

STRUCTURAL HEALTH MONITORING ON PIPELINE SYSTEM USING
UNSUPERVISED MACHINE LEARNING ALGORITHM

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A report submitted in partial fulfilment of the
requirements for the award of the degree of
Master of Engineering (Structure)

School of Civil Engineering
Faculty of Engineering
Universiti Teknologi Malaysia

JANUARY 2021

DEDICATION

This project report is dedicated to my father, who taught me that the best kind of knowledge to have is that which is learned for its own sake. It is also dedicated to my mother, who taught me that even the largest task can be accomplished if it is done one step at a time.

ACKNOWLEDGEMENT

In preparing this project report, I was in contact with many people, researchers, academicians, and practitioners. They have contributed towards my understanding and thoughts. In particular, I wish to express my sincere appreciation to my main thesis supervisor, Associate Professor Dr. Norhisham bin Bakhary for encouragement, guidance and evaluation.

I am also very thankful and indebted to my supervisor's current PhD students, Yong Kong Chen and Aminuddin for their continuous guidance, advices, assistance and motivation particularly Yong Kong Chen. He has been willing to offer his broad knowledge in related topics and allow me to contact him for assistance whenever as I see fit in order to ensure my dissertation's success. Therefore, I would like to express my utmost appreciation for all his help.

Last but not least, I would like to express my gratitude to my family for all their motivation whenever I feel like giving up. They have been encouraging me to keep going despite the difficulties that I have been through when preparing this dissertation.

ABSTRACT

Pipeline network system has been the most vital infrastructure for several needs ranging from residential, industrial, oil and gas, aerospace, automotive and many more. However, such system is also vulnerable to defects at some point during its lifespan. Therefore, a proper structural health monitoring on the pipeline system is vital to ensure optimum safety of users and efficient transportation of liquid and gas. The objectives of this study are to investigate the natural frequency of the pipeline, establish a machine learning algorithm for pipeline damage detection and demonstrate numerically the applicability of machine learning in defect identification on a pipeline. A total of 4 single long pipes pinned at both ends are modelled using ABAQUS software whereas the K-mean algorithm is built via Google Colaboratory. The pipes are in the form of 2D wire with no loads applied. The pipes are categorized into 2 natures i.e healthy and corroded and are partitioned into 4 parts. The corrosion is induced on 3 out of the 4 pipes specifically at one of the portioned parts prior to undergoing frequency analysis to acquire mode shapes with their respective natural frequencies. As for the algorithm, 2 clusters, 0 and 1 are determined and labelled as healthy and corroded respectively. Multiple mode number ranging from 0 to 11 that represent the range of 4 distinct natural frequency data for 4 different pipes are fed into the algorithm and classified based on the pre-determined clusters. Based on the results obtained, the presence of corrosion on the pipe influences the deformation of the pipe by imposing slightly higher natural frequency in the range of 1.03% to 10.4% and 2 out of 4 pipes with damage locations at 1 and 3 provide identical natural frequency. The algorithm exhibits inaccurate damage detection as it manages to identify two damage locations at 1 and 3 when only one mode number is fed but eventually provides accurate damage detection for all 3 locations when more than one mode number. However, due to the identical natural frequency for location 1 and 3, the damage localization cannot be performed by the algorithm. As a conclusion, the competency of K-mean clustering in defect identification has achieved a satisfactory remark with the exception of damage localization.

