DENOISING AUTOENCODER IN DAMAGE DETECTION OF PIPELINE USING GUIDED ULTRASONIC WAVE

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DEDICATION

This thesis is dedicated to my loved ones, who constantly support me throughout the PhD journey. It is also dedicated to my supervisors and research members who motivate and share wisdom with me.

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ABSTRACT

Pipeline condition monitoring is essential in critical sectors such as the petrochemical, nuclear and energy sectors. The guided ultrasonic wave (GUW) monitoring system is an available pipeline condition monitoring system that is gaining much attention owing to its portability, long coverage and high sensitivity to damage. However, environmental and operational conditions (EOCs) effects, especially temperature and random noise may generate unwanted peaks, which are falsely identified as damage. Attempts to deal with EOC effects have not solved the problem, especially for small damage cases (damage equal to or less than 5% cross sectional area loss (CSAL)). In this study, a new damage feature extraction method based on the residual reliability criterion (RRC) is proposed. The performance of the proposed method is measured using the established receiver operating characteristics (ROCs) performance evaluation method. The findings show that this method performs well, with an AUC value greater than 0.9, based on numerical model under 40 °C variations and 10% random noise level, and that the application of RRC is intuitively simple. To ensure the practicality of the method, a 6 metre long, 8 inches diameter experimental pipe model filled with liquid is used to form a GUW database of small damage under 30 °C variations by using Torsional T(0,1) excitation mode at 26 kHz centre frequency. However, the RRC underperformed when experimental data is used because the random noise generated by healthy and damaged signals interferes and generates high amplitude noise. Therefore, this study proposed a denoising autoencoder (DAE) neural network to deal with the effects of EOCs. A DAE decodes high-dimensional data into low-dimensional features and reconstructs the original data from these low-dimensional features. By providing GUW signals at a reference temperature, this structure forces the DAE to learn the essential features hidden within complex data. The proposed DAE showed perfect detection (AUC value of 1.0) using numerical model and performs well (AUC greater than 0.9) using experimental model in terms of small damage identification. Moreover, the proposed method showed superiority among other advanced EOC compensation techniques using both numerical and experimental models.

ABSTRAK

Pemantauan keadaan paip dalam sektor kritikal seperti bidang petrokimia, nuklear dan tenaga adalah sangat mustahak. Sistem pemantauan gelombang ultrasonik dibimbing (GUW) menarik perhatian besar atas kelebihannya dalam mudah alihan, liputan yang panjang, dan sensitiviti yang tinggi terhadap kerosakan. Namun, kesan daripada alam sekitar dan operasi (EOCs), terutamanya suhu dan bunyi rawak, boleh menghasilkan puncak yang tidak diingini, yang dikenal pasti secara kerosakan palsu. Percubaan untuk menangani kesan EOC tidak menyelesaikan masalah, terutamanya untuk kes kerosakan kecil (5% kehilangan luas keratan rentas (CSAL)). Dalam kajian ini, pengekstrakan ciri kerosakan baharu berdasarkan *residual reliability criterion* (RRC) telah dicadangkan. Prestasi kaedah yang dicadangkan diukur menggunakan kaedah penilaian *receiver operating characteristic*. Penemuan kajian ini menunjukkan prestasi yang baik (AUC melebihi 0.9) apabila pengunaan keputusan model numerical dalam perbezaan 40 darjah celcius dan 10% tahap bunyi rawak, dan menunjukkan kemudah fahaman aplikasi RRC. Untuk memastikan kepraktisan kaedah, sebatang paip (6 m panjang dan 8 inchi diameter) yang diisi cecair telah digunakan untuk membentuk pangkalan data GUW yang merangkumi isyarat GUW kerosakan kecil dalam perbezaan 30 darjah celcius dengan menggunakan mod pengujaan Torsional (0,1) di 26 kHz kekerapan. Namun, aplikasi RRC menunjukkan prestasi yang kurang baik semasa data eksperimen digunakan disebabkan oleh kebisingan yang dijana daripada gabungan isyarat yang sihat dan rosak dan menghasilkan amplitud yang lebih tinggi. Oleh itu, kajian ini mencadangkan rangkaian *neural denoising autoencoder* (DAE) untuk menangani masalah EOCs. DAE menyahkod data dimensi tinggi kepada data dimensi kecil dan membina semula data asal daripada data dimensi kecil yang dinyahkod ini. Dengan menyediakan isyarat GUW pada suhu rujukan, struktur ini memaksa DAE untuk mempelajari ciri penting yang tersembunyi dalam data yang rumit. Keputusan kaedah DAE menunjukkan pengesanan sempurna (1.0 AUC) dan mempunyai prestasi yang baik (AUC melebihi 0.9) dalam pengenalpastian kerosakan kecil menggunakan model eksperimen. Lebih-lebih lagi, kaedah yang dicadangkan juga menunjukkan keunggulan antara metodologi pemantauan GUW terkini yang lain menggunakan kedua-dua data model numerikal dan eksperimen.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

