COMPUTATIONAL BASED AUTOMATED PIPELINE CORROSION DATA ASSESSMENT

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ABSTRACT

Corrosion is a complex process influenced by the surrounding environment and operational systems which cannot be interpreted by deterministic approach as in the industry codes and standards. The advancement of structural inspection technologies and tools has produced a huge amount of corrosion data. Unfortunately, available corrosion data are still under-utilized. Complicated assessment code, and manual analysis which is tedious and error prone has overburdened pipeline operators. Moreover, the current practices produce a negative corrosion growth data defying the nature of corrosion progress, and consuming a lot of computational time during the reliability assessment. Therefore, this research proposes a computational based automated pipeline corrosion data assessment that provides complete assessment in terms of statistical and computational. The purpose is to improve the quality of corrosion data as well as performance of reliability simulation. To accomplish this, .Net framework and Hypertext Preprocessor (PHP) language is used for an automated matching procedure. The alleviation of deterministic value in corrosion data is gained by using statistical analysis. The corrosion growth rate prediction and comparison is utilized using an Artificial Neural Network (ANN) and Support Vector Machine (SVM) model. Artificial Chemical Reaction Optimization Algorithm (ACROA), Particle Swarm Optimization (PSO), and Differential Evolution (DE) model is used to improve the reliability simulation based on the matched and predicted corrosion data. A computational based automated pipeline corrosion data assessment is successfully experimented using multiple In-Line Inspection (ILI) data from the same pipeline structure. The corrosion data sampling produced by the automated matching is consistent compared to manual sampling with the advantage of timeliness and elimination of tedious process. The computational corrosion growth prediction manages to reduce uncertainties and negative rate in corrosion data with SVM prediction is superior compared to ANN. The performance value of reliability simulation by ACROA outperformed the PSO and DE models which show an applicability of computational optimization models in pipeline reliability assessment. Contributions from this research are a step forward in the realization of computational structural reliability assessment.

ABSTRAK

Kakisan adalah satu proses kompleks yang dipengaruhi oleh persekitaran dan sistem operasi yang tidak boleh ditafsirkan dengan pendekatan berketentuan seperti yang terkandung di dalam kod dan piawaian industri. Kemajuan dalam teknologi alatan dan pemeriksaan struktur telah menghasilkan sejumlah besar data kakisan. Walau bagaimanapun, data kakisan yang ada masih kurang digunakan. Kod penilaian yang kompleks, dan analisa manual yang rumit, terdedah kepada ralat telah membebankan pengendali talian paip. Selain itu, proses penganalisaan pertumbuhan data kakisan semasa, menghasilkan pertumbuhan kakisan negatif dan tidak mengikut pertumbuhan normal, selain mengambil masa yang lama dalam pengiraan dan penilaian kebolehpercayaan. Oleh itu, kajian ini mencadangkan satu sistem penilaian data kakisan talian paip pengkomputeran automatik yang menyediakan penilaian yang lengkap daripada segi statistik dan pengiraan. Tujuannya adalah untuk meningkatkan kualiti data kakisan dan prestasi simulasi kebolehpercayaan. Untuk mencapai hasrat ini, rangka kerja *.Net* dan bahasa pengaturcaraan Prapemproses Hiperteks (PHP) digunakan untuk prosedur sistem pemadanan automatik. Pengurangan nilai berketentuan dalam data kakisan diperolehi dengan menggunakan analisis statistik. Ramalan kadar pertumbuhan kakisan dan perbandingan hasilnya dilaksanakan menggunakan model Rangkaian Neural Buatan (ANN) dan Mesin Vektor Sokongan (SVM). Model Algoritma Pengoptimuman Tindak Balas Kimia Buatan (ACROA), Pengoptimuman Kawanan Partikel (PSO), dan Evolusi Kebezaan (DE), digunakan untuk meningkatkan simulasi kebolehpercayaan berdasarkan kakisan data yang telah dipadan dan diramalkan. Penilaian data kakisan talian paip pengkomputeran automatik berjaya diuji menggunakan pelbagai set data kakisan dari struktur talian paip yang sama. Persampelan data kakisan yang dihasilkan oleh sistem automatik adalah selaras berbanding persampelan manual dengan kelebihan penjimatan masa dan meringkaskan proses. Pengiraan ramalan pertumbuhan kakisan berjaya mengurangkan ketidaktentuan dan kadar negatif dalam data kakisan dengan prestasi model SVM yang lebih baik berbanding ANN. Nilai prestasi simulasi kebolehpercayaan oleh ACROA adalah lebih baik berbanding dengan PSO dan DE, yang menunjukkan kebolehupayaan model perkomputeran untuk mengoptimumkan penilaian kebolehpercayaan talian paip. Sumbangan daripada kajian ini adalah satu langkah ke hadapan dalam merealisasikan penilaian kebolehpercayaan struktur pengkomputeran.

