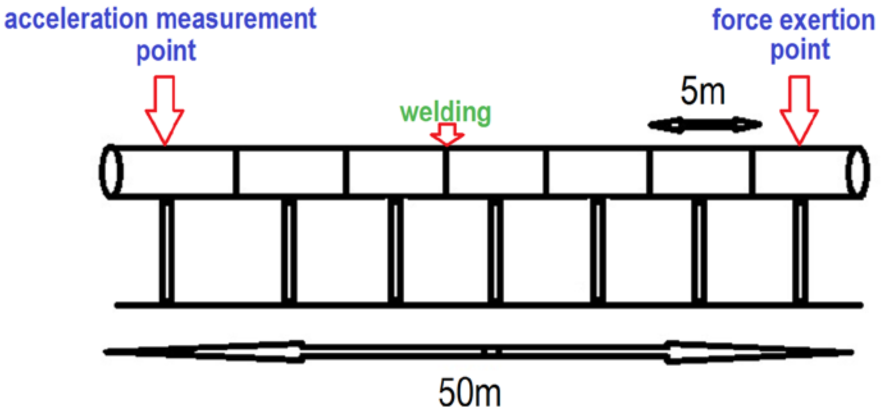

Figure 1. Case study for fault isolation

3.Verification of Node Types and Mesh Sizes of Final Element Model

Initially, modal analysis was performed on a sample pipe (depicted in Figure .2), then a finite element model (FEM) of the same pipe was constructed in Abaqus software package. As a result, a suitable element type and mesh size were chosen so as the natural frequencies of the model are close enough (with an error of less than 2%) to modal analysis results. The selected mesh size of 1 cm and element type pipe were used in the rest of FEMs of the paper. The density, elasticity modulus and poison ration of the pipe are 7861 kg/m^3, 207 GPa and 0.3 respectively.

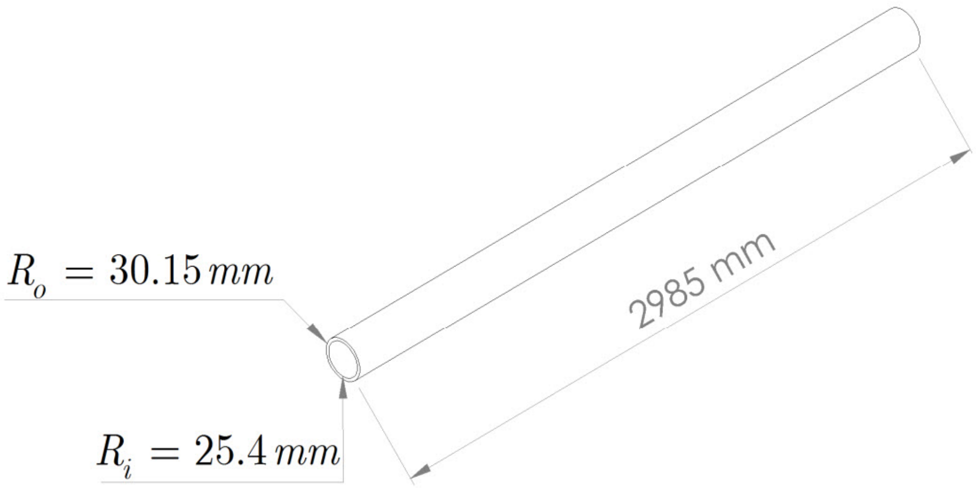

Figure 2. Sample pipe

Figure 3. Modal Analysis of the sample pipe

Table 1 lists some of the natural frequencies obtained from modal analysis and finite element analysis (FEA).

Table 1. Comparison of natural frequencies obtained from Modal Analysis and FEA results

FEA Results[Hz]	Modal Analysis [Hz]
40.101	40.020
110.03	110.95
214.26	216.55
351.05	356.018

After selection of element type and mesh size, the pipe is extended by 50 with weldings and bearings every installed every five meters. Bearing constrain axial motions of the pipe.