3D	-	Three Dimension
AE	-	Autoencoder
ANN	-	Artificial Neural Network
APCA	-	Adaptive Principal Component Analysis
AR	-	Autoregressive
AUC	-	Area Under Curve
BSM	-	Baseline Subtraction Method
BSS	-	Baseline Signal Stretch
CFRP	-	Carbon Fibre Reinforced Polymer
CNN	-	Convolution Neural Network
CSAL	-	Cross Sectional Area Loss
DAE	-	Denoising Autoencoder
DCDAE	-	Deep Convolution Denoising Autoencoder
EICA	-	Enhanced Independent Component Analysis
ELU	-	Exponential Linear Unit
EMAT	-	Electromagnetic Acoustic Transducer
EOC	-	Environmental and Operational Condition
F	-	Flexural
FEM	-	Finite Element Model
FRF	-	Frequency Response Function
GeLU	-	Gaussian error Linear Unit
GMM	-	Gaussian Mixture Model
GUW	-	Guided Ultrasonic Wave
h-NLPCA	-	hierarchy Non-Linear Principal Component Analysis
ICA	-	Independent Component Analysis
KLDEPM	-	Kullback-Leibler Divergence with Empirical Probability Measure
L	-	Longitudinal
LDI	-	Leak Detection Index
LSTC	-	Location Specific Temperature Compensation

MFL	-	Magnetic Flux Leakage
MHL	-	Mahalanobis distance method
MPM	-	Maximum Point Method
MSE	-	Mean Square Error
NDT	-	Non-Destructive Test
NLPCA	-	Non-Linear Principal Component Analysis
OBS	-	Optimal Baseline Selection
OD	-	Orthogonal Distance
OFDR	-	Optical Frequency Domain Reflectometry
OFS	-	Optical Fibre Sensor
PAC	-	Parametric Assurance Criterion
PC	-	Principal Components
PCA	-	Principal Component Analysis
PFA	-	Probability of False Alarm
PIG	-	Pipeline Inspection Gauge
POD	-	Probability of Detection
ReLU	-	Rectified Linear Unit
RFBN	-	Radial Basis Function Network
RMSProp	-	Root Mean Squared Propagation
ROC	-	Receiver Operating Characteristic
ROPCA	-	Robust Principal Component Analysis
RRC	-	Residual Reliability Criterion
SeLU	-	Scaled exponential Linear Unit
SHM	-	Structural Health Monitoring
SNR	-	Signal to Noise Ratio
SOM	-	Self Organizing Map
SVD	-	Singular Value Decomposition
T	-	Torsional
Tanh	-	Hyperbolic Tangent Function
USA	-	United States of America
USD	-	United States Dollar
VBDD	-	Vibration Based Damage Detection

