IMPLEMENTATION OF VIBRATION-BASED STRUCTURAL HEALTH MONITORING TECHNIQUE FOR IDENTIFICATION OF SIMULATED CORROSION DAMAGE IN STEEL PIPELINE USING NEURAL NETWORK

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A thesis submitted in
fulfilment of the requirement for the award of the
Doctor of Philosophy (Mechanical Engineering)

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JULY 2018

In the name of God, The most Gracious, The Most Merciful.

For my parents;

For my wife and children;

For my brothers and sisters.

ACKNOWLEDGEMENT

First of all, I would like to record inestimable gratitude and thankfulness to the one and the almighty creator for his mercy, help, and support to complete this work. I would like to thank Professor Dr.Shahruddin Bin Mahzan, an exquisite person of deep humanity who has introduced and guided me into the world of the Structural Health Monitoring. He has been not only a great consultant but also a dear friend. I express my deepest gratitude to Dr. Zaleha Binti Mohamed for her helping and advice. I would also like to thank the technician of Vibration Laboratory for his kindness and availability. Most importantly I would like to thank my parents whose genius inspired my scientific and academic development from its most early stages. Finally, I extend my great thanks to my wife and children for their patience, support and encouragement, friends who always next to me for help and assistance.

ABSTRACT

Corrosion defect has inevitably causes serious incidents in pipeline structures. Reduction in corrosion related incidents are highly desirable due to safety and cost efficiency. Current approaches have implemented destructive testing which highly cost and time consumptions. Moreover, the techniques were lacking in correlating corrosion behaviour and its damage severity. This research proposed several signal corrosion features extracted from time domain analysis which provide substantial information related to corrosion behaviour for damage classification analysis. Several corrosion damage scenarios were simulated with different depths indicating its severity conditions. Seven corrosion features in time domain were introduced and extracted from the strain signal obtained from multiple sensors attached to the pipeline structure. The aim was to obtain the monotonically linear behaviour in features which could provide good correlation between corrosion features and corrosion damage. The experimental features were validated with the computational simulation works done for undamaged case only representing the baseline conditions. These features were subsequently used as input parameters for artificial neural network to classify corrosion damage into six type of damage depth representing different damage severity. The results demonstrated only four corrosion features were found to have linear monotonically behaviour with impact damage which were maximum, minimum, peak to peak and standard deviation features. The simulation works obtained an average of 2 - 8% in relative error with the experimental results. The classification analysis also has demonstrated a feasible method for classifying damage into classes with the accuracy ranged from 84 – 98%. These findings were substantial in providing information for pipeline corrosion monitoring activities.

ABSTRAK

Kerosakan kakisan yang tidak dijangka boleh menyebabkan insiden serius dalam struktur saluran paip. Pengurangan dalam jumlah insiden berkaitan kerosakan pengaratan adalah sangat wajar kerana faktor kos dan keselamatan yang efisien. Pendekatan semasa telah melaksanakan ujian pemusnahan yang memerlukan kos dan masa yang tinggi. Lebih-lebih lagi, teknik-teknik sedia ada masih kurang dalam mengaitkan kelakuan kakisan dan keterukan kerosakannya. Kajian ini mencadangkan beberapa sifat isyarat kakisan yang diekstrak dari analisis domain masa yang memberikan maklumat yang ketara berkaitan dengan tingkah kakisan untuk analisis klasifikasi kerosakan. Beberapa senario kerosakan kakisan telah disimulasikan dengan kedalaman yang berbeza yang menunjukkan keadaan keterukannya. Tujuh ciri kakisan dalam domain masa telah diperkenalkan dan diekstrak daripada isyarat terikan yang diperolehi dari pelbagai sensor yang dilekatkan pada struktur saluran paip. Matlamatnya adalah untuk mendapatkan tingkah laku linear monotonik dalam ciri-ciri yang dapat memberikan hubungan yang baik antara ciri-ciri kakisan dan kerosakan kakisan. Ciri dari eksperimen ini telah disahkan dengan kaedah simulasi pengiraan yang dilakukan untuk kes tidak rosak bagi mewakili keadaan asas. Ciri-ciri ini kemudiannya digunakan sebagai input parameter dalam rangkaian saraf tiruan untuk mengklasifikasikan kerosakan kakisan kepada enam jenis kedalaman kerosakan yang mewakili keterukan kerosakan yang berbeza. Hasilnya menunjukkan hanya empat ciri kakisan yang didapati mempunyai perilaku monotonik linear dengan kerosakan kesan iaitu maksimum, minimum, puncak ke puncak dan ciri sisihan piawai. Kerja-kerja simulasi juga memperolehi purata 2 - 8% dalam ralat relatif dengan hasil eksperimen. Analisis klasifikasi juga telah menunjukkan kaedah yang dilaksanakan untuk mengklasifikasikan kerosakan ke dalam kelas dengan ketepatannya berkisar di antara 84 - 98%. Penemuan ini adalah penting dalam menyediakan maklumat untuk aktiviti pemantauan kakisan paip.

