Quantification of Uncertainties in Inline Inspection Data for Metal-loss Corrosion on Energy Pipelines and Implications for Reliability Analysis

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Abstract

One of the major threats to the oil and gas transmission pipeline integrity is metal-loss corrosion. Pipeline operators periodically inspect the size of the metal loss corrosion in a pipeline using in-line inspection (ILI) tools to avoid pipe failure which may lead to severe consequences. To predict pipe failure efficiently, reliability-based corrosion management program is gaining popularity as it effectively incorporates all the uncertainties involved in the pipe failure prediction. The focus of the research reported in this thesis is to investigate the unaddressed issues in the reliability-based corrosion assessment to assist in better predicting pipe failure.

First, a methodology is proposed to facilitate the use of RSTRENG (Remaining Strength of Corroded Pipe) and CSA (Canadian standards association) burst pressure capacity models in reliability-based failure prediction of pipelines. Use of RSTRENG and CSA models require the detail geometric information of a corrosion defect, which may not be available in the ILI reports. To facilitate the use of CSA and RSTRENG models in the reliability analysis, probabilistic characteristics of parameters that relate the detailed defect geometry to its simplified characterizing parameters was derived by using the high-resolution geometric data for a large set of external metal-loss corrosion defects identified on an in-service pipeline in Alberta, Canada.

Next, a complete framework is proposed to quantify the measurement error associated with the ILI measured corrosion defect length, effective length, and effective depth of oil and gas pipelines. A relatively large set of ILI-reported and field-measured defect data is collected from different in-service pipelines in Canada and used to develop the measurement error models. The proposed measurement error models associated with the ILI reported corrosion defect length,
effective length, and effective depth is the weighted average of the measurement errors of the corresponding Type I and Type II defects and the weighted factor is the likelihood of ILI reported corrosion defect being a Type I defect (without cluster error) or a Type II defect (with clustering error). A log-logistic model is proposed to quantify the weighted factor. The application of the proposed measurement error models is demonstrated by evaluating probability of failure of a real corroded pipe joint through system reliability analysis.

**Keywords:** Gas transmission pipeline, metal-loss corrosion, in-line inspection (ILI), measurement error, maximum defect depth, average defect depth, corrosion defect length, effective area, probability of burst, corrosion defect assessment
Dedication

To my mother Fouzea Yeasmin and my sister Tanzina Siraj Tannee

who taught me to be strong and resilient
Co-Authorship Statement


A version of Chapter 3 co-authored by Tammeen Siraj and Wenxing Zhou is under review by *Journal of Pressure vessel Technology*.
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List of Symbols

$A$ or $A_{\text{eff}}$ = Effective area of a corrosion defect

COV = Coefficient of variation

CDF = Cumulative density function

$c_j$ = The relative contribution of the $j$-th defect to $P_f$ for pipe system

DMA = Insolated individual anomaly

$D$ = Actual diameter of the pipe

$D_n$ = Nominal diameter of the pipe

$d_{\text{max}}$ = Maximum corrosion defect depth (actual or Laser scanned)

$d_{\text{max-ILI}}$ = ILI measured maximum corrosion defect depth

$d_{\text{avg}}$ = Average corrosion defect depth (actual or Laser scanned)

$d_{\text{eff}}$ = Effective corrosion defect depth (actual or Laser scanned)

$d_{\text{eff-ILI}}$ = ILI measured effective defect depth

FORM = First order reliability method

FS = Factor of safety

$FS_j$ = Factor of safety at $j$-th corrosion defect

$F(x)$ = Cumulative distribution function of random variable $X$

$g(\cdot)$ = Limit state function

$g_j(\cdot)$ = The $j$-th limit state function

ILI = In-line inspection

$l$ or $l_a$ = Corrosion defect length (Actual or Laser scanned)

$l_{\text{ILI}}$ = ILI measured corrosion defect length

$l_{\text{eff}}$ = Effective corrosion defect length (Actual or Laser scanned)

$l_{\text{eff-ILI}}$ = ILI measured effective corrosion defect depth

$M$ = Folias or bulging factor

MOP = Maximum operating pressure

$P_b$ = Pipe burst pressure

PDF = Probability density function

$p$ or $P$ = Internal pressure of a pipe
$P_f$ = Probability of failure

$P_{fj}$ = Probability of failure for $j$-th corrosion defect

$P_{ID}$ = Probability of a corrosion defect being Type I

$P_o$ = Maximum operating pressure

$s$ = Shortest distance to the surrounding corrosion anomalies

SMYS = Specified minimum yield strength

SMTS = Specified minimum tensile strength

t = Actual wall thickness of the pipe

$t_n$ = Nominal wall thickness of the pipe

$U$ = vector of independent standard normal variates

$UF$ = Utilization factor/safety factor

$u^*(j)$ = Design point involving the whole system associated with $\beta_j$

$x$ = Value of the vector $X$

$Z$ = Correlated standard normal variates transformed from vector $X$

$\xi$ = Model error associated with the burst pressure capacity models

$\rho$ = Pearson correlation

$\beta$ = Reliability index

$\Phi(\cdot)$ = CDF of standard normal distribution

$\Sigma$ = The correlation matrix of the $r$-dimensional standard normal distribution function

$\mu$ = Ratio between average defect depth and maximum defect depth

$\lambda$ = Ratio between effective defect length and defect length

$\eta$ = Ratio between effective defect depth and maximum defect depth

$\varepsilon_d$ = ILI vendor specified additive error for corrosion defect length

$\varepsilon_l$ = ILI vendor specified additive error for corrosion defect depth

$\sigma_y$ = Pipe yield strength

$\sigma_u$ = Pipe tensile strength

$\sigma_f$ = Flow stress

$\varepsilon_1$ = Defect length measurement error for Type I DMA
\( \varepsilon_2 \) = Defect length measurement error for Type I cluster
\( \varepsilon_3 \) = Defect length measurement error for Type II defect
\( \alpha_1 \) = Effective length measurement error for Type I DMA
\( \alpha_2 \) = Effective length measurement error for Type I cluster
\( \alpha_3 \) = Effective length measurement error for Type II defect
\( \delta_1 \) = Effective depth measurement error for Type I DMA
\( \delta_2 \) = Effective depth measurement error for Type I cluster
\( \delta_3 \) = Effective depth measurement error for Type II defect
1 Introduction

1.1 Background

Pipelines are the most efficient and economic systems to transport large quantities of crude oil and natural gas from the production sites to the end users. According to Natural Resources Canada, there are 840,000 kilometers of transmission, gathering and distribution pipelines in Canada. Of this amount, about 117,000 kilometers of pipelines are large-diameter transmission lines which covers most provinces with significant pipeline infrastructure (NRCan 2016). It is a challenging task to maintain such a vast pipeline network across the country; therefore, a practical strategy for inspecting and monitoring pipeline network is of critical importance to prevent possible failure.

Metal-loss corrosion is one of the main deteriorating mechanisms that compromise the structural integrity and safe operation of underground oil and gas pipelines (Vanaei et al. 2017). Corrosion in steel pipelines is an electro-chemical process that causes the pipes to deteriorate by reacting with its surrounding environment; whereas, the pipeline acts as the electrode, and the surrounding soil works as the electrolyte (Davis 2000). The coupled action of oxidation at anode with the removal of electrons and consumption of these electrons through a reduction action by the oxidant (such as, oxygen) forms the metal loss corrosion. Figure 1.1 shows a corrosion cell in a buried pipeline, where the anode, cathode and electrode exist in the same pipeline and the surrounding soil acts as an electrically conducive medium.
Most of the pipelines were protected by external coating and cathodic protection (CP) from corrosion. However, corrosion may commence due to a breakdown of the coating and/or the CP system (Hopkins 2014). As a result, it is crucial for pipeline operators to implement an effective, efficient corrosion management program to prevent failure and ensure safe operation of pipelines. Periodic inspection and maintenance is central to the pipeline corrosion management program (Alamilla et al. 2009; Miran et al. 2016). The high-resolution inline inspection (ILI) tools employing the magnetic flux leakage (MFL) or ultrasonic technologies (UT) are widely used to locate and measure corrosion defects on a pipeline. The in-line inspection corrosion data used for the analysis of the present study are all come from the MFL tool. During in-line inspections, MFL tools produce a magnetic flux in the pipe wall and the distortion from the flux field (also known as leakage) resulting from the presence of a corrosion defect correlate with the corrosion defect geometry (i.e. corrosion defect depth, length, and width, see Figure 1.2). It should be noted that

**Figure 1.1 Electrochemical cell in buried pipeline (Hopkins 2014)**

\[
\text{Oxidation: } 2Fe \rightarrow 2Fe^{2+} + 4e^{-} \\
\text{Reduction: } 2H_2O + O_2 + 4e^{-} \rightarrow 4OH^{-}
\]
MFL tool can differentiate the corrosion defects located on the external and internal surfaces of the pipe wall and the present study deals only with the corrosion on the external surface of a pipeline.

Figure 1.2 Schematic illustration of a typical corrosion defect geometry

Despite the immense advancement of the ILI technology, there are still inherent uncertainties associated with the ILI tool measurements due to imperfections in the tools and associated sizing algorithms (Al-Amin et al., 2012; Nessim et al., 2008). It is important to quantify these measurement uncertainties, as they may affect the accuracy of the corrosion defect assessment. Corrosion defect assessment is a crucial part of corrosion management program of a pipeline, whereas steps of corrosion management program involve in-line inspection, corrosion defect assessment and corrosion mitigation (Kishawy and Gabbar 2010). Over the past few decades, the reliability-based corrosion management programs are increasingly adopted by pipeline operators as, it can incorporate the uncertainties associated with parameters used in the corrosion assessment. The parameters associated with the corrosion assessment involves the pipe mechanical and
geometric parameters (i.e. pipe diameter, internal pressure, yield strength of the steel pipe etc.) and the geometric dimension associated with the corrosion defect (i.e. corrosion defect depth, length etc.). As probabilistic characteristics of the measurement uncertainties associated with ILI tools are required in the reliability analysis, studies have been conducted in the past decade to facilitate the use of reliability-based corrosion management programs, such as the development of probabilistic corrosion defect depth growth models (Al-Amin & Zhou, 2013; Maes et al., 2009; Zhang & Zhou, 2013) and corrosion defect depth measurement error models (Caley et al. 2007; Nessim et al. 2008; Al-Amin et al. 2012) based on ILI data.

Furthermore, oil and gas transmission pipelines, which are often operated at high internal pressures, may fail by burst due to the reduced pipe wall thickness caused by metal loss corrosion. A key component of reliability based corrosion management program is to predict the probability of the internal pressure of a pipeline exceeding the burst pressure capacity of a corroding pipeline over a period of time (Zhang and Zhou 2014). There are several empirical burst pressure capacity models currently used in practice, e.g. the B31G and B31G Modified models (Kiefner and Vieth 1989), Det Norske Veritas (DNV) model (DNV-RP-F101 2010a), the Canadian Standards Association (CSA) model (CSA 2015), and PCORRC and RSTRENG models (Zhou and Huang 2012) with varying degrees of predictive accuracy. Zhou and Huang (2012) quantified the model errors associated with the empirical burst pressure capacity models. Furthermore, several researchers (Ahammed & Melchers, 1996; Amirat et al., 2008; Zhou, 2010) also worked on the methodologies to evaluate the reliability of corroding pipelines. However, there still exist knowledge gaps and unaddressed issues that limit the application of the reliability-based methodologies in the pipeline corrosion management, as described in the following.
Burst pressure capacity models such as, the B31G, B31G Modified models, DNV model uses the simple geometric dimensions of a corrosion defect (i.e. corrosion defect length and maximum defect depth). On the other hand, the burst pressure capacity models such as RSTRENG and CSA use the detail geometric corrosion dimensions derived from the river-bottom profile of a corrosion defect, whereas the river-bottom profile referred to the two-dimensional projection of a three dimensional corrosion defect. According to Zhou and Huang (2012), the RSTRENG and CSA models are considered the most accurate burst capacity models compared with the other empirical models available. However, these models (i.e. RSTRENG and CSA models) are not easily applicable to corrosion defect assessments, as the required detail geometric characterizations of corrosion defects (derived from the river-bottom profile of a corrosion defect), are not always available from the ILI data.