LIST OF SYMBOLS

$\emptyset$	-	dilational scalar potential
λ	-	bulk wave velocities
∇^2	-	Laplace operator
τ	-	threshold
σ	-	standard deviation
a	-	circumferential length
$\tilde{A}$	-	mixing matrix
Amp	-	Amplitude
$b, \hat{b}$	-	bias
β	-	exponential decay rate
c	-	sample number
D	-	damaged features
ϵ	-	smoothing out constant
$f(\,)$	-	activation function of hidden layer
f_c	-	centre frequency of incident signal
$g(\,)$	-	activation function at final layer
$G(\,)$	-	non-quadratic function
h	-	hidden representation
H	-	healthy features
$\vec{H}$	-	equivoluminal vector potential
k	-	wave number
L, l	-	length, location
Ł	-	eigenvalues of covariance matrix
m	-	circumferential mode order
m_t	-	moving averages of gradient
$\hat{m}$	-	estimates of moving averages of gradient
n	-	axial mode order
n_c	-	number of cycles
η	-	learning rate

ρ	-	density
P	-	Orthogonality
$P_{reflected}$	-	peak amplitude of reflected excitation signal
r	-	reflection ratio
$\dot{r}$	-	radius
$\hat{r}$	-	reconstructed reflection ratio
t	-	time
μ	-	mean
$\ddot{\mu}$	-	Lamé constants
U	-	eigenvectors
v	-	standardized Gaussian variable
v_{t}	-	moving averages of squared gradient
$\hat{\mathrm{v}}$	-	estimates moving averages of squared gradient
$\vec{v}$	-	displacement vector
V	-	principal components matrix
$W, \widehat{W}$	-	weight matrices
$\widetilde{W}$	-	inverse matrix of mixing matrix Ã
x, X	-	input vector or matrix
$\hat{x}, X', \widehat{X}$	-	reconstructed output
$\bar{X}$	-	corresponding columns mean
x_{clean}	-	clean database input vector
x_{noise}	-	noisy database input vector
y	-	Gaussian variable of zero mean and unit variance
Z	-	orthogonal projection

CHAPTER 1

INTRODUCTION

1.1 Research background

In recent years, much attention has been paid to pipeline condition monitoring assessments in petrochemical plants. Petrochemical pipeline accidents in the USA have damaged nearly USD 7 billion in property, killed over 500 people, and injured over four thousand since 1986 (Groeger V., 2012). According to Jarvis and Goddard (2017), 70 per cent of mechanical integrity failures in petrochemical industries are due to pipeline damage. Each failure suffered losses for a sum of at least USD 50 million. In August 2012, the Chevron U.S.A. Inc. Refinery in Richmond, California ("the Chevron Richmond Refinery") experienced a catastrophic pipe rupture due to which high-temperature light gas oil spilt and vaporised into a large, opaque vapour cloud that engulfed 19 employees (U.S. Chemical Safety Board, 2015). Approximately 15,000 people from surrounding communities sought medical treatment at nearby medical facilities for ailments including breathing problems, chest pain, shortness of breath, sore throats and headaches. On December 3, 2014, the Co-op Refinery Complex in northeast Regina, Canada, experienced an explosion and fire caused by a pipe rupture at freezing temperature. No one was injured in the blast but an estimated USD 77 million in damage to buildings and equipment was recorded (Ellis, 2014).

Safety assurance of pipelines requires the monitoring of damage occurrences and condition changes. Since a structure experiences continuous loading and vibrations, a pipeline's material properties inevitably experience various modes of deterioration, such as corrosion, cracks, and creep, thereby affecting the structure's integrity. Moreover, exposure to extreme operating conditions and ageing can reduce the reliability and efficiency of a structure, thus threatening the safety of workers and reducing output quality. Therefore, it is vital to develop an efficient monitoring system that can detect the occurrence and intensity of damage in pipelines.