ABSTRAK

Sistem rangkaian saluran paip telah menjadi infrastruktur yang paling penting untuk beberapa keperluan. Walau bagaimanapun, sistem seperti itu juga rentan terhadap cacat pada suatu waktu selama jangka hayatnya. Oleh itu, pemantauan struktur kesihatan yang betul pada sistem saluran paip sangat penting untuk memastikan keselamatan pengguna yang optimum dan pengangkutan cecair dan gas yang cekap. Objektif kajian ini adalah untuk menyelidiki frekuensi semula jadi saluran paip, membuat algoritma pembelajaran mesin untuk mengesan kerosakan saluran paip dan menunjukkan secara numerik penerapan pembelajaran mesin dalam pengenalpastian kecacatan pada saluran paip. Sebanyak 4 paip panjang tunggal yang disematkan di kedua hujungnya dimodelkan menggunakan perisian ABAQUS sedangkan algoritma K-mean dibina melalui Google Colaboratory. Paip berbentuk wayar 2D tanpa beban dikenakan. Paip dikategorikan kepada 2 sifat iaitu sihat dan berkarat dan dibahagikan kepada 4 bahagian. Hakisan disebabkan oleh 3 dari 4 paip yang khusus pada salah satu bahagian yang dibahagi sebelum menjalani analisis frekuensi untuk memperoleh bentuk mod dengan frekuensi semula jadi masing-masing. Bagi algoritma, 2 kelompok, 0 dan 1 ditentukan dan dilabelkan sebagai sihat dan berkarat masing-masing. Nombor mod berganda antara 0 hingga 11 yang mewakili julat 4 data frekuensi semula jadi yang berbeza untuk 4 paip berbeza dimasukkan ke dalam algoritma dan dikelaskan berdasarkan kelompok yang ditentukan sebelumnya. Berdasarkan hasil yang diperoleh, kehadiran kakisan pada paip mempengaruhi ubah bentuk paip dengan mengenakan frekuensi semula jadi yang sedikit lebih tinggi dalam julat 1.03% hingga 10.4% dan 2 dari 4 paip dengan lokasi kerosakan pada 1 dan 3 memberikan semula jadi yang sama kekerapan. Algoritma menunjukkan pengesanan kerosakan yang tidak tepat kerana berjaya mengenal pasti dua lokasi kerosakan pada 1 dan 3 apabila hanya satu nombor mod yang diberi makan tetapi akhirnya memberikan pengesanan kerosakan yang tepat untuk ketiga-tiga lokasi apabila lebih dari satu nombor mod. Namun, kerana frekuensi semula jadi yang sama untuk lokasi 1 dan 3, penyetempatan kerosakan tidak dapat dilakukan oleh algoritma. Sebagai kesimpulan, kecekapan pengelompokan K-mean dalam pengenalpastian kecacatan telah mencapai pernyataan yang memuaskan kecuali pengecualian kerosakan

TABLE OF CONTENTS

	TITLE	PAGE
	DECLARATION	ii
	DEDICATION	iii
	ACKNOWLEDGEMENT	iv
	ABSTRACT	v
	ABSTRAK	vi
	TABLE OF CONTENTS	vii
	LIST OF TABLES	ix
	LIST OF FIGURES	x
	LIST OF ABBREVIATIONS	xii
	LIST OF SYMBOLS	xiii
	LIST OF APPENDICES	xiv
CHAPTER 1	INTRODUCTION	1
1.1	Introduction	1
1.2	Problem Statement	1
1.3	Objective of the Study	2
1.4	Scope of the Study	2
CHAPTER 2	LITERATURE REVIEW	3
2.1	Introduction	3
2.2	Overview of Structural Health Monitoring	3
2.3	Evolution of Structural Health Monitoring Techniques	4
2.4	Recent Studies on Structural Health Monitoring on Pipeline System	6
2.5	Structural Health Monitoring Methods	12
	2.5.1 Economic and Performance Feasibility	12
2.6	Conclusion	17

CHAPTER 3	RESEARCH METHODOLOGY	18
3.1	Introduction	18
3.2	Model the Pipeline	20
3.2.1	Nature of Pipeline	22
3.3	Frequency Analysis	23
3.4	Establish K-mean Algorithm	23
3.4.1	K-mean clustering	25
CHAPTER 4	RESULT AND DISCUSSION	26
4.1	Introduction	26
4.2	Mode Shapes	26
4.3	Natural Frequency	32
4.4	K-mean Clustering	33
CHAPTER 5		35
5.1	Introduction	35
5.1.1	Natural Frequency of the Pipeline	35
5.1.2	Applicability of K-mean Clustering in Damage Detection	35
5.2	Recommendation	36

LIST OF TABLES

TABLE NO.	TITLE	PAGE
Table 2-1	Summary of previous studies	14
Table 3-1	Pipe parameter	21
Table 3-2	K-mean algorithm information	24
Table 4-1	Natural frequency data	32
Table 4-2	Pipe cases and their respective cluster	33
Table 4-3	Pipe case and their respective cluster	34