Typically, the burst pressure at a corrosion defect is a function of the corrosion defect depth and length, along with the other physical and mechanical parameters of the pipeline. Measurement error models for ILI-measured maximum defect depth have been investigated by several researchers (e.g. Al-Amin et al. 2012; Caley et al. 2007; Nessim et al. 2008); on the other hand, the measurement error for the ILI-measured defect length has not been reported in the literature. Ellinger and Moreno (2016) pointed out a poor correlation between the ILI-reported defect lengths and corresponding field-measured defect lengths, which is largely due to the existence of clustering errors. In this study, the clustering error referred to the phenomena introduced during the ILI by erroneously including or excluding multiple or a single corrosion anomaly in or from a corrosion cluster. In cases where ILI tools do provide defect geometric characterization in addition to the defect maximum depth, length and width, no studies have been carried out to investigate
measurement errors associated with the ILI-reported detailed defect geometry within the context of the involvement of such geometry in the burst pressure prediction model such as RSTRENG.

1.2 Objective and Research Significance

The research conducted in this thesis is financially supported by Natural Sciences and Engineering Research Council (NSERC) of Canada and TransCanada Ltd. The objective of this research is summarized as follows:

1) Evaluate statistics of the detailed geometric defect profile to facilitate the use of RSTRENG (Remaining Strength of Corroded Pipe) and CSA (Canadian standards association) burst pressure capacity models in reliability analysis of corroded pipelines

2) Develop measurement error models associated with the corrosion defect length, and measurements associated with the effective portion of a defect, reported by ILI

3) Investigate implication of measurement error models for corrosion defect length and measurement associated with effective portion of a corrosion defect in the system reliability analysis.

It is expected that the outcome of this research will facilitate in accurately predicting the reliability-based assessment of corroded pipelines as well as the pipeline integrity management program.

1.3 Scope of the Study

This thesis consists of four main topics that are presented in Chapters 2 to 5, respectively. Chapter 2 presents a methodology to facilitate the application of the RSTRENG and CSA burst
pressure capacity models in the reliability analysis of corroded pipelines. The use of the CSA and RSTRENG burst pressure capacity models is desirable in the reliability analysis of corroded pipelines because they incorporate detailed defect geometric information and have relatively small model uncertainties. Since the detailed defect geometric information is not always available from ILI of corroded pipelines, this study facilitates the use of CSA and RSTRENG models in the reliability analysis by deriving probabilistic characteristics of parameters that relate the detailed defect geometry to its simplified characterizing parameters based on the high-resolution geometric data for a large set of external metal-loss corrosion defects identified on an in-service pipeline in Alberta, Canada.

Chapter 3 presents a framework to quantify the measurement error associated with lengths of corrosion defects on oil and gas pipelines reported by ILI tools based on a relatively large set of ILI-reported and field-measured defect data collected from different in-service pipelines in Canada. A log-logistic model is proposed to quantify the likelihood of a given ILI-reported defect being a Type I defect (without cluster error) or a Type II defect (with clustering error). The measurement error associated with the ILI-reported length of the defect is quantified as the average of those associated with the Type I and Type II defects, weighted by the corresponding probabilities obtained from the log-logistic model.

Chapter 4 presents the quantification of measurement error associated with the effective portions of a corrosion defect in an oil and gas pipe joint reported by ILI tools based on ILI and field measured corrosion defect data of several pipelines currently in service in Canada. The study specifically quantifies the measurement of effective length and effective depth of a corrosion defect. As ILI data involves clustering errors, this study accommodates the clustering error
associated with the ILI data into the proposed measurement error for effective length and effective of a corrosion defect. Consequently, the measurement error model quantified in this study will enable the use of RSRENG model in corrosion assessment, if ILI-reported defect profiles are available.

Chapter 5 presents the sensitivity of system reliability of corroded pipe joints to the proposed measurement error model for ILI measured corrosion defect length and measurement error model for ILI measured dimension for effective portion of a corrosion defect. The system reliability of a corroded pipelines is compared with the ILI vendors provided measurement errors for corrosion defects to the proposed measurement error models. A pipe joint that is a part of a pipeline currently in service in Canada is used as a case study.

1.4 Thesis Format

This thesis is prepared as an Integrated-Article Format as specified by the School of Graduate and Postdoctoral Studies at Western University, London, Ontario, Canada. A total of 6 chapters are included in this thesis. Chapter 1 presents a brief introduction with background, objective, and scope of the study. Chapter 2 to 5 consists of the main body of the thesis, each chapter addresses an individual topic and the key part of the published papers and submitted manuscripts. Finally, the last Chapter of this thesis consists of conclusion of the thesis and the future work.

Reference


2 Evaluation of Statistics of Metal-loss Corrosion Defect Profile to Facilitate Reliability Analysis of Corroded Pipelines

2.1 Introduction

The structural integrity of oil and gas pipelines may be compromised by metal loss corrosion defects. Pipeline operators commonly employ high-resolution inline inspection (ILI) tools to detect, locate, and size corrosion defects. Over the last decade or so, the reliability-based corrosion management program is being increasingly used (Cosham and Hopkins 2002; Stephens 2006; Stephens and Nessim 2006; Zhou et al. 2015) as it provides an effective framework to handle the uncertainties involved in the pipeline corrosion management. A crucial component of such a program is to predict the probability of burst of the corroded pipeline, i.e. the probability of the pipeline operating pressure exceeding its burst pressure capacity. Several semi-empirical burst capacity models for corroded pipelines are widely used in practice, for example, the American Society of Mechanical Engineers (ASME) B31G and B31G Modified models, the DNV and CSA models that are recommended in Det Norske Veritas (DNV) OS-F101 and Canadian Standards Association (CSA) Z662-15 respectively, the PCORRC and RSTRENG models (Cronin 2000; Zhou and Huang 2012). These models generally predict the burst capacity as functions of the defect depth and length, pipe geometry (i.e. diameter and wall thickness), and material strength (e.g., yield strength, tensile strength, or flow stress). The geometry of a typical metal-loss corrosion defect on a pipeline is illustrated in Figure 1. The length and depth of the defect are measured in the longitudinal and through-wall thickness directions, respectively, of the pipeline. Based on the defect geometry employed, the aforementioned burst capacity models can be classified as Type I or Type II models. Type I models, which include the B31G, B31G Modified, DNV and PCORRC,
require simplified characterizing parameters for the defect geometry, namely the maximum defect depth and length (Figure 2.1), to predict the burst pressure. On the other hand, Type II models, which include the RSTRENG and CSA models, require a so-called river-bottom defect profile (Figure 2.1) to predict the burst pressure. In particular, the RSTRENG model (Kiefner and Vieth 1989) involves identifying the effective portion of the defect profile that leads to the lowest predicted burst pressure, whereas the CSA model (CSA 2015) involves evaluating the average depth from the defect profile.

The burst capacity models are not perfectly accurate and therefore involve model errors. Zhou and Huang (2012) evaluated model errors associated with the aforementioned burst capacity models based on a large database of full-scale burst tests of corroded pipes reported in the literature. According to their report, Type II models are markedly more accurate than Type I models; this is expected since the former incorporate more information about the defect geometry than the latter in predicting the burst capacity. It follows that Type II models are more advantageous than Type I models in the reliability-based corrosion defect assessment. However, while ILI tools always report the maximum depth and length for a given detected corrosion defect, they quite often do not provide its detailed defect profile. To facilitate the use of Type II models in the reliability analysis, it is therefore desirable to develop statistical relationships between the defect profile and its simplified characterizing parameters.

Reports of statistical relationships between the defect profile and simplified characterizing parameters are scarce, if any, in the literature. The Canadian oil and gas pipeline standard CSA Z662-15 (CSA 2015) recommends that the ratio of the maximum to average defect depths be characterized by a shifted lognormal distribution with a mean value of 2.08, a coefficient of
variation (COV) of 50% and a lower bound of unity. As indicated in Z662-15, this distribution is derived based on the geometry of defects on the full-scale corroded pipe sections reported by Kiefner and Vieth (1989). It is however unclear how many data points are used to derive the distribution (a total of 98 corroded pipe sections are reported by Kiefner and Vieth (1989)) and how well the distribution fits the data. Furthermore, to the best of our knowledge, relationships between the effective portion of the defect profile and maximum defect depth or length are unavailable in the literature. It is therefore necessary to fill the above-described knowledge gap to improve the pipeline corrosion management practice.

**Figure 2.1 Typical defect characterization**

The objective of the work reported in this paper is to collect the geometric data of a large number of naturally-occurring corrosion defects on pipelines and employ the collected data to derive statistical relationships between the defect profile and its simplified characterizing parameters. To this end, defect geometric data for 470 external corrosion defects measured by laser
scanning devices are collected from an in-service natural gas pipeline located in Alberta, Canada. Statistical analyses are then carried out to derive the probability distributions of the average-to-maximum depth ratios, ratio between the average depth of the effective defect profile and maximum depth of the overall defect profile, and ratio between the length of the effective defect profile and length of the overall defect profile. The implications of the obtained results are then investigated by using the B31G Modified, CSA and RSTRENG models to evaluate the probabilities of burst of several representative pipelines containing corrosion defects with ILI-reported defect dimensions.

The rest of the paper is organized as follows. Section 2.2 briefly reviews the B31G Modified, RSTRENG and CSA models. Section 2.3 describes the defect geometric data collected from the gas pipeline in Alberta and statistical analyses carried out to develop the relationship between the defect profile and its simplified characterizing parameters. The implications of the obtained results for the reliability analysis of corroded pipelines are presented in Section 2.4, followed by concluding remarks in Section 2.5.

2.2 Burst Pressure Capacity Models

The CSA and RSTRENG models are both Type II burst capacity models and reviewed in this section. The B31G Modified model is a representative Type I burst capacity model and serves as a basis for the CSA and RSTRENG models; therefore, the B31G Modified model is also reviewed. Let $P_b$ denote the burst pressure capacity of a pipeline at a given corrosion defect. Then $P_b$ can be evaluated using the B31G Modified, CSA and RSTRNG models, respectively, as follows.
B31G Modified model

\[
P_b = \frac{2t(\sigma_y + 68.95)}{D} \left[ \frac{1 - 0.85d_{max}}{t} \right], \quad \frac{d_{max}}{t} \leq 0.8 \tag{2.1}
\]

CSA model

\[
P_b = \xi_2 \frac{2t\sigma_f}{D} \frac{1 - \frac{d_{avg}}{t}}{1 - \frac{d_{avg}}{tM}}
\]

\[
\sigma_f = \begin{cases} 
1.15\sigma_y, & \sigma_y \leq 241\text{MPa} \\
0.9\sigma_u, & \sigma_y > 241\text{MPa}
\end{cases}
\tag{2.3}
\]

\[
M = \begin{cases} 
\sqrt{1 + 0.6275 \frac{l^2}{Dt} - 0.003375 \frac{l^4}{(Dt)^2}}, & \frac{l^2}{Dt} \leq 50 \\
3.3 + 0.032 \frac{l^2}{Dt}, & \frac{l^2}{Dt} > 50
\end{cases}
\tag{2.4}
\]

RSTRENG model

\[
P_b = \min\{P_{bj}\} \quad j = 1, 2, ..., n \tag{2.5}
\]

\[
P_{bj} = \xi_3 \frac{2t(\sigma_y + 68.95)}{D} \frac{1 - \frac{A_j}{l_j^2t}}{1 - \frac{A_j}{M_j l_j t}} \quad \frac{d_{max}}{t} \leq 0.8 \quad j = 1, 2, ..., n \tag{2.6}
\]

where, in Eqs. (2.1) through (2.6), \(d_{max}\), \(d_{avg}\) and \(l\) denote the maximum depth, average depth, and length of the corrosion defect respectively; \(D\) and \(t\) are the pipe outside diameter and wall thickness, respectively; \(\sigma_y\), \(\sigma_u\) and \(\sigma_f\) are the pipe yield strength, tensile strengths, and so-called flow stress, respectively; \(\sigma_y + 68.95\) (MPa) is an empirical equation employed in the B31G Modified and RSTRENG models to determine \(\sigma_f\), \(M\) is the Folias or bulging factor to account for the stress concentration at the defect, and \(\xi_1\), \(\xi_2\) and \(\xi_3\) are the model errors associated with the
B31G Modified, CSA, and RSTRENG models, respectively. To apply the RSTRENG model, one needs to generate \( n \) sub-defects based on the defect profile, each sub-defect being a contiguous portion of the overall defect. The area and length of the \( j \)-th \((j = 1, 2, \ldots, n)\) sub-defect are denoted by \( A_j \) and \( l_j \), respectively, and the corresponding Folias factor \( M_j \) is evaluated by replacing \( l \) with \( l_j \) in Eq. (2.4). The sub-defect that has the lowest burst capacity is defined as the effective portion of the overall defect, with the corresponding area and length defined as the effective area \((A_{\text{eff}})\) and length \((l_{\text{eff}})\) of the defect, respectively (see Figure 2.1). It should be clarified that the B31G Modified, CSA, and RSTRENG models as originally proposed do not include the model errors, i.e. \( \xi_1 \), \( \xi_2 \) and \( \xi_3 \) respectively. They are included in Eqs. (2.1), (2.2) and (2.6), respectively, because the model error is a key random variable that must be considered in the reliability analysis of corroded pipelines.