The pipeline condition monitoring non-destructive test (NDT) is classified into local and global methods. Examples of local NDTs suggested by the American Petroleum Institute 570 (API 570, 2009) include penetration, radiography, eddy current and conventional ultrasonic tests. The efficiency of these methods has been hindered due to the size, complexity, accessibility and required prior knowledge of the damage information of pipeline systems in petrochemical industries. Meanwhile, global NDTs can be used to monitor the condition of longer coverage pipelines without prior knowledge of the damage. Examples of global NDT applications in pipeline condition monitoring include smart pigging systems, optical fibre sensing and guided waves. However, a smart pigging system and optical fibre sensing method require pre-consideration during the pipeline design, where specially designed pipeline for pig entry and reconstruction of fibre optic network system is required, which limits the application of these methods in existing and ageing petrochemical plants.

The guided ultrasonic wave (GUW) method is a popular way to monitor pipeline integrity. A GUW is an elastic wave that travels through solid materials. The wave propagation characteristics depend on the structure's material properties and boundary conditions (Yeung & Ng, 2019). A GUW setup can consist of a spatial array of sensors transmitting and receiving elastic waves through the medium during pipeline damage detection. The elastic waves that travel through the pipeline are reflected when the thickness of the material changes, thus indicating damage to the pipeline system. The advantages of GUWs include their ability to travel long distances at high speeds without substantial attenuation (El Mountassir et al., 2020; Yu et al., 2021); examine entire cross-sections, even for coated and insulated structure inspections (Matineh Eybpoosh et al., 2017); and detect minor defects using nonlinear ultrasonic waves (Marcantonio et al., 2019).

However, GUW monitoring systems often produce false damage detections due to environmental and operational conditions (EOCs). These include uncertainties due to variations in external factors such as temperature, humidity, air pressure, and random noise (El Mountassir et al., 2020). Among these factors, temperature differences and random noise have the most significant effect on a GUW system's performance in detecting damage in pipelines (Sohn, 2007). Temperature changes can cause GUW signals to stretch or compress, thus distorting the wave's shape (Y. Lu & Michaels, 2005). Meanwhile, random noise commonly caused by instrumental, environmental and procedural effects can generate undesirable noise in a GUW system. The existence of these EOCs jeopardises the accuracy of pipeline condition monitoring results, especially when the damage severity is minor. Hence, a small reflected wave could be submerged in the errors produced by EOCs. In conventional GUW monitoring, a single sensor of the portable rings can inspect more than 50m of a pipe from a single location. However, this coverage comes at a cost of lower sensitivity, where the detection performance for a damage size of 5% CSAL or less is often affected by various EOCs, indicating a need for more extensive research (Chua & Cawley, 2020; Dobson & Cawley, 2016).

Researchers have suggested several methods to counter the effect of EOCs, ranging from traditional statistical methods (Mazzeranghi & Vangi, 1999) to more intelligent approaches such as physics-based (Deng & Murakawa, 2006; Roy et al., 2014) and data-driven-based methods (Clarke et al., 2010; Anurag Dhutti, Tumin, et al., 2019; Matineh Eybpoosh et al., 2016; H. Liu et al., 2019; Y. Lu & Michaels, 2005). These methods, which can be defined as manual identification techniques, suffer from several limitations. For example, traditional statistical methods require an assumption of the error with a specific distribution, which is rarely possible in practice.

Physics-based approaches face difficulties in modelling complex dynamic systems based on the actual working environment, and they face limitations when being updated via data measured online (Zhao et al., 2019). Data-driven-based methods require a set of baseline data with pre-defined conditions for further baseline matching or baseline stretching to compensate for the effects of EOCs.

These manually designed features require a significant amount of human expertise, especially in complex domain cases.

Moreover, conventional data-driven-based methods require expert supervision during several stages because they need to be trained step by step. The joining process for different optimised modules can reduce the final efficiency of the whole system (Zhao et al., 2019). Due to these limitations, advanced methods that counter the effects of EOCs, such as the statistical learning-based method have been adopted recently (Ahn et al., 2019; Hoang & Tran, 2019).