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LIST OF SYMBOLS AND ABBREVIATIONS

AE	Acoustic Emission
ANNs	Artificial Neural Networks
BPNN	Back Propagation Neural Network
DS	Damage Severity (depth)
DSP	Digital Signal Processing
ET	Eddy Current Testing
FEM	Finite Element Method
GW	Guided Waves
MLP	Multi-layer Perceptron
MSE	Mean Square Error
NC	Numerical Control Machine
NDE	Nondestructive Evaluation
NDT	Nondestructive Testing
NNs	Neural Networks
PHMSA	Pipeline and Hazardous Materials Safety Administration
PR	Pattern Recognition
RT	Radiographic Testing
SHM	Structural Health Monitoring
UT	Ultrasonic Testing
Z	Output of Perceptron
δ	Activation Function of the Neuron
k_j	Predicted Output Neural Network
σ	Output Unit's Threshold
W_i	Connection Weight of the i^{th} input
y_j	Actual Output of Neural Network

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CHAPTER 1

INTRODUCTION

This chapter gives a brief explanation about pipeline integrity (corrosion problem and current monitoring techniques). Also, the research problem background and statement are stated and then followed by research objectives. Furthermore, other aspects such as research scope and organization of the thesis are presented.

1.1 Background of Study

Pipeline networks are one of the important civil constructions. They play an important role in the world economy. The economy of the world is heavily dependent upon an extensive network of distribution and transmission pipelines to transport the energy sources. They are used widely in industry, such as oil and gas transportation, chemical industry and various kinds of power plants. Pipelines constructions have an influence on human, environmental, economic and aesthetic aspects of societies, and associated activities contribute significantly to the overall national product of the states. Therefore, all the governments and companies all over the world give high attention to good design, quality materials and durable and safe utilization of pipeline networks. Moreover, the aging of pipelines makes structural monitoring and maintaining of its structural integrity and reliability more and more essential.

The collapse of pipes often leads to critical ramifications. The most serious impacts involve human victims, partial or complete failure of infrastructure, and economic impact. Moreover, the malfunction of pipelines may induce serious environmental pollution and risks especially for those in proximity to pipelines. (Williams, 2012). Actually, the economic effect of pipeline structural failure is twofold: direct and indirect. The costs of reconstruction represent the direct impact, whereas the indirect impact involves losses in the other branches of the economy. Pipelines are liable to an extensive variety of damages and defects. Some of the most common causes of failure in pipelines are corrosion, stress cracks, seam welds cracks, material flaws, aging and externally induced damage by excavation equipment. Over the last decades, accidents caused in pipelines have been reported frequently all over the world. As stated by Cosham *et.al.* (2007), metal corrosion is a major threat to the structural integrity of underground oil and gas pipelines worldwide. The damage to the pipeline needs to be identified and the significance of the damage clearly defined (Shaik, 2015).

1.2 Pipeline Corrosion

One of the most frequent problems with the structural integrity of industrial pipelines is corrosion. The environment and the age of the pipeline itself are the two factors which drive the pipeline corrosion. Therefore, much effort has been put in by many companies, individuals and others in supporting the integrity of these ageing pipelines and finding the keys for the solutions of corrosion problems. Pipeline corrosion is the deterioration of pipe material and the related system due to its interaction with the working environment. In other words, as stated by Thodi *et al*. (2009) corrosion is defined as loss of material as a result of chemical reaction between a metal or metal alloy and its environment. It affects pipeline and accessories made of both metals and non-metals.

According to Ossai *et al*. (2015), every year a large amount of money is spent on different forms of corrosion control measures in order to maintain the integrity of pipelines. Pipeline corrosion and the related catastrophic failures can cost billions of dollars to the economy. For example, Figure 1.1 shows that the corrosion was responsible for 18 percent of the significant incidents (both onshore and offshore) during the 20 year period from 1988 through 2008 in the United

States alone, as reported by Pipeline and Hazardous Materials Safety Administration (PHMSA) (Fessler, 2008).