### 2.3 Statistical Analysis of Defect Geometric Data

#### 2.3.1 Data Description

The corrosion geometric data analyzed in this study are collected from the corrosion assessment field reports for an in-service natural gas pipeline located in Alberta, Canada. Due primarily to the deterioration of the coating condition, ILI tools found a significant number of corrosion defects on the external surface of the pipeline. The assessment reports were prepared by the contractors retained by the pipeline operator to excavate and repair corroded pipe joints (a typical pipe joint is about 12 m long) that contained critical defects and were therefore deemed in need of repair based on fitness-for-service assessments of defects using the relevant ILI information. The reports reviewed in this study cover a period of 7 years, from 2004 to 2011. For each of the excavated pipe joints, the repair crew used a high-resolution laser-scanning device to capture the detailed geometry of the corrosion defects on the pipe joint by dividing the pipe joints
into several segments [see Figure 2.2(a)]. Figure 2.2(b) depicts the laser-scanned image for one arbitrarily selected defect in the pipe segment shown in Figure 2.2(a). The RSTRENG model was employed afterward to evaluate the burst capacities at the defects based on the laser-scanned defect geometry. The reports document key geometric data for the defects, including $d_{\text{max}}$, $d_{\text{avg}}$, $l$, $A_{\text{eff}}$, and $l_{\text{eff}}$, obtained from the laser scanning device and RSTRENG assessments. It must be emphasized that although all the excavated pipe joints contained critical corrosion defects, the laser scan captured the geometry of all the defects (i.e. critical as well as non-critical defects) on a given joint. Therefore, the defect geometric data collected from the assessment reports are considered representative of the entire defect population as opposed to the population of critical defects only.
By reviewing the assessment reports, the geometric data for a total of 470 corrosion defects were collected. The values of $d_{\text{max}}, d_{\text{avg}}$, and $l$ for these defects range from 9.9 to 84.6\% of the pipe wall thickness ($t$), from 2.9 to 41.5\%$t$, and from 16 to 5420 mm, respectively. Figure 2.3 depicts the relationships between $d_{\text{max}}$ and $l$, and between $d_{\text{avg}}$ and $l$ for the 470 defects. The Pearson correlation coefficients (i.e. $\rho$) evaluated from the data are shown in the corresponding panels of the figure. The figure suggests that there are negligible correlations between $d_{\text{max}}$ and $l$, and $d_{\text{avg}}$ and $l$. 

Figure 2.2 (a) Laser scan picture of a segment of a pipe joint, and (b) Laser scan picture of a corrosion defect of the corresponding pipe segment
2.3.2 Statistical Analysis

For the statistical analyses, the following quantities are defined.

\[
\mu = \frac{d_{\text{avg}}}{d_{\text{max}}} \quad (2.7a)
\]

\[
\lambda = \frac{l_{\text{eff}}}{l} \quad (2.7b)
\]

\[
\eta = \frac{A_{\text{eff}}}{l_{\text{eff}}d_{\text{max}}} \quad (2.7c)
\]

It follows from Eq. (2.7) that \(0 < \mu \leq 1\) is the average-to-maximum depth ratio; \(0 < \lambda \leq 1\) is the ratio between the effective length and total length of the defect, and \(0 < \eta \leq 1\) is the ratio between the average depth (i.e. \(A_{\text{eff}}/l_{\text{eff}}\)) of the effective portion of the defect and \(d_{\text{max}}\). Given \(d_{\text{max}}\), \(l\), \(\mu\), \(\lambda\) and \(\eta\), one can evaluate \(d_{\text{avg}} = \mu d_{\text{max}}\), \(l_{\text{eff}} = \lambda l\) and \(A_{\text{eff}} = \lambda \eta l d_{\text{max}}\). Figure 2.4 depicts the relationships between \(\mu\) and \(d_{\text{max}}\), \(\mu\) and \(l\), \(\lambda\) and \(d_{\text{max}}\), \(\eta\) and \(d_{\text{max}}\), \(\lambda\) and \(l\), \(\eta\) and \(l\), and \(\lambda\) and \(\eta\), with the corresponding Pearson correlation coefficients given in the corresponding panels of the
The figure suggests that there are negligible correlations between $\mu$ and $d_{\text{max}}$, $\mu$ and $l$, $\lambda$ and $d_{\text{max}}$, $\eta$ and $d_{\text{max}}$, $\eta$ and $l$, and $\lambda$ and $\eta$, and a relatively strong correlation between $\lambda$ and $l$. 

(a) $\rho = -0.22$

(b) $\rho = -0.31$

(c) $\rho = -0.13$

(d) $\rho = -0.12$
Figure 2.4. Relationship between (a) $\mu$ and $d_{\text{max}}$, (b) $\mu$ and $l$, (c) $\lambda$ and $d_{\text{max}}$, (d) $\eta$ and $d_{\text{max}}$, (e) $\lambda$ and $l$, (f) $\eta$ and $l$, and (g) $\lambda$ and $\eta$

Figure 2.5 depicts the empirical cumulative distribution functions (CDF) of $\mu$, $\lambda$ and $\eta$ obtained from the 470 data points, whereby the empirical CDF for the $i$-th ($i = 1, 2, \ldots, 470$) data point equals $i/471$, as well as CDF of the corresponding best-fit distributions. Given that $\mu$, $\lambda$ and $\eta$ are all bounded between zero and unity, the standard beta distribution is a natural choice to fit the data. The Kolmogorov-Smirnov test (Ang and Tang 1975) confirms that the standard beta distribution is the best fit distribution for $\mu$, $\lambda$ and $\eta$ compared with the gamma, lognormal, and
exponential distributions. The means, coefficients of variation (COV) and corresponding
distribution parameters $q$ and $r$ for $\mu$, $\lambda$ and $\eta$ are summarized in Table 2.1. The probability density
function (PDF) of a standard beta-distributed variate $Y$, $f_Y(y)$, is given by

$$f_Y(y) = \frac{1}{B(q,r)} y^{q-1}(1 - y)^{r-1} \quad (0 \leq y \leq 1)$$

(2.8)

$$B(q,r) = \frac{\Gamma(q)\Gamma(r)}{\Gamma(q+r)}$$

(2.9)

where $B(q, r)$ is the beta function; $\Gamma(\bullet)$ is the gamma function, and the mean and COV of $Y$ are
given by $q/(q+r)$ and $\sqrt{\frac{r}{q(q+r+1)}}$, respectively. Table 2.1 indicates that for the 470 defects analyzed,
$d_{avg}$ is on average 32% of $d_{max}$; $l_{eff}$ is on average 61% of $l$, and $A_{eff}/l_{eff}$ is on average 48% of $d_{max}$.
Furthermore, $\mu$, $\lambda$ and $\eta$ all have relatively high variability with COV values ranging from about
25 to 50%.

It is noted that the probabilistic characteristics of $\mu$, $\lambda$ and $\eta$ obtained in the present study
are based on the corrosion defect data collected from a single in-service pipeline and may not be
applicable to other pipelines, if the morphology of the corrosion defect is largely influenced by
relevant pipe attributes such as the coating properties, as well as properties of the surrounding
soils. The potential dependence of the corrosion morphology on the coating and soil properties is
beyond the scope of the present study but should be investigated in the future.
Table 2.1 Basic statistics of $\mu$, $\lambda$ and $\eta$

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Mean</th>
<th>COV</th>
<th>Best-fit distribution</th>
<th>Beta distribution parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\mu$</td>
<td>0.32</td>
<td>44%</td>
<td>Beta</td>
<td>$q$ = 3.242, $r$ = 6.912</td>
</tr>
<tr>
<td>$\lambda$</td>
<td>0.61</td>
<td>49%</td>
<td></td>
<td>$q$ = 1.025, $r$ = 0.655</td>
</tr>
<tr>
<td>$\eta$</td>
<td>0.48</td>
<td>27%</td>
<td></td>
<td>$q$ = 6.795, $r$ = 7.444</td>
</tr>
</tbody>
</table>

(a)

Cumulative distribution function (CDF)

Data
Fitted Beta distribution
2.4 Practical Implications

2.4.1 Probability of Burst of Corroded Pipeline

The practical implications of the parameters $\mu$, $\lambda$ and $\eta$ described in Section 2.3 for the evaluation of the probability of burst of corroded pipelines are discussed in this section. The limit
state function, \( g \), for the evaluation of the probability of burst of a pipeline containing a corrosion defect is expressed as,

\[
g = P_b - p
\]  \hspace{1cm} (2.10)

where \( p \) is the pipeline operating pressure, \( P_b \) is the pipe burst pressure capacity at the defect, and \( g \leq 0 \) represents burst (i.e. failure).

The probability of failure (burst), \( P_f \), is given by,

\[
P_f = \int_{g \leq 0} f_X(x) \, dx
\]  \hspace{1cm} (2.11)

where \( f_X(x) \) denotes the joint PDF of the vector of \( n \) random variables, \( X = [X_1, X_2, \ldots, X_n]^T \) (\( T \) denotes transposition), that are involved in the limit state function, including the defect geometric dimensions, pipe yield or tensile strength, model error and pipeline operating pressure. The first-order reliability method (FORM) (Melchers 1999a) is employed in this study to evaluate the integral in Eq. (2.11). It follows that \( P_f \) is approximated by \( \Phi(-\beta) \), where \( \Phi(\bullet) \) is the CDF of the standard normal distribution function, and \( \beta \) is the reliability index representing the shortest distance between the origin and limit state surface in the standard normal space. The value of \( \beta \) is obtained through a constrained optimization analysis in the FORM with the constraint being \( g \leq 0 \) in the standard normal space.