Models based on advanced statistical learning methods can be divided into supervised, semi-supervised, and unsupervised learning models, which perform pattern recognition, clustering and information extraction procedures (Ahn et al., 2019; Hoang & Tran, 2019; H. Liu et al., 2019). For example, Eybpoosh et al. (2016) applied a supervised method based on sparsity discriminant to discriminate damaged operating pipelines from healthy ones under various EOCs. This method forces the optimisation algorithm to assign zero coefficients to the undamaged case with a limited range of EOCs in the training stage. This method exhibited satisfactory damage identification performance when tested using an algorithm with a wide range of EOCs and damage sizes.

In other work, Modarres et al. (2018) employed a supervised convolution neural network (CNN) to identify damage patterns regardless of image scale, location and noise. This neural network is a robust classification technique, even in noisy environments. Bouzenad et al. (2019) proposed a semi-supervised K-means algorithm as a damage detection threshold to trigger the system when a defect becomes critical. Labelled data are fed into this algorithm to identify the threshold distance at the beginning of the monitoring stage. In contrast, unlabelled data are fed into the algorithm during the monitoring stage. The system is triggered when a new cluster forms as the damage threshold is exceeded.

However, supervised and semi-supervised learning methods suffer the drawback of requiring a preliminary analysis of the damaged pipe state as input labels, which are generally not available in practice (Entezami & Shariatmadar, 2018). These labels, which define the various operating, environmental and damage conditions, are impractical, as this information requires expensive and time-consuming manual inspection and labelling processes for each observation (Bull et al., 2020).

Therefore, several researchers have employed unsupervised learning methods that work with unlabelled data to describe the complex underlying distributions of structural health monitoring (SHM) data. Unsupervised learning decomposition methods, such as singular value decomposition (SVD) (C. Liu et al., 2015b), independent component analysis (ICA) (Dobson & Cawley, 2016) and principal component analysis (PCA) (M-A Torres-Arredondo et al., 2016), have been adopted as additional optimisation methods for damage detection. These optimisation methods eliminate EOC effects while retaining the signals' critical damage features. PCA and ICA decompose signals into multiple components, maximising the statistical independence only between the components; SVD enforces the orthonormal properties of components and the weight matrices (C. Liu et al., 2017). In the comparison study done by Liu et al. (2017), both SVD and ICA can achieve great performance (with AUC value greater than 0.9) with only 32 number of measurements recorded within 60 °C variations, for a severity as low as 0.5% CSAL using permanent GUW sensors. On the other hand, using the similar GUW database, the widely used baseline subtraction method (BSM) remained low performance (with AUC value lower than 0.9) throughout the variations in EOCs and increasing number of measurements. Overall, both ICA and SVD outperforms BSM, with ICA generally the better of the two in damage detection under variations of EOCs.

Several unsupervised decomposition learning applications have detected damage in pipes under different EOCs (Dobson & Cawley, 2016; El Mountassir et al., 2020; Matineh Eybpoosh et al., 2017; C. Liu et al., 2015b; M-A Torres-Arredondo et al., 2016). However, these methods retained only low-dimensional features and overlooked the crucial small damage features. Liu et al. (2017)

demonstrated that when the ICA and SVD decomposition methods were applied, the damage-related components could not be identified by the directionality. Furthermore, some amplitudes of other components are more significant than the damage-related components. Unfortunately, the damage-related components can be identified only by their monotonicity, which requires more damage-related components with similar damage cases.

This study was conducted to search for an efficient unsupervised learning technique that can effectively retain sufficient damage-related features under different EOC effects. This was done by proposing two new unsupervised learning methods that improve damage detectability using GUW-based pipeline condition monitoring. The first method involved an RRC method based on reliability theory that is sensitive to small damage. The RRC damage index calculates the deviations between baseline (undamaged) and monitored (damaged) signals following an unsupervised learning method. An unsupervised learning method is defined as a relationship learning algorithm that requires features of only one known condition, which is the undamaged condition (Entezami & Shariatmadar, 2018). As the baseline signals are obtained under near-similar EOCs, the deviations measured from the RRC index can be used as an essential damage feature representation to perform damage localisation and severity estimations.