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LIST OF ABBREVIATIONS

ACROA	-	Artificial Chemical Reaction Optimization Algorithm
AFV	-	Average Fitness Value
ANN	-	Artificial Neural Networks
ANN-CGM	-	Artificial Neural Network Corrosion Growth Model
AR	-	Accuracy Rate
BFA	-	Bacterial Foraging Algorithm
BPANN	-	Backpropagation Artificial Neural Networks
CDA	-	Corrosion Defect Assessment
CDF	-	Cumulative Distribution Function
CGM	-	Computational Growth Model
CompRAM	-	Computational Reliability Assessment Model
COV	-	Correlation coefficients
Cr	-	Corrosion rate
d	-	*depth*
DE	-	Differential Evolution
ER	-	Error rate
F	-	F-measure
GA	-	Genetic Algorithm
ILI	-	In-line Inspection
IUR	-	Improved Unit Range
l	-	*length*
LSF	-	Limit State Function
MAE	-	Mean Absolute Error
MLP	-	Multi Layer Perceptron
MoD	-	Mitigation of Defect
MSE	-	Mean Squared Error

PDF	-	Probability Distribution Function
POF	-	Probability of Failure
PSO	-	Particle Swarm Optimization
R^2	-	Correlation coefficient
RAE	-	Relative Absolute Error
RMSE	-	Root Mean Square Error
RRSE	-	Root Relative Squared Error
SVM-CGM	-	Support Vector Machine Corrosion Growth Model
w	-	*width*
wt	-	*wall thickness*

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CHAPTER 1

INTRODUCTION

1.1 Overview

Oil and gas industry utilized pipelines as their main infrastructure to transport their goods. Millions of kilometres of pipelines are laid out across the globe either onshore or offshore cannot escape from deterioration over their lifetime of service. However, the number of accidents has also dramatically increased with the increasing number of operating pipelines (Hopkins, 1995; Paik, *et al.*, 2004; Noor, 2006; Chae *et al.*, 2001; Dawson, 2004: Mohd and Paik, 2013; Mohd *et al.*, 2014). Thus, a Pipeline Integrity Management (PIM) becomes an important research field in pipeline lifetime starting from its design, operation, maintenance and replacement. Pipeline can fail due to many factors including construction errors, material defects, operational errors, control system malfunctions, third parties excavations and corrosion. Data on pipelines accidents and their causes compiled by the U.S Department and Transportation's Research and Special Program Administration, Office of Pipeline Safety (RSPA/OPS) shows that corrosion either external or internal is the most common cause of pipeline accidents with total percentage of 36.6 percent (Li *et al.*, 2009). Cost incur based on corrosion interpreted via repair, lost and contaminated product, environmental damage and possible human safety and health. Corrosion is a complex process influenced by surrounding environment and operational systems which cannot be interpreted by deterministic approach as in the industry codes and standards (Mustaffa, 2011). Hence, the Corrosion Management System (CMS) need to be reviewed with an alternative solution on assessing its condition (Zhang, 2014). The main focus of this study is to identify, apply and judge the suitability of the computational methods in evaluating the pipeline reliability of offshore pipeline subjected to internal corrosion. The analysis involves in every stage of assessment will entirely based on the in-line inspection (ILI) data collected at different time interval of the pipelines.