To carry out the FORM analysis, the vector of random variables \( X \) needs to be transformed to a vector of \( n \) independent standard normal variates \( U = [U_1, U_2, \ldots, U_n]^T \). If the individual random variables in \( X \) are mutually independent, the transformation can be straightforwardly achieved through the inverse normal transformation, i.e. \( U_i = \Phi^{-1}(F_i(x_i)) \) \((i = 1, 2, \ldots, n)\), where
The inverse of the standard normal distribution function, \( \Phi^{-1}(\bullet) \), and \( F_i(x_i) \) is the CDF of \( X_i \) (Der Kiureghian 2005). If the individual random variables in \( X \) are correlated, the Nataf transformation (Der Kiureghian 2005) is commonly used. That is, \( X \) is first transformed to a set of \( n \) correlated standard normal variates \( Z = [Z_1, Z_2, \ldots, Z_n]^T \) through the inverse normal transformation, and \( Z \) is then transformed to \( U \) through \( U = L^{-1}Z \), where \( L \) is the lower-triangular matrix obtained from the Cholesky decomposition of the correlation matrix associated with \( Z \). Empirical equations have been developed by Der Kiureghian and Liu (Der Kiureghian and Liu 1986) to evaluate the correlation coefficient between \( Z_i \) and \( Z_k \) given the correlation coefficient between \( X_i \) and \( X_k \) \((i, k = 1, 2, \ldots, n)\) for various marginal distributions. The difference between the two correlation coefficients is in general small; therefore, the former can be considered to approximately equal the latter. Note that the reliability analysis carried out in the present study corresponds to the defect assessment to identify critical defects to be repaired immediately after ILI. Therefore, the analysis does not consider the growth of corrosion defects over time or fluctuation of the pipeline operating pressure with time; in other words, the time-invariant reliability analysis is carried out.

### 2.4.2 Analysis Cases and Probabilistic Characteristics of Input Parameters

The analysis considers nine representative natural gas pipelines corresponding to a nominal pipe outside diameter of 762 mm, three pipe steel grades (X42, X52 and X70), and a maximum operating pressure (MOP) of 6.0 MPa. The nominal pipe wall thicknesses \( t_n \) of the nine analysis cases are determined as follows:

\[
t_n = \frac{P_o D_n}{2UF SMYS} \tag{2.12}
\]
where \( P_o \) denotes MOP; SMYS is the specified minimum yield strength of the pipe steel; \( D_n \) denotes the nominal pipe outside diameter, and \( UF \) (\( UF < 1 \)) is the utilization factor (i.e. safety factor) that limits the pipe hoop stress due to MOP to a fraction of SMYS. Three values of \( UF \), namely 0.80, 0.72 and 0.60, that are typical for natural gas transmission pipelines in Canada are considered in the analysis. Table 2.2 summarizes the attributes of the nine pipeline cases considered in the analysis.

<table>
<thead>
<tr>
<th>Case No.</th>
<th>( P_o ) (MPa)</th>
<th>Steel Grade</th>
<th>SMYS (MPa)</th>
<th>SMTS(^\dagger) (MPa)</th>
<th>( D_n ) (mm)</th>
<th>( t_n ) (mm)</th>
<th>( UF )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>6</td>
<td>X42</td>
<td>290</td>
<td>414</td>
<td>762</td>
<td>9.9</td>
<td>0.80</td>
</tr>
<tr>
<td>2</td>
<td>6</td>
<td>X42</td>
<td>290</td>
<td>414</td>
<td>762</td>
<td>10.9</td>
<td>0.72</td>
</tr>
<tr>
<td>3</td>
<td>6</td>
<td>X42</td>
<td>290</td>
<td>414</td>
<td>762</td>
<td>13.1</td>
<td>0.60</td>
</tr>
<tr>
<td>4</td>
<td>6</td>
<td>X52</td>
<td>359</td>
<td>455</td>
<td>762</td>
<td>8.0</td>
<td>0.80</td>
</tr>
<tr>
<td>5</td>
<td>6</td>
<td>X52</td>
<td>359</td>
<td>455</td>
<td>762</td>
<td>8.8</td>
<td>0.72</td>
</tr>
<tr>
<td>6</td>
<td>6</td>
<td>X52</td>
<td>359</td>
<td>455</td>
<td>762</td>
<td>10.6</td>
<td>0.60</td>
</tr>
<tr>
<td>7</td>
<td>6</td>
<td>X70</td>
<td>483</td>
<td>565</td>
<td>762</td>
<td>5.9</td>
<td>0.80</td>
</tr>
<tr>
<td>8</td>
<td>6</td>
<td>X70</td>
<td>483</td>
<td>565</td>
<td>762</td>
<td>6.6</td>
<td>0.72</td>
</tr>
<tr>
<td>9</td>
<td>6</td>
<td>X70</td>
<td>483</td>
<td>565</td>
<td>762</td>
<td>7.9</td>
<td>0.60</td>
</tr>
</tbody>
</table>

\(^\dagger\) SMTS denotes the specified minimum tensile strengths

For each of the analysis cases, it is assumed that the pipeline contains a corrosion defect with the ILI-reported maximum depth \( (d_{\text{max-ILI}}) \) and length \( (l_{\text{ILI}}) \). Four \( \frac{d_{\text{max-ILI}}}{t_n} \) values (0.3, 0.4, 0.5 and 0.6), and five \( l_{\text{ILI}} \) values (50, 150, 250, 350, and 500 mm) are considered such that the failure probability of a given pipeline is analyzed for 20 different sets of \( d_{\text{max-ILI}} \) and \( l_{\text{ILI}} \). For each set of \( d_{\text{max-ILI}} \) and \( l_{\text{ILI}} \), three reliability analyses are carried out by employing the B31G Modified, CSA and RSTRENG models, respectively. The analysis employing the B31G Modified model involves \( d_{\text{max}} \) and \( l \), which can be evaluated from \( d_{\text{max-ILI}} \) and \( l_{\text{ILI}} \), respectively, by considering the measurement errors associated with \( d_{\text{max-ILI}} \) and \( l_{\text{ILI}} \) as described in the following sections. For
analyses employing the CSA and RSTRENG models, \( \mu, \lambda \) and \( \eta \) are used to evaluate \( d_{\text{avg}}, l_{\text{eff}} \) and \( A_{\text{eff}} \) from \( d_{\text{max}} \) and \( l \), i.e. \( d_{\text{avg}} = \mu d_{\text{max}} \) for the CSA model, and \( l_{\text{eff}} = \lambda l \) and \( A_{\text{eff}} = \lambda \eta l d_{\text{max}} \) for the RSTRENG model. The probabilistic characteristics of parameters \( \mu, \lambda \) and \( \eta \) are given in Table 2.1. Based on the results shown in Figure 2.4, \( \mu, \lambda, \eta, d_{\text{max}}, \) and \( l \) are considered mutually independent except that \( \lambda \) and \( l \) are considered correlated with the corresponding correlation coefficient equal to -0.67 in the reliability analysis. This correlation coefficient is assumed to be the same as that in the correlated normal space in the FORM analysis. To investigate the sensitivity of the analysis results to the correlation between \( \lambda \) and \( l \), FORM analyses are also carried out by assuming \( \lambda \) and \( l \) to be independent.

Table 2.3 summarizes the probabilistic characteristics of the random variables associated with the pipe geometric and material properties, and \( d_{\text{max}} \) and \( l \). It is assumed that all the random variables in the table are mutually independent. Statistical information provided in Annex O of CSA Z662-15 (CSA 2015b) indicates that \( t/t_n \) generally follows a normal distribution with the mean ranging from 1.0 to 1.01 and COV ranging from 1.0 to 1.7\%. Hence, \( t/t_n \) is assigned a normal distribution with the mean equal to unity and COV equal to 1.5\% in the present study. The actual pipe outside diameter typically equals the nominal outside diameter with negligible uncertainty (CSA 2015b). It is also indicated in CSA Z662-15 that both normal and lognormal distributions are adequate to characterize \( \sigma_y/\text{SMYS} \) and \( \sigma_u/\text{SMTS} \), with the mean values close to 1.1 and COV values ranging from 3 to 3.5\%. Jiao et al. (Jiao et al. 1995) suggested that \( P/P_o \) (i.e. ratio of the maximum annual pressure and MOP) follows a Gumbel distribution with a mean between 1.03 and 1.07 and a COV between 1 and 2\%. Hence, the present study considers \( P/P_o \) follows a Gumbel distribution with the mean equal to unity and COV equal to 3\%. Zhou and Huang (2012) developed
the model errors associated with various burst pressure capacity models based on 150 full-scale burst tests of pipe segments containing single isolated natural corrosion defects. The probabilistic characteristics of model errors associated with the B31G Modified ($\xi_1$), CSA ($\xi_2$) and RSTRENG ($\xi_3$) models, respectively, as shown in Table 2.3 are based on the results reported by Zhou and Huang (2012). The characteristics of the three model errors suggest that the CSA and RSTRENG models are markedly more accurate than the B31G Modified model.

The ILI-reported maximum defect depth and defect length are assumed to be related to the actual maximum defect depth and defect length, respectively, by additive measurement errors (DNV-RP-F101 2010b; Zhou and Nessim 2011) as follows:

$$d_{\text{max}-\text{ILI}} = d_{\text{max}} + \varepsilon_d$$  \hspace{1cm} (2.13)

$$l_{\text{ILI}} = l + \varepsilon_l$$  \hspace{1cm} (2.14)

where $\varepsilon_d$ and $\varepsilon_l$ are the measurement errors associated with $d_{\text{max}-\text{ILI}}$ and $l_{\text{ILI}}$, respectively. It is commonly assumed in the literature (Caleyo et al. 2007; DNV-RP-F101 2010b; Zhou and Nessim 2011; Zhou et al. 2015) that $\varepsilon_d$ and $\varepsilon_l$ are normally-distributed random variables with a zero mean. The standard deviations of $\varepsilon_d$ and $\varepsilon_l$ can be derived from ILI tool specifications (Stephens and Nessim 2006). For example, typical ILI tool specifications state that $d_{\text{max}-\text{ILI}}$ is within $d_{\text{max}} \pm 10\% t_n$ 80% of the time, and that $l_{\text{ILI}}$ is within $l \pm 10$ mm 80% of the time (Stephens and Nessim 2006). It can then be inferred that the standard deviations of $\varepsilon_d$ and $\varepsilon_l$ are 7.8% $t$ and 7.8 mm, respectively.
Table 2.3 Probabilistic characteristics of random variables in the reliability analysis

<table>
<thead>
<tr>
<th>Variable</th>
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<tr>
<td>( P/P_o )</td>
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<td>3.0</td>
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<tr>
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<tr>
<td>( \xi_2 )</td>
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<tr>
<td>( \xi_3 )</td>
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<td>1.067</td>
<td>16.5</td>
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*The values are standard deviation.

2.4.3 Analysis Results and Discussion

The results of the reliability analysis are shown in Figure 2.6. In this figure, the probability of failure (i.e. burst), \( P_f \), are plotted against \( \frac{d_{\max} - \text{ILI}}{t_n} \) (i.e. 0.3, 0.4, 0.5, and 0.6). Nine cases with different combinations of the steel grade (X42, X52, and X70) and \( UF \) (0.72, 0.8, and 0.6) are shown in Figures 2.6(a)-(i). Each of the \( \frac{d_{\max} - \text{ILI}}{t_n} \) values on the horizontal axis corresponds to four vertical lines representing results of the reliability analysis based on the B31G Modified model, CSA model, RSTRENG model with independent \( \lambda \) and \( l \) (case 1), and RSTRENG model with correlated \( \lambda \) and \( l \) (case 2), respectively. The five points on a given vertical line in the order of the highest to the lowest points correspond to \( \text{ILI} \) of 500, 350, 250, 150, and 50 mm, respectively. In other words, the greater is the ILI-reported defect length, the higher is the failure probability with all the other parameters being the same.