The second method involved a new approach of an unsupervised learning-based method using a denoising autoencoder (DAE). This method can overcome the limitations of supervised and semi-supervised neural network models by considering EOCs without labelling the data. Moreover, a DAE can mitigate the limitations faced by previous unsupervised learning methods by providing clean signals that reduce the relatively large amplitudes of non-damage-related components. The clean input is the pre-selected data with the least false damage detection due to EOCs at the reference temperature. False damage detection due to EOCs occurs when unnecessary peaks that exceed the damage threshold are detected.

Traditionally, autoencoders (AEs) compress the original high-dimensional input vector to produce a robust low-dimensional feature vector at the bottleneck layer (Pathirage et al., 2018). The nonlinear dimension reduction process preserves important damage features under ambient EOCs. Thus, in this case, EOCs are perhaps better described as another form of latent variables compared to when traditional decomposition methods such as PCA, ICA, and SVD are used (Y. Wang et al., 2016). DAEs, a variant of AEs, learn to reconstruct targeted values by giving noise-corrupted and noise-free input, which leads to the discovery of robust damage features (Shang et al., 2021). The DAE investigated in this study reduces false damage detections caused by EOCs by reconstructing the signals based on clean signals. It exploits fully connected layers as hidden layers whose parameters grow exponentially with the number of layers and are gradually obsolete due to considerable computational costs (Shang et al., 2021).

In this study, the performance and effectiveness of the proposed methods are demonstrated through numerical and experimental models of a straight pipeline. Detailed parametric studies on the effect of different levels of EOCs and different levels of damage are conducted. In addition, comparisons of the proposed methods with other feature extraction methods are also presented to show the efficiency of the proposed methods.

1.2 Problem statement

GUW damage detection has been widely used for pipeline condition monitoring. However, the quality of signals generated on-site is often corrupted by EOC effects, such as temperature variations and random noise. Such EOC effects in GUW-based pipeline condition monitoring have been extensively researched. Temperature variation changes a material's stiffness, thereby shifting the time phase and amplitude of GUW signals (Gorgin et al., 2020; Y. Lu & Michaels, 2005). Meanwhile, random noise forms micro-grass-like noise, which generates unwanted peaks and submerges small damage signals (J. Chen et al., 1999; M. S. Salmanpour et al., 2018). As a result, conventional GUW systems are insensitive to damage sizes of smaller than 5% cross-sectional area loss (CSAL) under EOC effects (Dobson & Cawley, 2016).

For small damage detection, the damage sensitivity of a GUW system can be improved by minimising the effects of EOCs. Physics-based, data-driven and advanced statistical learning-based EOC compensation techniques have been developed to tackle these EOC effects. According to the literature, advanced statistical learning-based techniques have emerged as promising techniques that apply sophisticated algorithms to find meaningful trends within a database of given GUW signals. Unsupervised learning stands out among various advanced statistical learning-based techniques as a valuable EOC compensation strategy owing to its advantage of requiring no labelling effort and its capability to deal with a huge amount of high-dimensional data. However, the unsupervised learning method has not sufficiently addressed the problem of EOCs in GUW applications. Current unsupervised learning methods such as SVD, PCA, and ICA do not store sufficient damage features, limiting their application in higher levels of damage detection such as damage localisation and severity estimation (Ozdagli & Koutsoukos, 2019).

Due to these limitations of the existing method, an RRC-based method is proposed in this study to establish the relationship between healthy and damaged features using an unsupervised learning method. The RRC features store most damage information by calculating the differences between the healthy and damaged GUW databases under similar EOCs. However, the application of RRC causes additional errors due to the differences in EOC effects between healthy and damaged features when the experimental model is used. This leads to unwanted peaks that create false damage detection and submerge small damage features.

A DAE-based method is proposed to deal with significant EOC effects using an experimental database. DAE, another variant of the AE neural network, performs EOC compensation by forcing the model to reconstruct noisy GUW signals by giving noise-free GUW signals. The DAE investigated in this study reduces false damage detections caused by EOCs by reconstructing the signals based on clean signals. It exploits fully connected layers as hidden layers whose parameters grow exponentially with the number of layers and are gradually obsolete due to considerable computational costs (Shang et al., 2021).