4.Initial Analysis of FEM Simulation Results

FEM simulations and fast Fourier transform, as detailed in section 2, result in 16 acceleration versus frequency series of data with 3kHz bandwidth, one series for fault-less and 15 with a fault. The selected bandwidth of 3 kHz then was divided into 100 areas of 30 Hz. The average magnitude of acceleration was derived for any of them. That is, each pipe location is represented by 100 values of average acceleration. For faulty pipe, all these numbers were subtracted from the ones of the faultless pipe. As a result, 100 numbers associated with 100 frequency areas (0~3000 Hz) are obtained for each fault location. These array is called ‘signature’.

Then variance of each signature number across all fault locations was calculated. This shows, how sensitive this signature number is respect to change of fault location. Interestingly, figure 4 shows that the most sensitive signature elements or frequency areas are different from the ones which witness the highest accelerations, i.e. resonance points. In this research, the elements of signature associated with variances>0.2, 10 numbers, were selected and called ‘selective signature’.

5.Fault Isolation using Fuzzy Inference Systems

Linear Sugeno-type fuzzy inference systems were used in this research [11]. The inputs to a fuzzy inference system or model are the signature or selective signature elements, and the output is the fault location. We have access to 15 test results to model, validate and test the fuzzy inference system.

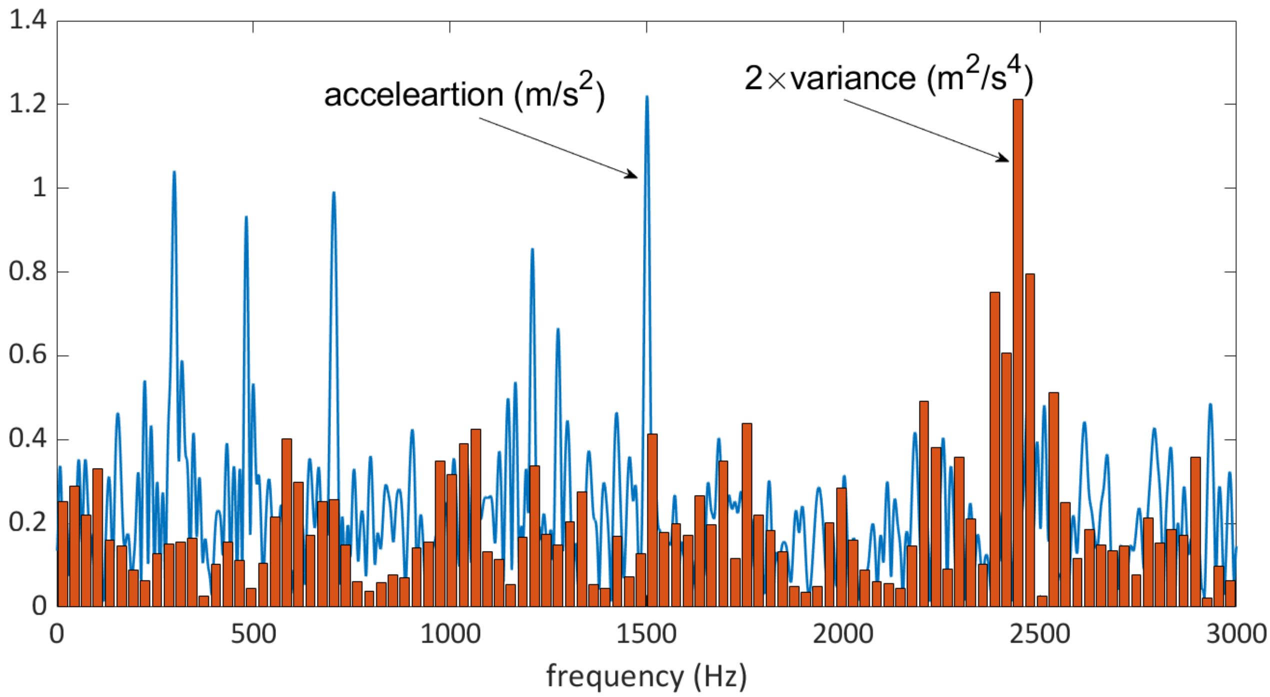

Figure 4. Acceleration recorded for the faultless pipe and variance of signature elements