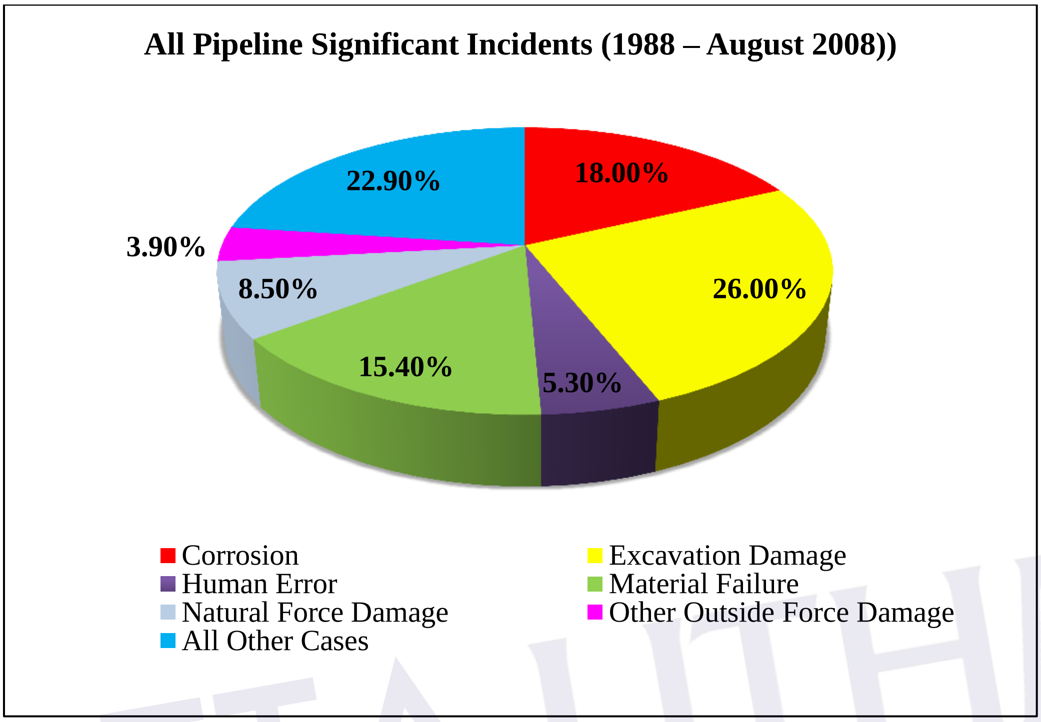

Figure 1. 1: Causes of significant incidents in onshore and offshore pipelines (Fessler, 2008)

Pipelines are subjected to internal and external agents that can cause corrosion affecting their safety, integrity, and profitability. Corrosion causes metal losses that may hamper the supply of energy and could lead to substantial damage to the ecology. In additional word, corrosion is a big problem because it has the potential to reduce a pipeline's life by premature degradation. It mainly affects pipeline made of metals such as copper, aluminium, cast iron, carbon steel, stainless steel and alloy steel pipes used for buried, underground, submerged or other pipelines. The severity of corrosion varies depending on the type of corrosion. The kind of corrosion that is experienced may vary as well (Mattson, 1996). Figure 1.2 demonstrates an example of traditional pitting corrosion which can attack pipeline structure.

Figure 1. 2: Example of traditional pipe pitting corrosion (Popoola et al., 2013)

Typical corrosion forms that can be found on the external surfaces of the pipelines include uniform or general corrosion, pitting, crevice corrosion, intergranular corrosion, erosion corrosion, environment-induced cracking and stress corrosion cracking.

In general, pipeline corrosion has many and varied serious effects on the safety, reliability and efficiency operation of pipeline structures. Even though the amount of metal destroyed is quite small the need for expensive replacements may occur and restoring pipelines to the safe operating condition is the main goal of all pipeline owners. Therefore detection of pipeline defects as early as possible during inspection and maintenance is very important.

1.3 Approaches for Pipeline Corrosion Monitoring

Corrosion monitoring is one of the main components of corrosion control strategies. Therefore, most of companies over the world work to establish and implement good techniques for corrosion monitoring. The monitoring procedure signifies the ongoing monitoring of the corrosion process and the measures taken to control it. As a result, operators can evaluate corrosion damage and predict remaining life, reliability and the safety of structures.