Figures 2.6(a)-(i) show that \( P_f \) corresponding to the B31G Modified model increases significantly as the defect becomes more critical (i.e., deeper and longer defects). For example, as
shown in Figure 2.6(a), when the defect length increases from 50 to 150 mm with \( \frac{d_{\text{max}} - ILI}{t_n} = 0.3 \), \( P_f \) increases approximately by 500\%, 100\%, and 40\%, respectively, corresponding to the B31G Modified, CSA, and RSTRENG models (for both cases 1 and 2). As \( \frac{d_{\text{max}} - ILI}{t_n} \) increases from 0.4 to 0.5 with \( l_{ILI} = 150 \) mm, \( P_f \) increases by approximately 160\%, 60\%, and 20\%, respectively, corresponding to the B31G Modified, CSA, and RSTRENG (both cases 1 and 2), respectively. These results suggest that the \( P_f \) corresponding to the B31G Modified model is highly sensitive to the change in the defect size, compared with those corresponding to the CSA and RSTRENG models. For a given defect with relatively large \( \frac{d_{\text{max}} - ILI}{t_n} \) and \( l_{ILI} \) (e.g. for the defect with \( \frac{d_{\text{max}} - ILI}{t_n} = 0.6 \) and \( l_{ILI} = 500 \) mm shown in Figure 2.6(a)), \( P_f \) corresponding to the B31G Modified model can be order-of-magnitude higher than those corresponding to the CSA and RSTRENG models.

Figure 2.6 also indicates that \( P_f \) corresponding to the RSTRENG model varies in a more gradual fashion in response to the change in the defect sizes compared with those corresponding to the B31G Modified and CSA models. This is likely attributed to that the use of \( \lambda \) and \( \eta \), both of which are less than unity, for converting \( d_{\text{max}} \) and \( l \) to \( l_{\text{eff}} \) and \( A_{\text{eff}} \) makes the calculated failure probability less sensitive to the changes in \( \frac{d_{\text{max}} - ILI}{t_n} \) and \( l_{ILI} \). The values of \( P_f \) corresponding to the two cases of RSTRENG models are practically identical for all the analysis cases considered. This suggests that the correlation between \( \lambda \) and \( l \) has virtually no effects on \( P_f \). It follows that such a correlation can be ignored, and \( \lambda \) and \( l \) can be simply considered as independent in the reliability analysis.

Figure 2.6 suggests that \( P_f \) corresponding to the CSA model is sensitive to the steel grade, especially for cases involving X42 and X52. To better illustrate this observation, \( P_f \) corresponding
to the B31G Modified, CSA and RSTRENG models are compared for different steel grades in Figure 2.7. As shown in Figure 2.7(a) where \( \frac{d_{\text{max}-ILI}}{t_n} = 0.5, l = 250 \text{ mm and } UF = 0.8 \), if the pipe steel grade changes from X42 to X52, \( P_f \) increases by approximately 50\%, 550\%, and 60\% for the B31G modified, CSA, and RSTRENG (case 1 and case 2) models, respectively. As shown in Figure 2.7(b) where \( \frac{d_{\text{max}-ILI}}{t_n} = 0.3, l = 50 \text{ mm and } UF = 0.72 \), if the pipe steel grade changes from X52 to X70, \( P_f \) increases by approximately 100\%, 350\%, and 40\% for the B31G modified, CSA, and RSTRENG (case 1 and case 2) models, respectively. The sensitivity of \( P_f \) corresponding to the CSA model to the steel grade can be explained by the fact that the tensile strength \( \sigma_u \) (as opposed to \( \sigma_y \)) is used in the CSA model. Note that the nominal pipe wall thickness is always determined based on \( \sigma_y \) from the well-known Barlow equation. Note further that relatively low-grade steels such as X42 tend to have relatively high \( \sigma_u/\sigma_y \) values, whereas higher steel grades such as X52 and X70 tend to have lower \( \sigma_u/\sigma_y \) values. It follows that \( P_f \) obtained based on the CSA model can increase significantly as the steel grade increases, if \( UF, d_{\text{max}-ILI}/t_n \) and \( l_{ILI} \) remain the same. For analysis cases involving the X70 steel, the values of \( P_f \) corresponding to the CSA and RSTRENG models are similar, which suggests that the definitions of flow stress included in the two models lead to similar values of the flow stress.
(a) $UF = 0.8, D_n = 762 \text{ mm}, t_n = 9.9 \text{ mm}, MOP = 6 \text{ MPa}, X42$

(b) $UF = 0.8, D_n = 762 \text{ mm}, t_n = 8 \text{ mm}, MOP = 6 \text{ MPa}, X52$
(c) $UF = 0.8, D_n = 762$ mm, $t_n = 5.9$ mm, MOP = 6MPa, X70

(d) $UF = 0.72, D_n = 762$ mm, $t_n = 10.9$ mm, MOP = 6MPa, X42
(e) \( UF = 0.72, D_n = 762 \text{ mm}, t_n = 8.8 \text{ mm}, \text{MOP} = 6\text{MPa}, \text{X52} \)

(f) \( UF = 0.72, D_n = 762 \text{ mm}, t_n = 6.6 \text{ mm}, \text{MOP} = 6\text{MPa}, \text{X70} \)
(g) $UF = 0.6, D_n = 762 \text{ mm}, t_n = 13.1 \text{ mm}, MOP = 6\text{MPa}, X42$

(h) $UF = 0.6, D_n = 762 \text{ mm}, t_n = 10.6 \text{ mm}, MOP = 6\text{MPa}, X52$
(i) $UF = 0.6$, $D_n = 762$ mm, $t_n = 7.9$ mm, $MOP = 6$ MPa, X70

Figure 2.6 Probability of failure for various analysis cases

$l = 250$ mm, $d_{max-IL}/t_n = 0.5$, $UF = 0.8$
Figure 2.7 Comparison of probabilities of failure for steel grades X42, X52, and X70 with
(a) \( l = 250 \text{ mm}, d_{\text{max-ILI}/t_n} = 0.5 \) and \( UF = 0.8 \), (b) \( l = 50 \text{ mm}, d_{\text{max-ILI}/t_n} = 0.3 \) and \( UF = 0.72 \)

2.5 conclusion

This study facilitates the use of the CSA and RSTRENG burst pressure capacity models in the reliability assessment of corroded pipelines by investigating the statistical relationships between the corrosion defect profile and its simplified characterizing parameters, i.e. \( d_{\text{max}} \) and \( l \). Three random quantities are defined and analyzed in the study, namely the average-to-max defect depth ratio \( (\mu) \), the ratio between the effective and overall length of the defect \( (\lambda) \), and ratio between the average depth of the effective portion of the defect to \( d_{\text{max}} \) \( (\eta) \). To evaluate the statistical properties of \( \mu, \lambda \) and \( \eta \), the detailed geometric information obtained from the laser scanning device and RSTRENG assessments for 470 external corrosion defects identified on an in-service natural gas pipeline located in Alberta, Canada is collected and analyzed. The analysis results indicate that \( \mu, \lambda \) and \( \eta \) follow the standard beta distribution with means equal to 0.32, 0.61
and 0.48, respectively, and COV equal to 44, 49 and 27%, respectively. The implications of \( \mu, \lambda \) and \( \eta \) are investigated by evaluating the probability of failure (burst) of nine representative natural gas pipelines with different attributes, each of which contains one of 20 representative corrosion defects. The ILI-reported maximum defect depth of the 20 defects ranges from 30 to 60% of the pipe wall thickness, and the ILI-reported defect length ranges from 50 to 500 mm. The reliability analysis results suggest that the failure probability corresponding to the B31G Modified model is highly sensitive to the change in the ILI-reported maximum defect depth and length. By using the more accurate CSA and RSTRENG model in the reliability analysis through the application of \( \mu, \lambda \) and \( \eta \), the sensitivity of the failure probability to the change in the ILI-reported defect size is reduced. In particular, the failure probability corresponding to the RSTRENG model varies gradually as the ILI-reported defect sizes vary. Finally, the failure probability corresponding to the CSA model is observed to be sensitive to the steel grade of the pipeline, especially for cases involving relatively low-grade steels such as X42 and X52.

Finally, the applicability of probabilistic characteristics of \( \mu, \lambda \) and \( \eta \) to pipelines with different coating properties and properties of the surrounding soils needs to be confirmed by collecting corrosion defect data from a large set of pipelines and/or investigating the potential dependence of the corrosion morphology on coating and soil properties in future studies.

Reference


performance assessment and calibration of in-line inspections of oil and gas pipelines.”


3  Quantification of Measurement Errors in the Lengths of Metal-loss Corrosion Defects Reported by Inline Inspection Tools

3.1 Introduction

Metal-loss corrosion is a leading cause of failure for buried oil and gas steel pipelines (CSA 2015; Lam and Zhou 2016). A corrosion defect on a pipeline (either the external or internal surface) has an irregular three-dimensional geometric shape characterized by its maximum depth ($d_{\text{max}}$), length ($l$) and width ($w$), as illustrated in Figure 2.1. The corresponding reduction in the pressure containment capacity of the pipeline depends to a large extent on the depth and length of the defect, but is negligibly affected by its width (Kiefner and Vieth 1989). The high-resolution inline inspection (ILI) tool is used extensively in the pipeline industry to measure and record metal-loss corrosion defects on pipelines. Corrosion defects may be classified as isolated individual anomalies or clusters. A corrosion cluster consists of a colony of anomalies that are considered to interact with each other, i.e. the reduction in the pipeline pressure containment capacity is due collectively to all the anomalies (as opposed to individual anomalies) in the cluster. Various so-called interaction rules have been proposed in the literature to identify interacting corrosion anomalies (Benjamin et al. 2016). Although the ILI technology has advanced immensely, there are measurement errors associated with the sizes of corrosion defects reported by ILI tools due to limitations of the sensors in the tool and associated sizing algorithms (Fenyvesi and Dumalski 2005; Nessim et al. 2008; NACE SP0102 2010). It is important to quantify the measurement errors associated with the ILI-reported defect sizes: undersized defects may result in corrosion mitigation not being carried out in a timely manner, whereas oversized defects may result in mitigations that are costly but unnecessary. As the pipeline industry is increasingly focusing on the reliability/risk-
based pipeline integrity management practice (Cosham and Hopkins 2002; Stephens 2006; Stephens and Nessim 2006; Zhou et al. 2015), it is desirable to develop probabilistic characteristics of measurement errors associated with ILI-reported defect sizes such that they can be readily incorporated in the reliability and risk assessment framework.

While the measurement error associated with the ILI-reported defect depth has been investigated extensively (Caley et al. 2007; Nessim et al. 2008; Al-Amin et al. 2012), studies on the measurement error associated with the ILI-reported defect length are scarce in the literature. Ellinger and Moreno (2016) reported that there is a poor correlation between the ILI-reported and corresponding field-measured defect lengths, the latter typically considered to be error free and equivalent to the actual lengths, due likely to the clustering error existing in the ILI-reported defect lengths. The clustering error is defined as the error introduced during the clustering process by erroneously including (excluding) a single, or multiple individual anomalies in (from) a cluster.

The objective of the present study is to develop probabilistic models to quantify the measurement error associated with the ILI-reported defect length based on a large set of ILI-reported and field-measured defect lengths collected from buried in-service pipelines in Canada. Specifically, a methodology is developed to classify ILI-reported defects into two different types, namely Type I and Type II defects. The former are defects without clustering errors, whereas the latter are defects with clustering errors. The measurement errors associated with the ILI-reported lengths of Type I and Type II defects, respectively, are then quantified. The implications of the defect classification methodology and measurement errors quantified for the reliability analysis of corroded pipelines are investigated through a realistic pipeline example.
The rest of the paper is organized as follows. Section 3.2 describes the corrosion defect data collected and analyzed in the present study, i.e. ILI-reported and field-measured lengths for corrosion defects found on pipelines operated by a major Canadian pipeline operator; Section 3.3 presents the proposed methodology for defect classification; Section 3.4 describes the quantification of measurement errors associated with ILI-reported lengths of Type I and Type II defects, and the numerical example is described in Section 3.5 followed by discussions and concluding remarks in Section 3.6.