The proposed fuzzy model has n rules. Each rule receives all inputs and has a membership function per input. The output of each membership function is a membership grade. In this research, for j th rule and i th input (u_i), the Gaussian membership function of Equation 1 was employed to produce a membership grade, μ_{ij}.

$$\mu_{ij} = \exp\left(-\frac{(u_i - c_{ij})^2}{2\sigma_{ij}{}^2}\right). \tag{1}$$

where c_{ij} and σ_{ij} are the centre and width of the membership function, respectively. The product of membership grades of a rule was considered as the weight of the rule, as shown in the denominator of Equation 2. Weight of a rule is a number between zero and one. Moreover, any rule has an output which is a linear combination of its inputs, as shown in the numerator of (2). The output of the whole model is the weighted sum of rules outputs:

$$\hat{y} = \frac{\sum_{j=1}^{n}\left(\overbrace{\left(\sum_{i=1}^{3} a_{ij}u_i + a_j\right)}^{j^{th}\ rule\ output}\prod_{i=1}^{3}\mu_{ij}\right)}{\sum_{j=1}^{n}\underbrace{\prod_{i=1}^{3}\mu_{ij}}_{j^{th}\ rule\ weight}}. \tag{2}$$

In order to develop the fuzzy model two steps were taken: (i) Model generation: finding the number of rules, n, and initial estimation of model parameters, a_{ij}, a_j , c_{ij} and σ_{ij}. (ii) Model identification: determining model parameters accurately. Both of these steps as well as test were carried out with aforementioned 15 sets of data.

Subtractive clustering technique, detailed in [12], was used for model generation with these coefficients: Range of Influence=0.5, Squash Factor=1.25, Accept Ratio=0.1 and Reject Ratio= 0.15.

For model identification, first, the 'model error', E, was defined to represent the discrepancy of real and estimated (with ^) value of the head:

$$E = \frac{\sum_{for\ a\ series\ of\ data}(\hat{y} - y)^2}{number\ of\ data\ sets}. \tag{3}$$

In this research, 11 data sets with fault locations of 3,6,9, 15.5, 21,24,27,30.5, 36,39, 45.5 meters were used as the 'modelling data'. The model error calculated for the modelling data is called the 'modelling error'. The parameters of the model were adjusted (or trained) using an iterative algorithm [12] so as to minimise the training error. The training algorithm, at each iteration, includes the least square of error [13] to adjust the parameters of the rules' outputs (a_{ij}, a_j) and error back propagation with gradient (or steepest) decent method [14] to adjust the parameters of membership functions (c_{ij} and σ_{ij}). At each iteration, the model error for another series of 25 data sets, namely the 'validation data', with fault locations of 9 and 42 meters is also calculated: the 'validation error'. At a point, the validation error starts to increase, while the training error continues to decrease. This situation is called overfitting and is a sign to stop the iterative algorithm of identification [15].

6.Results and Discussion

Both developed fuzzy models, with the full and selective signatures were tested with the data of faults locations of 18 and 33 meters from the force source. The estimated locations are 12.0/17.1 and 39.0/24.5 metres. Considering the number of data sets used in modelling (11 sets), the achieved accuracy is promising. Interestingly, standard deviation of estimation for models developed with full and selective signatures are 6.0 and 3.8 meters; while the number of model parameters are 1111 and 341, respectively. As a result, use of selective signature is a better option.

7.Conclusion

This research investigated use of mechanical waves to identify changes in pipelines structure. It is shown that with use of numerical models of the faultless pipeline, fast Fourier transform, statistical methods and fuzzy inference systems, a fault can be located in a simple pipeline with a reasonable accuracy. Numerical simulation results for only 15 fault locations were employed in this research. Accuracy could remarkably improve if more numerical simulation results were available. The authors identified two constraints to the proposed approach for health monitoring, (i) large extent of computations, (ii) need to have an accurate numerical model of the pipeline.

8.Acknowledgements

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