1.3 Research objectives

The objectives of the present research are as follows:

(a) To develop a residual reliability criterion (RRC)-based guided ultrasonic wave (GUW) pipeline condition monitoring method considering the effects of environmental and operational conditions (EOCs).

(b) To develop an unsupervised learning denoising autoencoder (DAE)-based GUW pipeline condition monitoring method.

(c) To investigate the performance of the proposed method to consider EOCs, the presence of damage, damage locations, and damage severities for pipeline condition monitoring.

(d) To validate the proposed GUW pipeline condition monitoring method using experimental data.

1.4 Research significance

EOC effects, such as temperature variation and random noise, remain significant drawbacks of GUW application in pipeline condition monitoring. These effects corrupt the quality of the signal received at the receiver by generating unwanted peaks. Thus, this study proposes two methods to deal with the EOC problem in GUW damage detection. Using a numerical model, the first method (based on RRC theory) magnified the deviations between the healthy and damaged model and showed good sensitivity to small damage features. However, when the level of EOCs varies substantially between the healthy and damaged case, additional errors are generated when using the experimental model, thus degrading the damage detection performance. Therefore, a second method based on DAE neural network was also proposed. With the proper selection of DAE architecture and training database parameters, the DAE can provide precise information regarding damage location and severity despite an increase in EOCs. The improvement in small damage detection under EOCs is the most significant feature of the proposed DAE method.

1.5 Research scope

This research focused on using GUW data with RRC and DAE strategies to improve damage detection performance under EOCs, particularly temperature variation and random noise. The scope of this research includes the following areas:

i. The literature is reviewed to investigate the damage detection methods that have been used in pipeline condition monitoring and the EOC compensation techniques that have been used in SHM applications.
ii. GUW damage detection is performed using a straight pipeline structure with damage features characterised by cross-sectional area loss only, excluding the considerations of other pipeline features such as the presence of pipe joints, pipe bends, valves and different supports and pipeline materials.
iii. Torsional T(0,1) mode is adopted as the mode of GUW excitation. The signals near the excitation source and end boundary are ignored in numerical and experimental models for simplicity.
iv. The applicability and practicality of the proposed method are demonstrated by a numerical and experimental model of straight pipeline structures. Due to the large scope of the research, fieldwork was not conducted.

1.6 Thesis structure

The structure of this thesis is as follows:

Chapter 1 presents the research background, problem statements, research objectives, research significance, research scope and thesis structure.

Chapter 2 presents a comprehensive review of various pipeline condition monitoring methods. The pros and cons of each method are discussed. The selected GUW is then described, and the issues with the GUW method (particularly due to EOCs effects) are emphasised. Several approaches to compensate for EOC effects in GUW-based pipeline condition monitoring are discussed.

Chapter 3 consists of the detailed research methodology for GUW, RRC and DAE, along with detailed descriptions of the numerical analyses and experimental verifications adopted in this study.

Chapter 4 demonstrates the application of the RRC-based method in damage detection. The parametric study was conducted to study the sensitivity of the proposed RRC under the influence of damage location, damage severities, temperature variations and random noise. Additionally, the RRC method is compared with other feature extraction methods. At the end of this chapter, an experimental verification of RRC is conducted, and the results are presented.

Chapter 5 demonstrates the application of the DAE-based method in damage detection. The selection of the architecture parameters of the DAE and the training database parameters are performed, and the selected parameters are presented. The trained DAE is then adopted to perform sensitivity studies under the influence of damage location, damage severities, temperature variations, and random noise. Furthermore, this method's damage detection performance is compared with that of other feature extraction methods using a numerical model.

Chapter 6 verifies the applicability of the proposed DAE method using an experimental model. Additionally, this method's small damage detection performance is compared with that of other feature extraction methods.

Chapter 7 provides the conclusions and findings of this study. Recommendations for future work are also presented.

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LIST OF PUBLICATIONS

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