1.2 Research Motivation

Previous studies show the incapability of the deterministic or industry code methods in dealing with ILI data are infeasible economically and practically. The limitation was mostly hinders by the uncertainties that occur in every stage of CDA. Eventhough exist a standards design and codes to provide guidance on the design, standards, constructions and operations of pipelines, the use of codes need to be customized to suit the operation of different environment and conditions (Alkazraji, 2008). Moreover, previous reliability model develop is based on experimental works using a controlled parameters which not the case of real applications. Therefore, motivation of this reasearch is to study and model the reliability of the pipeline from the inspection data (metal loss or ILI data) including the uncertainties govern by it.

The specific motivation leads to this research is simplified as follows:

1) Identification of internal corrosion as one of the major factors that leads to pipeline failure. This triggers an extensive inspection process that generates a huge number of ILI data (metal loss) that is still under utilized. This fact has been proved by Mustafffa (2011), Yahaya (2000), Noor (2006), and Mohd and Paik (2013). Futhermore, using ILI data from repeated inspection on a single pipeline can determine the corrosion rate of it (Desjardin, 2002).

2) *The complexity and time consuming data analysis process* tends to overburden the operators involved and may result in poor planning and maintenance scheduling. Often the operators focused the research on reliability assessment rather than the preceding data modelling and analysis which tend to affect the overall result of pipeline condition prediction.

3) *Traditional analysis* process provides insufficient information to be use for reliability assessment which leads to inaccurate result due to insignificant variables (Noor, 2006; Mustaffa, 2011).

4) *Pipeline codes and standards:* Confusion on adoption of different codes and standards by different countries for guidance in design, construction and operation of pipelines (Alkazraji, 2008). Most of the early design standards were prepared via experimental and/or numerical works, which might differ for different condition and operating practice. Further, the variables and parameters in the laboratory works are manipulated depending on the needs of studies that not represent a real application. Therefore, discrepencies aspects remain unsolved issues among pipeline operators.

5) *Implementation of new computational reliability methods vs deterministic methods for structure assessment*: The use of reliability based computational methods is not to replace the current assessment (deterministic methods), rather it will provide an alternative benchmarks for IRM process. It is less favourable when knowledge about it is still not well understood among industries.

It is important to notice that the new computational method in CDA is by means of complimentary or alternative rather than replacing the current practice. The proposed model is hope to provide a more variation and solution towards IRM management and pipeline integrity preservation.

1.3 Problem Background

In Reliability Based Corrosion Management Systems (RB-CMS) three main parts related to reliability studies is necessary to complete the CMS cycle namely; inspection process, assessment process, and mitigation process (Zhang, 2014; Desjardin, 2002; Noor, 2006). The inspection process of the oil and gas pipeline related to corrosion will produce defect data which known as in-line inspection (ILI) data. Meanwhile in assessment process, a defect will go through an analysis process or known as Corrosion Defect Assessment (CDA). Result from this process is used for Mitigation of Defect (MoD) by means of coating, inhibitors, or even replacement towards pipeline sustainable and effective inspection, repair, and maintenance scheme (IRM). The execution of RB-CMS sequential process is repeated several times dependings on the results from the engineering process until end of the pipeline lifetime. The challenge is how to build a system capable of processing a data and turn it into knowledge in the context of managing pipeline integrity (Wiegele *et al.*, 2004). The importance of CDA in producing an acceptable result was governed by the uncertainties inherits from the interpretation of the ILI, modelling of the corrosion progress and the simulation of its reliability. Thus, the problems in this study centered its discussion on two major problems.

First, the ILI data are in low quality due to uncertainties and use of simplistic approaches in interpreting the corrosion growth (Mustaffa, 2011; Kariyawasam and Wang, 2012). Due to advancement of pipeline inspection technology, abundance of ILI data was available. Unfortunately, it is still under-utilize and this was agreed by Lecchi (2011), Perich *et al.* (2003), Kamrunnahar *et al.* (2005), Clouston and Smith (2004), Clausard (2006), Noor (2006), Det Norske Veritas (1999), B31G (1991), and Chouchaoui and Pick (1994). It has been acknowledged that the current practice of pipeline integrity assessment is lack proper guidelines focusing on issues related to data quantification (sampling and data analysis), as well as the intelligent reliability analysis due to the abovementioned research problems (Zio, 2009; Niu *et al.*, 2010; Kuniewski *et al.*, 2008; Noor, 2006; Mustaffa, 2011). This problem occurred due to:

1) *Uncertaitnties in ILI data*: Particularly for corrosion inspection, the ILI tools such as Magnetic flux leakage (MFL) has also been considered as source of uncertainties (Maes and Salama, 2008; Zhang, 2014, Kariyawasam and Wang, 2011; Mustaffa, 2011).