Accurate monitoring system techniques represent the main solution for this serious problem. In practice, a combination of several different techniques can be applied. For instance, oil and natural gas companies commonly use both destructive and non-destructive inspection techniques to ensure the integrity of transmission lines. In fact, implementation of most of these techniques needs to stop the pipeline from working temporarily. Some of the commonly used techniques are radiographic testing, smart pig method, magnetic flux leakage method, ultrasonic detection technique, electromagnetic acoustic transducer technique, pressure difference method, ultrasound wave method, and so on. However, such methods are limited to providing the inspection of pipeline inner damage, namely effective in detecting corrosion or radial deformation of pipeline, but incapable of detecting exterior damage such as scour-induced free span (Bao *et al.*, 2013).

1.4 Structural Health Monitoring (SHM)

Actually, all the documented cases of pipeline accidents indicate that the current approaches used for monitoring the structural integrity of pipelines is not completely sufficient and there is still justification for seeking improvements (Thien, 2006). The associated costs of structural damage from accidents are quite big, enormous loss from each and every fatality. Also, it is noticeable that the application of some types of both destructive and non-destructive inspection techniques requires the pipeline to be taken temporarily out of service, which raises the monitoring costs. As a result, the need for a monitoring system which is more reliable, cheaper and has numerous benefits for pipeline operators have become clear.

Good monitoring systems should be employed to find out appropriate data that can be used for optimization of the operation, maintenance and repair processes of the pipelines. Structural health monitoring (SHM) is one of the techniques which can be used to provide accurate and in-time information concerning the structural condition and performance. As stated by (Kessler, 2002) SHM is an emerging technology that can be defined as continuous, autonomous, real-time, in-service monitoring of the physical conditions of a structure by means of embedded or attached sensors with minimum manual intervention. SHM provides the ability of a system to detect adverse changes within a system’s structure to enhance reliability and reduce maintenance costs. The process of SHM involves the use of an array of sensors distributed over a structure to make periodic observations of the system’s dynamic response. The observations are then analysed to determine if damage exists in the system and therefore to estimate the health status of the system. Besides being used to detect the pipeline condition deterioration under normal operation environment after an extreme event such as a pipeline experiencing a severe earthquake, an SHM system can also be used ‘for rapid condition screening and to provide, in near real-time, reliable information regarding the integrity of the structure’ (Farrar *et al.*, 2005). Ideally, the output from an SHM system allows engineers to perform a quantitative evaluation of the structural conditions and assess its ability to safely and reliably perform its designed function. Although the SHM of pipeline system is far less developed than that of the bridge structures, some remarkable work has been reported in recent years (Bao *et al.*, 2013).

1.5 Advantages of SHM As Compared With The Current Techniques

The hydrostatic tests have risks that relating with further damaging the pipeline. So, there is a clear advantage of non-destructive approaches over destructive tests. The most important advantage is the very little risk of the structure to be damaged during a particular NDT test. In addition, the different NDT techniques typically give very detailed results about the status of the structure. Even though NDT techniques have the ability to give good results compared to destructive testing methods, there are still some key drawbacks of these techniques.

The most crucial disadvantage with NDT forms is that the used sensing mechanism is typically only temporarily installed in the pipeline structure. This type of installation method creates two problems. On one side, the testing is only performed at scheduled intervals because the sensing technicality is not available all the time. Therefore, the testing method relies on a pre-set schedule. In the case of long term damage like corrosion, this schedule is usually enough to discover the damage before it creates a threat to the structural integrity of the pipeline. On the other side, with short time scale events, such as excavation or an earthquake, a testing schedule may allow the pipeline to operate under dangerous conditions. The second difficulty that produced from the temporary sensor installation arises from the need to obtain direct access to the structure in order to perform the NDT.

Because pipelines are typically installed underground, direct access to the pipeline might require excavation works. In some areas, this excavation works can become especially expensive if access to the pipeline requires digging beneath a roadway. Furthermore, sometimes the excavation process itself causes damage to the pipeline.

Another important disadvantage of NDT techniques is that some types require that the pipeline is taken temporarily out of service. This side of the testing method increases the cost of NDT techniques. The most common NDT techniques implement a sensing mechanism which is sent down the interior of the pipeline. With oil pipelines, the contents of the pipeline provide coupling between the transducer and the pipe material, so the contents need not be removed. With natural gas pipelines, however, the gas provides poor coupling, which may require that the pipeline is filled with a coupling material, such as water. Because of this rather expensive complication, NDT techniques are not commonly used with natural gas pipelines. In addition, the geometry of a pipeline limits the ability to use certain NDT techniques. The sensing mechanism is limited by the size in which it can be efficiently packaged, meaning that the techniques can only be used with pipes which have a certain diameter size. The geometry of pipe bends and fittings can also limit the compatibility of these techniques (Thien, 2006). SHM system, when employed with pipelines, can address each of the issues described above. The most significant benefit is that the sensor array for an SHM system could be permanently installed in the pipeline structure. With a permanent installation, the pipeline operator could likely perform damage detection measurements as often as he wishes with much less financial repercussions. Therefore, the potential of a short time duration event going undetected would be much less likely. In the event of an earthquake or other natural disaster, the operator could check the structural integrity of the pipeline system immediately following the event.