LIST OF FIGURES

FIGURE NO.	TITLE	PAGE
Figure 2-1	Brief overview of the evolution of damage detection technique (Fen N. S., 2019)	6
Figure 2-2	Pipeline leakage detection method (Shama et al., 2017)	7
Figure 2-3	Network model (Hussein et al., 2017)	8
Figure 2-4	Sensor designed for pipeline monitoring (Mountassir et al., 2018)	9
Figure 2-5	Schematic of pipe with a travelling force (Zajam et al., 2019)	10
Figure 2-6	Pipeline stress distribution (left) and transverse displacement (right) (Sun et al., 2019)	10
Figure 2-7	Overview of SHM on pipeline system	11
Figure 3-1	Research methodology processes	19
Figure 3-2	Finite element model of the 2D wire modelled in ABAQUS	20
Figure 3-3	Cross-sectional area of the pipe	20
Figure 3-4	Corrosion location 1	22
Figure 3-5	Corrosion location 2	22
Figure 3-6	Corrosion Location 3	23
Figure 3-7	K-mean clustering tutorial (Teknomo K., 2007)	24
Figure 4-1	Mode shape 1 for healthy pipe	27
Figure 4-2	Mode shape 2 for healthy pipe	27
Figure 4-3	Mode shape 3 for healthy pipe	27
Figure 4-4	Mode shape 4 for healthy pipe	28
Figure 4-5	Mode shape 5 for healthy pipe	28
Figure 4-6	Mode shape 6 for healthy pipe	28
Figure 4-7	Mode shape 7 for healthy pipe	29
Figure 4-8	Mode shape 8 for healthy pipe	29
Figure 4-9	Mode shape 1 for corroded pipe	29

Figure 4-10	Mode shape 2 for corroded pipe	30
Figure 4-11	Mode shape 3 for corroded pipe	30
Figure 4-12	Mode shape 4 for corroded pipe	30
Figure 4-13	Mode shape 5 for corroded pipe	30
Figure 4-14	Mode shape 6 for corroded pipe	31
Figure 4-15	Mode shape 7 for corroded pipe	31
Figure 4-16	Mode shape 8 for corroded pipe	31
Figure 4-17	Clustering result for one mode number	33
Figure 4-18	Clustering result for more than 1 index number	34

LIST OF ABBREVIATIONS

UTM	-	Universiti Teknologi Malaysia
CNN	-	Convolutional Neural Network
FE	-	Finite Element
NDT	-	Non-Destructive Test
SHM	-	Structural Health Monitoring
ANSYS	-	Analysis System,
PWAS	-	Piezoelectric Water Active Sensor
GaPO ₄	-	Gallium Phosphate
EMI	-	Electromechanical Impedance
LDV	-	Laser Doppler Vibrometry

LIST OF SYMBOLS

%	-	Percent
m ³	-	Cubic metre
Pa	-	Pascal
K	-	Kilo
G	-	Giga
m	-	Metre
mm	-	Millimetre
N	-	Newton
s	-	Second
kg	-	Kilogram

LIST OF APPENDICES

APPENDIX	TITLE	PAGE
Appendix A	Google Colab code for K-Mean	63

CHAPTER 1

INTRODUCTION

1.1 Introduction

Pipeline network system has been the most vital infrastructure for several needs ranging from residential, industrial, oil and gas, aerospace, automotive and many more. However, such system is also vulnerable to defects at some point during its lifespan. Damage on the pipeline is almost difficult to be inspected and monitored especially when embedded. Defects occurred would not only disrupt the transportation of liquid and gas but also contribute to unwanted environmental issues. Therefore, a proper structural health monitoring on the pipeline system is vital to ensure optimum safety of users and efficient transportation of liquid and gas. Hence, necessary inspection and repair approaches are addressed to solve this issue.

1.2 Problem Statement

Initially, the inspection is conducted through conventional method typically human-based visual inspection which only relies on visual aid by trained and certified personnel. However, Li et al., (2019) justified that the accuracy of human-conducted damage identification is highly dependent on the mastery and experience of involved personnel. Another pitfall of this method is that it is less economical when it comes to large-scale inspection. Moreover, certain pipeline system is embedded into the ground thus making it more difficult to conduct. Despite another method named vibration-based monitoring system is introduced to address the limitations of human-based visual inspection, the system consumes high cost mainly on installation and maintenance of the system's vast sensor network (Feng and Feng, 2018). As a mean to address this restriction, computer-based approaches have been proposed and widely

studied among researchers. For instance, artificial intelligence (AI) can be defined as the simulation of human intelligence in machines that are programmed to behave like a human being and mimic their moves. It is a broad field that consists of machine learning, neural network and deep learning. In this study, machine learning is chosen for structural health monitoring on a pipeline system due to its decent simplicity.

1.3 Objective of the Study

The objectives of this study are:

- To investigate natural frequency of the pipeline
- To establish a machine learning algorithm for pipeline damage detection
- To demonstrate numerically the applicability of machine learning in damage detection on a pipeline.

1.4 Scope of the Study

The aim of this study is to demonstrate the applicability of an established machine learning algorithm on defect identification within a pipeline system. The damage case investigated on the pipeline is limited to corrosion on a pre-determined location within the pipeline. The pipeline is also restricted to a single pipeline and numerically modelled using ABAQUS software. On the other hand, k-mean clustering is chosen as one of the machine learning algorithms for this study and is built using Google Colaboratory via Internet due to its ease-to-use with no required pre-installations.

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