2) Based on (Kuniewski *et al.*, 2008; Kamrunnahar *et al.*, 2005), *imprecise corrosion data sampling* was due to the limited resolution of inspection tools, imperfect measurement of defect dimension, pipeline material properties operational load and the rate of corrosion growth result in uncertain description of the pipeline condition. As been suggested by Kuniewski *et al.*, 2008 and Noor, 2006, besides the manual procedure on processing the sample data, the sampling size is not accurately fit a current analysis. For example the manual feature matching process is a time consuming, inconsistent and might be vulnerable to human error. Since the diagnosis and interpretation of the corrosion effects depends solely on the experience and the capability of the engineers and inspection personnel.

3) The *complexity of statistical analysis* often views as a too academic by plant engineers and inspection personnel distance themselves from this kind of method. Although a standard exists for the statistical analysis of laboratory corrosion test data, no such standard exists for the analysis of inspection data relating to corrosion measurement (HSE, 2002; Mohd and Paik, 2013).

Secondly, a reliability assessment for both offshore and land based structures becoming important especially in risk-based inspection and maintenance planning (Lecchi, 2011; Zio, 2009; Faber and Straub, 2001; Nakken and Valrsgaard, 1995). For the assessment of structural condition, much attention is focus on the conventional method or industrial practice being tested by a number of authors (Shu et. al., 2009; Melchers and Jeffrey, 2007). Their results show that these approaches are too rigid in estimating the current and future states of an existing structure. This was due to factors such as:

1) The *simulation-based statistical analysis tends to be time consuming and requires a high level of expertise* to complete the task. Typically a much higher level of accuracy is required both for predictions of structural safety and for predictions of likely future corrosion (Lecchi, 2011). Thus, a model to speed up the performance of simulation is much needed. With that, computational models for reliability assessment come into the picture.

2) *Uncertainties in modelling*, whereby the current implementation used a predefined safety factor or limit states that might differ from one pipeline from the others thus the modelling did not present the real condition of the assess pipeline (Mustaffa, 2011). Moreover, a deterministic and statistical model is a model-driven method compared to computational which is a data-driven method.

The above discussion is summarized and illustrated in Figure 1.1. The flow of CDA research problem and their causes is outline. The successful implementation of RB-CMS depends on CDA to give an insight of the condition of current operating pipeline. The decision from this would benefit the whole process of IRM and at the same time help the pipeline operator preserving their resources and hinder from catastropics event.