3.2 Corrosion Defect Data

3.2.1 Overview of ILI and Field Measured Data

The data employed in the present study involve corrosion defects found on the external surfaces of 237 pipe joints in 28 in-service pipelines in Canada owned and operated by a major Canadian pipeline operator. Note that a pipe joint, typically 12 to 24 m long, is the basic unit of a pipeline. The nominal pipe outside diameters ($D_n$) and wall thicknesses ($t_n$), and steel grades of the 237 pipe joints range from 324 to 762 mm, 3.18 to 12.7 mm, and X42 to X70, respectively. All 237 pipe joints were subjected to one ILI between 2011 and 2016, and subsequent corrosion mitigations (i.e. joints being excavated, repaired or replaced, and reburied) between 2013 and 2017. The differences between the times of ILI and corresponding corrosion mitigation for the 237 pipe joints range from months to three years. For each joint, all the corrosion defects on the joint were measured in the ditch using a laser scanning device during the corrosion mitigation. Given that the laser scanning device can be considered error free (Al-Amin et al. 2012), the field-measured defect sizes at the time of corrosion mitigation then equal the actual defect sizes. It is further assumed that the growth of corrosion defects is negligible between the times of ILI (i.e.
between 2011 and 2016) and corrosion mitigations (i.e. between 2013 and 2017); therefore, the ILI-reported and corresponding actual sizes of the defects on the 237 pipe joints are known.

Before presenting details of the corrosion defect data collected in this study, we briefly describe the characterization and reporting of corrosion defects by the ILI tool and laser scanning device as they are relevant to how the ILI-reported and field-measured defects are compared and matched. A corrosion anomaly is typically reported by the ILI tool as a “box” as illustrated in Figure 3.1, whereby the length, width and depth of the box are denoted by \( l_{ILI} \), \( w_{ILI} \) and \( d_{max-ILI} \), respectively (see anomaly 3 in Figure 3.1). It should be emphasized that \( l_{ILI} \), \( w_{ILI} \) and \( d_{max-ILI} \) do not necessarily equal the actual length, width and maximum depth, respectively, of the anomaly due to measurement errors associated with the ILI tool. On the other hand, the laser scanning device can capture the detailed geometry of the anomaly with negligible errors. For a group of adjacent anomalies (e.g. anomalies 1, 2, 3 in Figure 3.1), the interaction rule is applied to identify if the anomalies form a cluster. In this study, the widely-used ASME B31.4 interaction rule (ASME 2016), as illustrated in Figure 3.1, is employed to identify corrosion clusters in the ILI report. The B31.4 interaction rule is also known as the \( 3t_n \times 3t_n \) rule in the pipeline industry. According to this rule, two neighboring corrosion anomalies are considered to belong to the same cluster (i.e. interacting with each other), if two \( 3t_n \times 3t_n \) boxes that are drawn around the individual anomalies, respectively, are overlapping (Figure 3.1). The interaction rule is applied successively until all interacting individual anomalies have been identified. The length and width of the corresponding cluster can then be determined straightforwardly, as illustrated in Figure 3.1, where anomalies 1 and 2 form a cluster. It follows that the length, width and maximum depth of the cluster identified based on the ILI data do not necessarily equal those of the cluster identified based on the laser scan data. Anomaly 3 in Figure 3.1 does not belong to any cluster per the \( 3t_n \times 3t_n \) rule; therefore, it is
an isolated individual anomaly and commonly referred to as a “DMA” in the pipeline industry. For consistency with the typical practice, the term DMA is used in the rest of the paper.

A so-called “river-bottom” procedure (Kiefner and Vieth 1989) is typically employed to determine the depth profile of a defect (either a cluster or DMA), i.e. the variation of the depth over the length of the defect. The procedure involves projecting the depth of the three-dimensional defect onto a longitudinal plane that passes the center of the pipe (see Figure 2.1) to result in a two-dimensional river-bottom depth profile. Since individual anomalies in the cluster are characterized by ILI as boxes, the river-bottom depth profile of the cluster obtained based on the ILI information resembles a step function (see Figure 3.1).

Figure 3.1 Schematic diagram of ILI measured, and Laser scanned corrosion defect (DMA and cluster)
3.2.2 Corrosion Data Matching

An ILI-reported defect, hereafter referred to as a target defect, is either a DMA or a cluster. In this study, a target DMA without clustering error is identified as a Type I DMA; a target cluster without clustering error is identified as a Type I cluster, and target DMA and clusters with clustering errors are combined and identified as Type II defects. The clustering error may be caused by a variety of factors such as the imperfect detectability of the ILI tool (i.e. some anomalies missed by ILI), positioning error and sizing error of the ILI tool. The ILI-reported and field-measured corrosion defects on a given pipe joint are compared in terms of their positions (i.e. circumferential and longitudinal positions) to identify the three types of defect, and to establish the dataset of $l$ and $l_{ILI}$ for each type of defect to quantify the measurement error associated with $l_{ILI}$. The circumferential position of a defect is reported as the o’clock position, whereas its longitudinal position is reported as the distance to the upstream girth weld on the pipe joint. Figure 3.2 illustrates the identification of a Type I target DMA, where DMA3619 as reported by ILI is considered to match the nearby field-measured individual anomaly. Note that the positions of these two anomalies do not completely coincide due to the positioning error associated with the ILI tool. However, the differences between the positions of the ILI-reported and corresponding field-measured tools are within prescribed tolerances: typically, $\pm 1\%$ longitudinally and $\pm 15\sim 30$ minutes circumferentially (corresponding to $\pm 40\sim 80$mm for a 610 mm-diameter pipeline) (Dawson et al. 2012).
Figure 3.2 Laser scan picture of ILI to field corrosion anomaly matching

Figure 3.3 Classification of ILI detected target defects

Figure 3.3 illustrates the identification of Type I clusters and Type II defects. The open source image processing software Processing (Reas and Fry 2014) is used to overlay the ILI-
reported and field-measured defects in the figure. In Figure 3.3, different colors of boxes are used to represent the corrosion defects: white boxes represent the clusters and DMAs identified by ILI; black boxes represent the clusters and DMAs identified by the laser scanning device, and the grey boxes are the ILI-reported individual anomalies that are either part of or adjacent to a target cluster. The target cluster (i.e. white box) in scenario (a) of Figure 3.3 is a Type I cluster, as the laser scan-identified cluster (i.e. black box) contains the same set of ILI-identified individual anomalies (i.e. grey boxes) as the target cluster. On the other hand, the two ILI-identified clusters in scenario (b) of Figure 3.3 correspond to the same laser scan-identified cluster, i.e. clustering errors exist. In the case where multiple ILI-identified clusters correspond to the same laser scan-identified cluster, the ILI-identified cluster with the lowest predicted burst pressure (typically the one with $d_{\text{max-ILI}}$ closest to the depth of the laser scan-identified cluster) is matched with the laser scan-identified cluster. Specifically, for scenario (b), the larger white box is matched with the black box - the corresponding $l_{\text{ILI}}$ and $l$ are included as a data point in the Type II defect dataset - whereas the smaller white box is not included in the analysis. In scenario (c) of Figure 3.3, all the ILI-identified anomalies (i.e. grey and white boxes) are DMAs; however, a large cluster is identified by the laser scan to enclose many individual anomalies, i.e. clustering errors exist. In this case, the DMA with the lowest predicted burst pressure (i.e. the white box shown, typically the one with $d_{\text{max-ILI}}$ closest to the depth of the laser scan-identified cluster) is matched with the black box. The corresponding $l_{\text{ILI}}$ and $l$ are included as a data point in the Type II defect dataset, whereas the other DMAs in scenario (c) are not considered in the analysis.

By following the above-described approach for defect classification and matching, a total of 522 ILI-reported corrosion defects on the 237 pipe joints are collected in this study. The 522 defects consist of 414 clusters and 108 DMAs; the 414 clusters consist of 195 Type I clusters and
219 Type II defects, and the 108 DMAs consist of 93 Type I DMAs and 15 Type II defects. The values of $d_{\text{max-ILI}}$ as percentages of $t_n$ range from 15 to 83% for the 414 clusters, and from 10.2 to 67.0% for the 108 DMAs; $l_{\text{ILI}}$ ranges from 18.4 to 915 mm for the 414 clusters, and from 8.9 to 87.0 mm for the 108 DMA. The histograms of the ILI-reported defect depths and lengths are shown in Figure 3.4.

![Histograms](image)

Figure 3.4 Histograms of ILI-reported defect sizes (a) depths of clusters, (b) lengths of clusters, (c) depths of DMA, and (d) lengths of DMA
3.3 Preliminary Data Analysis

The ILI-reported lengths are plotted versus corresponding field-measured lengths (i.e. actual lengths) in Figures 3.5(a), 3.5(b) and 3.5(c) for all 522 defects collected in this study, the 288 Type I defects (DMAs and clusters) and 234 Type II defects, respectively. The $R^2$ values obtained from the linear regression analysis (Seber and Lee 2003) are also shown in these figures. Figures 3.5(a) and 3.5(c) indicate poor correlations between $l_{ILI}$ and $l$ for all the defects combined (i.e. both Type I and Type II) and for Type II defects, respectively, whereas Figure 3.5(b) indicates a relatively strong correlation between $l_{ILI}$ and $l$ for Type I defects. These figures suggest that the clustering error introduces large measurement errors in $l_{ILI}$. This underscores the importance of classifying ILI-reported defects into Type I and Type II defects and quantifying the measurement errors associated with these two types of defects separately. The methodology proposed in this study for the defect classification is described in the next section.
Figure 3.5 Field measured defect length vs. ILI measured defect length for (a) all defects (Type I and Type II), (b) for Type I defects, and (c) for Type II defects

3.4 Classification of Type I and Type II Defects

3.4.1 Identification of Influencing Parameter

Since pipeline integrity engineers need to carry out engineering critical assessments of corrosion defects based on the ILI information obtained for a given pipeline and determine if subsequent corrosion mitigation actions are necessary, this implies that a methodology is needed to differentiate between Type I and Type II defects based only on the ILI information and without the field measurement data. Due to the inherent uncertainties involved in differentiating between these two types of defects, a probabilistic (as opposed to deterministic) methodology is proposed in the present study. The methodology involves evaluating the probability of a given ILI-reported defect (i.e. the target defect) being a Type I defect, denoted by $P_{ID}$. It follows that the probability of the defect being a Type II defect equals $1 - P_{ID}$. Note that the target defect can be either a DMA or a cluster. Explorative data analyses are carried out to identify key influencing parameters for $P_{ID}$. 
It is observed that $P_{ID}$ is sensitive to the separation distance between the target defect, and its closest neighboring defect. It must be emphasized that the separation distance is obtained from the ILI report as opposed to the field measurement information. Let $s$ denote such a distance for a target DMA or cluster. It follows from the $3t_n \times 3t_n$ interaction rule that $s$ is greater than $6t_n$. The evaluation of $s$ for DMA and cluster is illustrated in Figures 3.6(a) and 3.6(b), respectively.

Consider that there are $n$ individual anomalies, $ID_1, ID_2, \ldots, ID_n$, surrounding the target DMA as reported by ILI. Note that each of the $n$ individual anomalies can be either a DMA or belong to a cluster. Let $s_{ci}$ and $s_{li}(i = 1, 2, \ldots, n)$ denote the distances between the $i^{th}$ anomaly and target DMA in the pipe circumferential and longitudinal directions, respectively. It follows that

$$s = \min_i s_i$$

where $s_i = \sqrt{s_{ci}^2 + s_{li}^2}$. Note that $s_{ci} (s_{li}) = 0$ if two anomalies overlap in the circumferential (longitudinal) direction.
Figure 3.6 Schematic diagram for calculation of $s$ for (a) DMA, and (b) cluster

The evaluation of $s$ for a target cluster is illustrated in Figure 3.6(b), where a cluster containing $m$ individual anomalies denoted by $ID_{C1}, ID_{C2}, \ldots, ID_{Cm}$, is surrounded by $n$ individual anomalies ($ID_1, ID_2, \ldots, ID_n$). Let $s_{cij}$ and $s_{lij}$ ($i = 1, 2, \ldots, n; j = 1, 2, \ldots, m$) denote the circumferential and longitudinal separation distances, respectively, between the $i^{th}$ anomaly surrounding the cluster and $j^{th}$ anomaly within the cluster. It follows that

$$s = \min_{i,j} s_{ij}$$

(3.2)

where $s_{ij} = \sqrt{s_{cij}^2 + s_{lij}^2}$. Figure 3.7 depicts the separation of Type I and Type II defects as a function of $s$ for the 522 DMA and clusters collected in this study. As indicated in the figure, the likelihood of a target DMA or cluster being a Type I defect increases with $s$, which intuitively
makes sense. It is noted that the horizontal axis in the figure is truncated after 40 as all the target defects are Type I defects for \( s > 40t_n \).