Accordingly, the operator could potentially take all severely damaged pipelines out of service before a leak could accumulate sufficient material to cause an explosion. In addition, a permanently installed system would enable the operator to perform an inspection following any excavation project in the vicinity of a pipeline. A permanent installation would also eliminate the need to perform excavation in order to obtain direct access to the pipeline. If the sensor array was permanently installed on the pipeline structure, then the need to obtain temporary access to the pipe would no longer exist, leading to reduced costs. Finally, SHM system would have fewer limitations regarding the design of the pipeline. The proposed technique is compatible with even small pipe sizes. In fact, the proposed method could potentially be adapted to applications outside of transmission and distribution pipelines, such as chemical plant pipe networks and the tubes in industrial heat exchangers (Alleyne *et al.*, 1996).

1.6 Monitoring Needs And Benefits

The fundamental goal of the monitoring process is to detect unusual structural behaviours that show an indication of an unhealthy structural condition. Detection of an unwanted condition leads for a comprehensive inspection of the structure, diagnosis and finally replacement or repairing works.
Actually, the importance of monitoring is related to the safety of structures and consequently with the safety of human lives and preservation of nature and goods. Monitoring gives chance to operators to detect in early stage any unusual structural behaviours. Regarding pipeline networks, the benefits concern for different aspects. The correct monitoring technique will provide the end user with an early alert system suitable for detecting and notifying about the structural status of the pipeline structure during its working lifespan. Failures and damages will be quickly identified by the user in order to plan appropriate response measures.

Early detection of a structural malfunction allows for an in-time refurbishment intervention that involves limited maintenance costs (Radojicic *et al.*, 1999). Moreover, the increasing of new materials, new construction technologies, and new structural systems make the necessity to find more knowledge about their on-site performance, to control the problems and to verify design objectives. As stated by Glisic and Inaudi (2008), hidden structural information can be found out by applying good monitoring systems consequently, allows for better exploitation of traditional materials and better exploitation of existing structures. In this case, the same structure can accept a higher load; and more performance is obtained without additional construction costs.

For example, as mentioned by Inaudi (2001), "The benefits that can be derived from the implementation of an SHM system can be subdivided into two main categories: hard benefits and soft benefits. Hard benefits include benefits that can be economically quantified, such as immediate/deferred cost savings or increased value. Soft benefits include intangible benefits that the owner of an SHM system perceives and for which he/she is ready to pay a price, but that cannot be directly quantified. Soft benefits include image, prestige, adherence to standards or trends or reduction of perceived risk. Some benefits are a mix of hard and soft benefits. For example, a reduction of risk could lead to a saving in insurance cost and increase in safety, therefore creating both a hard benefit (decrease of costs) and a soft benefit (peace of mind)".

Finally, it can be concluded that implementation of appropriate monitoring approaches helps prevent the social, economic and ecological impact that may occur in the case of structural deficiency in pipeline structure.

1.7 Problem Statement

Pipelines are susceptible to a wide variety of damage and aging defects. One of the most common causes of pipeline failure is corrosion. Therefore, maintaining pipelines structural integrity, reliability and reduction in the number of corrosion incidents in pipelines are strongly desirable regarding safety and financial reasons. In fact, significant improvements in corrosion detection, assessment, and mitigation technology have been made. However, all the current approaches are not sufficient completely in terms of cost, time consumption and damage identification accuracies. Although most of the experimental tests which had conducted in the field of pipe tests gave good indications, further researches are needed to assess the performance of the proposed methods. Here, the Vibration-based structural health monitoring method is the suggested technique for extract simulated corrosion damage sensitive features that can be correlated with impact events for damage identification in a steel pipe structure.

1.8 Aim And Objectives

The main goal of this thesis is to demonstrate the ability of vibration-based structural health monitoring system for continuous pipe monitoring using mounted piezoelectric transducers, to correctly identify the presence of simulated corrosion damage and to recognize the severity of different sizes of corrosion damage in the steel pipe body. In order to achieve the aim, several objectives are highlighted as follows:

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