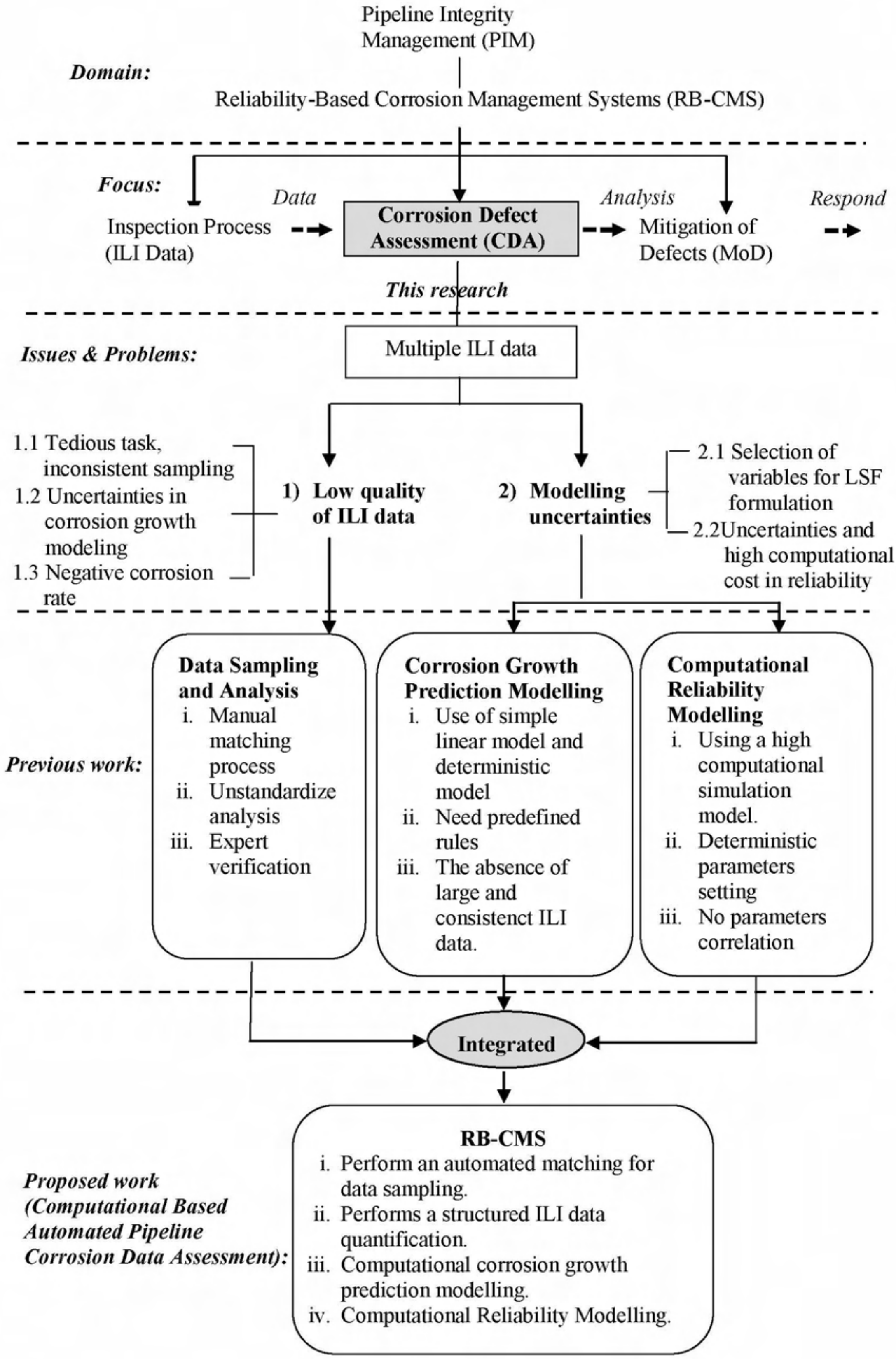

Figure 1.1: Taxonomy on research motivation

To compensate the shortcomings of the sampling and matching methods an automated matching procedure and a structured statistical method is use to handle the timeliness and accuracies of the task involved. Instead of relying on experimental data, a large amount of inspection data from real structures will give a better insight and accurate information in corrosion assessment. The source of uncertainty inherent in the in-line inspection data and its significance in the context of corrosion reliability analysis was discussed. Implementation of computational model gives significance result for corrosion prediction as compared to the strategy of deterministic techniques. Therefore, prediction based on computational models supported by the available ILI data for comparison provides alternative measures in pipeline maintenance decision.

1.4 Problem Statement

The absence of inspection data quantification standard and predictive corrosion modelling for maintenance of offshore pipeline may cause some difficulties (Lechhi, 2011; M. Kamrunnahar *et al.*, 2005; Clouston and Smith, 2004; Yahaya, 1999; Clausard, 2006; Perich *et al.*, 2003). In the context of corrosion management, the essence of this approach is to combine important pipeline parameter based on in-line inspection data within a computational reliability assessment model for probability of failure estimation. A key element in this analysis approach is explicit consideration of all significant forms of uncertainty, including the uncertainties inherent in the data obtained from in-line inspection. It is hope that this alternative reliability-based process can provide the basis for an industry-accepted approach and an assessment method to manage pipeline integrity with respect to corrosion.