![Figure 3.7 Relationship between defect classification and \( s \) for corrosion defect data](image)

### 3.4.2 Framework for Determining \( P_{ID} \)

Based on discussions presented in Section 3.4.1, a framework to evaluate \( P_{ID} \) for an ILI-reported defect is proposed and shown in Figure 3.8. As shown in the figure, the probability of a target DMA or cluster being a Type I defect, denoted by \( P_{ID} \), is a function of \( s \). The evaluation of \( P_{ID} \) is described in the following sections.

![Figure 3.8 Framework for determining \( P_{ID} \)](image)
3.4.3 Evaluation of $P_{ID}$

3.4.3.1 $P_{ID}$ Model

The empirical $P_{ID}$ values are plotted versus $s/t_n$ for the 522-corrosion data in Figure 3.9. Similar to Figure 3.8, Figure 3.9 only shows data with $s \leq 40t_n$. To compute empirical values of $P_{ID}$, the range of $s$ for the data, from $6.03t_n$ to $630t_n$, is divided into 10 contiguous intervals (Table 3.1). The empirical value of $P_{ID}$ for the $k^{th}$ ($k = 1, 2, \ldots, 10$) interval, $P_{ID,k}$, is then evaluated as $P_{ID,k} = r_k/n_k$, where $r_k$ and $n_k$ are the number of Type I defects, and number of Type I and Type II defects in the $k^{th}$ interval, respectively. The representative value of $s/t_n$ for the $k^{th}$ interval, $s_k/t_n$, is taken as the average of the lower and upper bound values of $s/t_n$ associated with the interval.

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<th>Range of $s/t_n$</th>
<th>$P_{ID}$ Calculation</th>
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<tr>
<td></td>
<td>$r_k$</td>
</tr>
<tr>
<td>Lower Upper Average</td>
<td></td>
</tr>
<tr>
<td>6 7 6.5</td>
<td>41</td>
</tr>
<tr>
<td>7 8 7.5</td>
<td>26</td>
</tr>
<tr>
<td>8 9 8.5</td>
<td>33</td>
</tr>
<tr>
<td>9 10 9.5</td>
<td>21</td>
</tr>
<tr>
<td>10 11 10.5</td>
<td>21</td>
</tr>
<tr>
<td>11 12 11.5</td>
<td>15</td>
</tr>
<tr>
<td>12 15 13.5</td>
<td>30</td>
</tr>
<tr>
<td>15 20 17.5</td>
<td>26</td>
</tr>
<tr>
<td>20 30 25</td>
<td>25</td>
</tr>
<tr>
<td>30 630 330</td>
<td>50</td>
</tr>
</tbody>
</table>
Figure 3.9 suggests that $P_{ID}$ is approximately exponentially related to $s/t_n$. Therefore, the log-logistic model (Hosmer and Lemeshow 2013) is adopted to characterize $P_{ID}$ as follows:

$$P_{ID} = \frac{e^{\theta_1 + \theta_2 \ln\left(\frac{s}{t_n}\right)}}{1 + e^{\theta_1 + \theta_2 \ln\left(\frac{s}{t_n}\right)}}$$  (3.3)

where $\theta_1$ and $\theta_2$ are coefficients of the log-logistic model. The $k$-fold cross-validation resampling method (Kuhn and Johnson 2013) is employed to evaluate $\theta_1$ and $\theta_2$. In this method, the entire defect dataset is divided into $k$ datasets of roughly equal size; $\theta_1$ and $\theta_2$ are evaluated (i.e. training of the model) using the $(k-1)$ folds, and the validation of the model is performed on the remaining 1-fold. The process of the $k$-fold cross validation resampling technique is schematically illustrated in Figure 3.10. The final values of $\theta_1$ and $\theta_2$ are the averages of the values evaluated in each fold. The value of $k$ is typically chosen to be 5 or 10, although other values have been suggested in the literature (Fushiki 2011; Kuhn and Johnson 2013). In this study $k$ is selected to be 5. It should be noted that the present study uses the stratified cross-validation (Witten and Frank 2000), whereby the Type I and Type II defects present in each fold are represented in the same proportions as in the entire dataset.
The values of $\theta_1$ and $\theta_2$ are evaluated to be -7.56 and 3.50, respectively, using the maximum likelihood method (Berens 1983; Cook et al. 2000). The fitted $P_{ID}$ model is depicted along with the empirical values of $P_{ID}$ in Figure 3.11.
3.4.3.2 Assessment of Fit of the Model

To evaluate the calibration ability of Eq. (3.3), where calibration quantifies how accurate Eq. (3.3) predicts \( P_{ID} \) to the true \( P_{ID} \) value, the Hosmer-Lemeshow (HL) test (Hosmer and Lemeshow 2013) is adopted in this study. In the HL test, the training data are usually divided into several groups with roughly equal number of data points in each group. The HL statistics, denoted by \( H \), for Eq. (3.3) is evaluated from the following equation:

\[
H = \sum_{i=1}^{g} \frac{(O_i - N_i \bar{P}_{ID})^2}{N_i \bar{P}_{ID}(1 - \bar{P}_{ID})}
\]  

(3.4)

where \( g \) is the number of groups; \( O_i \) is the observed number of Type I defects in the \( i \)th group; \( N_i \) is the total number of defect data in the \( i \)th group, and \( \bar{P}_{ID} \) is the average predicted \( P_{ID} \) for the \( i \)th group. The variable \( H \) follows asymptotically a chi-square distribution when the null hypothesis, i.e. the predicted \( P_{ID} \) equals the observed \( P_{ID} \), is valid with \( (g - 2) \) degrees of freedom if \( g > p + 1 \), where \( p \) is the number of predictors (i.e. \( p = 1 \)) in the \( P_{ID} \) model (Hosmer and Lemeshow 2013). The null hypothesis is accepted if \( h < \chi^2_{g-2}^{-1}(1 - \alpha) \), where \( h \) is a given value of \( H \); \( \chi^2_{g-2}^{-1}(.) \) denotes the inverse of the chi-square distribution with \( (g - 2) \) degrees of freedom, and \( \alpha \) is the one-sided significance level, selected to be 5% in this study. The training data are divided into 10 groups, and \( h \) is estimated to be 7.19 and less than the value of \( \chi^2_{10-2}^{-1}(1 - \alpha) = 15.51 \) for \( g = 10 \). The results suggest that the predicted \( P_{ID} \) values agree well with the observed \( P_{ID} \) values.

3.4.3.3 Selection of Threshold \( P_{ID} \)

Given Eq. (3.3), it is also desirable to suggest a threshold value of \( P_{ID} \), denoted by \( P_{IDT} \), such that a target DMA or cluster with \( P_{ID} \geq P_{IDT} \) can be considered a Type I DMA or cluster deterministically. This is valuable if deterministic differentiation of Type I and Type II defects is
desirable in practice. To this end, the present study employs Youden’s J index (Youden 1950) defined as follows to find $P_{IDT}$.

\[ J = f_{TP} + f_{TN} - 1 \]  (3.5)

where $f_{TP}$ and $f_{TN}$ are commonly referred to as the sensitivity and specificity, respectively, in the literature (Kuhn and Johnson 2013), and given by,

\[ f_{TP} = \frac{n_{TP}}{n_{TP} + n_{FN}} \]  (3.6)

\[ f_{TN} = 1 - f_{FP} = \frac{n_{TN}}{n_{FP} + n_{TN}} \]  (3.7)

In Eqs. (3.6) and (3.7), $n_{TP}$, $n_{FN}$, $n_{FP}$, and $n_{TN}$ denote the numbers of true positives, false negatives, falsepositives, and true negatives, respectively, resulting from the application of Eq. (3.3) and selected value of $P_{IDT}$ (e.g. 0.5) (see Table 3.2).

<table>
<thead>
<tr>
<th>Table 3.2 Four possible outcomes for the predicted and actual defect type</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual Defect Type</td>
</tr>
<tr>
<td>-------------------</td>
</tr>
<tr>
<td>Predicted defect type</td>
</tr>
<tr>
<td></td>
</tr>
</tbody>
</table>

By varying $P_{IDT}$ from zero to unity, the corresponding $f_{TP}$ and $f_{TN}$ values vary and result in different $J$ values. The optimal threshold $P_{IDT}$ corresponds to the $P_{IDT}$ value with the maximum $J$ value. The average optimal threshold $P_{IDT}$ value corresponding to the validation data sets from the
5-fold cross validation is evaluated to be 0.56. The average $f_{TP}$ and $f_{TN}$ evaluated for all the validation data sets (from 5-fold cross validation) equal 64% and 83%, respectively.

### 3.5 Measurement Error

To quantify measurement errors associated with $l_{ILI}$ of DMA and clusters, three multiplicative measurement errors are defined, i.e. $\varepsilon_1 = l/l_{ILI}$ for Type I DMA, $\varepsilon_2 = l/l_{ILI}$ for Type I cluster, and $\varepsilon_3 = l/l_{ILI}$ for Type II defects (DMA and clusters). The probabilistic characteristics of $\varepsilon_1$, $\varepsilon_2$ and $\varepsilon_3$ are obtained from the corresponding values of $l$ and $l_{ILI}$ for 93, 195, and 234 data points, respectively. The Kolmogorov-Smirnov test (Ang and Tang 1975) suggests that the lognormal distribution is the best-fit distribution for $\varepsilon_1$, $\varepsilon_2$ and $\varepsilon_3$, among a suite of candidates such as the gamma and exponential distributions. The fitted distributions, together with the empirical cumulative distribution function (CDF) values, are plotted in the lognormal probability paper (Ang and Tang 1975) in Figure 3.12, where $F(\bullet)$ and $\Phi^{-1}(\bullet)$ denote the CDF of the lognormal distribution function and inverse of the standard normal distribution function, respectively. Note that the empirical CDF for the $i$-th ($i = 1, 2, \ldots$) data points is evaluated as $i/94$, $i/196$ and $i/235$ for $\varepsilon_1$, $\varepsilon_2$ and $\varepsilon_3$, respectively.