Thus, the following issues will be considered in order to solve the problem:

1) How to design an automated application for matching a repeated ILI data in a timely manner and consistency?

2) How to measure the statistical relationship among the defect parameter?

3) How to predict the corrosion growth variable before proceeding to its reliability assessment?

4) How to design and model an explicit LSF for reliability based model in order to predict the pipeline probability of failure base on ILI data?

5) How to model the computational method to enhance the reliability computational performance?

1.5 Research Objectives

Providing the above problem statement, the research objectives are:

1) To develop an automated matching system and ILI data quantification analysis to improve the data quality for reliability assessment.

2) To develop a corrosion rate model using computational methods for improving the uncertainties in corrosion rate prediction.

3) To develop computational model for improving the simulation based reliability performance of ILI data.

1.6 Research Scopes

The following scopes and limitations have been made mainly due to lack of data in developing deterioration models in this study:

1) The development of the corrosion related models are totally based on the physical evidence from metal loss volume.

2) The effects of material properties, operational condition, and environmental parameters upon corrosion growth are not considered.

3) The data involved a repeated and random inspection data detailing the volume of metal loss.

4) ANN and SVM are used as non-linear model to predict the corrosion growth.

5) Three types of engineering structures transporting crude oil pipelines is chosen involving three different sample set of metal loss data are used to validate the quality and performance of proposed application and model.

6) An optimization of reliability simulation adopting an ACROA, PSO, and DE are used to enhance the performance of reliability assessment process.

7) The inspection data for internal pipeline inspection provided by various inspection vendors such as Petronas, Exxon Mobile, BP Amoco and Rosen from Year 1990 until Year 2001.

1.7 Research Significance

The significance of this study is two-folds: computational and structural aspects. From computational aspect, the proposed method is intended to improve the precision of pipeline reliability assessment from ILI data with inherent inspections uncertainties. It serves as an automated system for tedious and time consuming task of experimental prediction. Thus minimizing the variants and correcting the negative rates from the ILI data. Furthermore, the computational reliability simulation improved the simulation performance in terms of simulation time as compared to the previous works using Monte Carlo simulation. From structural assessment aspects, the integrity prediction embodies reliability assessment information that provide details insight into the states of the structure such as prediction of corrosion rates (Cosham, 2001; Valor, 2003), deriving an explicit LSF (Mustaffa, 2011), and prediction of the failure probabilities (Noor, 2006; Mustaffa, 2011). In assessing structure integrity, combination of this knowledge provides an option to improve the procedure of the assessment as well as optimizing the large volume of inspection data available. Furthermore, the proposed statistical analysis and computational modelling will allow the pipeline operator to design a proper inspection programs and maintenance. For example, in maintenance planning and decision making, a reliability and integrity assessment contributes to minimize the operating structure cost. List of publication produced by this study is listed in Appendix A.

1.8 Summary

This chapter gives an overview of the research conducted in this study. The explanations include overview of the research area, research motivation, problem background, problem statement, objectives, limitations, and contributions of the study. This thesis is organized into seven chapters. A brief description on the content of each chapter as follows: Chapter 1 defines the challenges, problems, objectives, scopes and significance of the study. Chapter 2 reviews the main subjects of interest, which are automated matching system and ILI data quantification, computational based model for corrosion rate prediction, rigidity of current code practices, limit states functions concepts, and reliability assessment model. Chapter 3 presents the design of the computational reliability assessment model that support the objectives of the study; this includes data sources instrumentations and analyses. Chapter 4 details the sampling and analysis of ILI data, and development of that is resilient towards uncertainties parameters. The analysis results is validated using chi square method, regression analysis and comparison against real ILI data obtain from inspection. Chapter 5 describes the prediction of corrosion growth variables for selected pipeline that addresses the problem of negative corrosion growth as well as uncertainties inherent in inspection data. The ANN-CGM and SVM-CGM is used to model the corrosion growth rate and a performance comparison is made. Chapter 6 simulates a reliability of pipeline conditions represented by computational optimization methods ACROA, PSO and DE to overcome simulation performance problem face by the current method. Chapter 7 draws a general conclusion of the accomplished results and presents the findings of the study as well as recommendations for future study.

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