The means and standard deviations of $\varepsilon_1$, $\varepsilon_2$, and $\varepsilon_3$ are summarized in Table 3.3. As expected, the mean and standard deviation of $\varepsilon_3$ are markedly greater than those of $\varepsilon_1$ and $\varepsilon_2$ as shown in the table, indicating high uncertainty in the measurement error associated with $l_{ILI}$ of Type II defects.
Table 3.3 Basic statistics of defect length measurement error

<table>
<thead>
<tr>
<th>Measurement error</th>
<th>Symbol</th>
<th>Mean</th>
<th>Standard deviation</th>
<th>Best-fit distribution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Type I DMA</td>
<td>$\varepsilon_1$</td>
<td>1.32</td>
<td>0.86</td>
<td>Lognormal</td>
</tr>
<tr>
<td>Type I cluster</td>
<td>$\varepsilon_2$</td>
<td>1.01</td>
<td>0.30</td>
<td></td>
</tr>
<tr>
<td>Type II defects</td>
<td>$\varepsilon_3$</td>
<td>2.89</td>
<td>3.55</td>
<td></td>
</tr>
</tbody>
</table>

(a)
Figure 3.12 z-score of empirical cumulative distribution function (CDF) vs. the logarithmic value of (a) $\epsilon_1$, (b) $\epsilon_2$, and (c) $\epsilon_3$

Note that $\epsilon_1$, $\epsilon_2$ and $\epsilon_3$ are applicable if a DMA or a cluster is known (or assigned) to be a Type I or Type II defect. For a given target DMA with a probability of $P_{ID}$ being a Type I defect (i.e. a probability of $(1-P_{ID})$ being a Type II defect), the probability distribution of the measurement
error ($\epsilon_{DMA}$) associated with $l_{ILI}$ can be evaluated as a weighted average of the distributions of $\epsilon_1$ and $\epsilon_3$ as follows (Everitt and Hand 1981):

$$F_{DMA}(\epsilon_{DMA}) = P_{ID}F_1(\epsilon_{DMA}) + (1 - P_{ID})F_3(\epsilon_{DMA})$$ (3.8)

where $F_{DMA}(\bullet), F_1(\bullet)$ and $F_3(\bullet)$ are CDF of $\epsilon_{DMA}$, $\epsilon_1$, and $\epsilon_3$, respectively. It follows that the actual length of the target DMA equals $\epsilon_{DMA}l_{ILI}$. Similarly, the probability distribution of the measurement error ($\epsilon_{CL}$) associated with $l_{ILI}$ for a given target cluster is given by,

$$F_{CL}(\epsilon_{CL}) = P_{ID}F_2(\epsilon_{CL}) + (1 - P_{ID})F_3(\epsilon_{CL})$$ (3.9)

where $F_{CL}(\bullet)$ and $F_2(\bullet)$ are CDF of $\epsilon_{CL}$ and $\epsilon_2$, respectively. It follows that the actual length of the target cluster equals $\epsilon_{CL}l_{ILI}$.

Finally, it must be emphasized that the proposed $P_{ID}$ model as well as probabilistic characteristics of $\epsilon_1$, $\epsilon_2$ and $\epsilon_3$ are predicated on the specific defect interaction rule adopted in this study, i.e. the B31.4 interaction rule or $3t_n \times 3t_n$ rule. The application of another interaction rule may result in a different framework for the measurement error associated with $l_{ILI}$.

### 3.6 Implications for Reliability Analysis

#### 3.6.1 Numerical Example

A numerical example involving a corroded natural gas pipeline is used to investigate the impact of the proposed measurement error model on the reliability analysis. The pipeline has a nominal pipe outside diameter ($D_n$) of 762 mm, a pipe steel grade of X52, a maximum operating pressure (MOP) of 6.0 MPa, and a nominal pipe wall thicknesses ($t_n$) of 7.97 mm. It is assumed that the pipeline contains a single corrosion defect reported by ILI. As summarized in Table 3.5
(\(d_{\text{max-ILI}}\) denotes the ILI-reported maximum defect depth), 16 different scenarios with respect to the ILI-reported defect sizes are considered in the reliability analysis. In terms of the measurement error associated with \(l_{\text{ILI}}\), two cases are considered. In Case I, the measurement error implied by the typical vendor specification of the ILI tool is applied. For the ILI-reported defect length, the typical tool specification states that \(l_{\text{ILI}}\) is within ±10 mm of the actual defect length \(l\) 80% of the time (Stephens and Nessim 2006). This implies that \(l = l_{\text{ILI}} + \varepsilon\), where \(\varepsilon\) is a normal variate with a zero mean and a standard deviations equal to 7.8 mm (Stephens and Nessim 2006). Note that \(\varepsilon\) is the same for DMA and clusters. In Case II, the measurement error model proposed in the present study is applied; that is, \(l = \varepsilon_{\text{DMA}}l_{\text{ILI}}\) for DMA and \(l = \varepsilon_{\text{CL}}l_{\text{ILI}}\) for clusters, where probability distributions of \(\varepsilon_{\text{DMA}}\) and \(\varepsilon_{\text{CL}}\) are given by Eqs. (3.8) and (3.9), respectively.

The failure condition is defined as the pipeline’s burst pressure capacity at the corrosion defect, \(p_b\), being exceeded by the pipeline’s internal operating pressure, \(p\). Therefore, the limit state function, \(g\), for the reliability analysis is defined by

\[
g = p_b - p \quad (3.10)
\]

The well-known B31G Modified model (B31G-M) (Kiefner and Vieth 1989) is used to evaluate \(p_b\):

\[
p_b = \xi_1 \frac{2t(\sigma_y + 68.95)}{D} \left[ 1 - \frac{0.85 d_{\text{max}}}{\frac{t}{2} \left( 1 - 0.85 d_{\text{max}} \right)} \right], \quad \frac{d_{\text{max}}}{t} \leq 0.8
\]

\[
M = \begin{cases} 
1 + 0.6275 \frac{l^2}{dt} - 0.003375 \frac{l^8}{(Dt)^2}, & \frac{l^2}{dt} \leq 50 \\
3.3 + 0.032 \frac{l^2}{dt}, & \frac{l^2}{dt} > 50
\end{cases} \quad (3.12)
\]
where $\sigma_y$ is the pipe yield strength; $\sigma_y + 68.95$ (MPa) is the empirically-defined flow stress; $M$ is the Foliass factor, and $\xi_1$ is the model error associated with B31G-M.

The probability of failure, $P_f$, is evaluated from the following integral:

$$P_f = \int_{g \leq 0} f_X(x) \, dx$$

(3.13)

where $f_X(x)$ is the joint probability density function (PDF) of the vector of random variables, $X$, that are relevant to the analysis such as the measurement error associated with the ILI-reported defect sizes, and pipe geometric and material properties. The value of $P_f$ is evaluated using the first-order reliability method (FORM) (Melchers 1999b), whereby $P_f \approx \Phi(-\beta)$ with $\beta$ being the so-called reliability index and $\Phi(\bullet)$ being the CDF of the standard normal distribution function.

The probability distributions of basic random variables involved in the reliability analysis, as well as sources of the corresponding statistical information, are summarized in Table 3.4. All the basic random variables are assumed mutually independent. The actual maximum defect depth $d_{max}$ is expressed as (DNV-RP-F101 2010b; Zhou and Nessim 2011):

$$d_{max} = d_{max-ILI} + \varepsilon_d$$

(3.14)

where $\varepsilon_d$ denotes the measurement error associated with $d_{max-ILI}$, and is assumed to be a normal variate with a zero mean and a standard deviation of $7.8\%t_n$ (Stephens and Nessim 2006; DNV-RP-F101 2010b).
Table 3.4 Statistical information of basic random variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Distribution</th>
<th>Mean</th>
<th>COV (%)</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>$t/t_n$</td>
<td>Normal</td>
<td>1.0</td>
<td>1.5</td>
<td></td>
</tr>
<tr>
<td>$\sigma_{/SMYS}$</td>
<td>Lognormal</td>
<td>1.1</td>
<td>3.5</td>
<td>CSA (2015)</td>
</tr>
<tr>
<td>$D/D_n$</td>
<td>Deterministic</td>
<td>1.0</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>$P/P_o$</td>
<td>Gumbel</td>
<td>1.0</td>
<td>3.0</td>
<td>Jiao et al. (1995)</td>
</tr>
<tr>
<td>$\varepsilon_1$ (%$t_n$)</td>
<td>Normal</td>
<td>0</td>
<td>7.8*</td>
<td>Stephens and Nessim (2006)</td>
</tr>
<tr>
<td>$\varepsilon_2$ (mm)</td>
<td>Normal</td>
<td>0</td>
<td>7.8*</td>
<td>Present study</td>
</tr>
<tr>
<td>$\varepsilon_2$</td>
<td>Lognormal</td>
<td>1.32</td>
<td>65.2</td>
<td></td>
</tr>
<tr>
<td>$\varepsilon_3$</td>
<td>Lognormal</td>
<td>1.01</td>
<td>29.7</td>
<td></td>
</tr>
<tr>
<td>$\xi_1$</td>
<td>Lognormal</td>
<td>2.89</td>
<td>122.8</td>
<td></td>
</tr>
<tr>
<td>$\xi_2$</td>
<td>Lognormal</td>
<td>1.297</td>
<td>25.8</td>
<td>Zhou and Huang (2012)</td>
</tr>
</tbody>
</table>

* The values represent standard deviation

3.6.2 Analysis Results

As observed from the analysis results summarized in Table 3.5, the reliability indices corresponding to Case I are higher than those of Case II for all 16 scenarios, due to higher uncertainties in the measurement error associated with $l_{III}$ in Case II than those in Case I. For shallow and short corrosion defects such as those considered in scenarios 1 and 2, the differences between the reliability indices for Case I and Case II are negligible. For relatively deep and long corrosion defects such as those considered in scenarios 7 and 8, there are marked differences between the reliability indices for Case I and Case II. For other scenarios where the corrosion defects are deep or long, the difference between the reliability indices for Case I and Case II is a function of $P_{ID}$: the higher value of $P_{ID}$, the smaller the difference. For Case II, the reliability index increases with the increase of $P_{ID}$, all else being the same, e.g. scenarios 3 and 4 as well as 9 and 10. This is expected as the uncertainty of the length measurement error decreases with the increase of $P_{ID}$.  

Table 3.5 Results of the reliability analysis of the corroded pipeline example

<table>
<thead>
<tr>
<th>Scenario No.</th>
<th>Defect Type</th>
<th>$l_{ILI}$ (mm)</th>
<th>$d_{\text{max}}-\text{ILI} / t_n$</th>
<th>$s/t_n$</th>
<th>$P_{ID}$</th>
<th>$\beta$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>DMA</td>
<td>15</td>
<td>0.3</td>
<td>7</td>
<td>0.32</td>
<td>2.81</td>
</tr>
<tr>
<td>2</td>
<td>DMA</td>
<td>15</td>
<td>0.3</td>
<td>13</td>
<td>0.80</td>
<td>2.80</td>
</tr>
<tr>
<td>3</td>
<td>DMA</td>
<td>50</td>
<td>0.3</td>
<td>7</td>
<td>0.32</td>
<td>2.64</td>
</tr>
<tr>
<td>4</td>
<td>DMA</td>
<td>50</td>
<td>0.3</td>
<td>13</td>
<td>0.80</td>
<td>2.64</td>
</tr>
<tr>
<td>5</td>
<td>DMA</td>
<td>15</td>
<td>0.3</td>
<td>7</td>
<td>0.32</td>
<td>2.79</td>
</tr>
<tr>
<td>6</td>
<td>DMA</td>
<td>15</td>
<td>0.5</td>
<td>13</td>
<td>0.80</td>
<td>2.79</td>
</tr>
<tr>
<td>7</td>
<td>DMA</td>
<td>50</td>
<td>0.3</td>
<td>7</td>
<td>0.80</td>
<td>2.43</td>
</tr>
<tr>
<td>8</td>
<td>DMA</td>
<td>50</td>
<td>0.5</td>
<td>13</td>
<td>0.80</td>
<td>2.43</td>
</tr>
<tr>
<td>9</td>
<td>Cluster</td>
<td>150</td>
<td>0.3</td>
<td>7</td>
<td>0.32</td>
<td>2.08</td>
</tr>
<tr>
<td>10</td>
<td>Cluster</td>
<td>150</td>
<td>0.3</td>
<td>13</td>
<td>0.80</td>
<td>2.08</td>
</tr>
<tr>
<td>11</td>
<td>Cluster</td>
<td>300</td>
<td>0.3</td>
<td>7</td>
<td>0.32</td>
<td>1.74</td>
</tr>
<tr>
<td>12</td>
<td>Cluster</td>
<td>300</td>
<td>0.3</td>
<td>13</td>
<td>0.80</td>
<td>1.74</td>
</tr>
<tr>
<td>13</td>
<td>Cluster</td>
<td>150</td>
<td>0.5</td>
<td>7</td>
<td>0.32</td>
<td>1.39</td>
</tr>
<tr>
<td>14</td>
<td>Cluster</td>
<td>150</td>
<td>0.5</td>
<td>13</td>
<td>0.80</td>
<td>1.39</td>
</tr>
<tr>
<td>15</td>
<td>Cluster</td>
<td>300</td>
<td>0.3</td>
<td>7</td>
<td>0.32</td>
<td>0.85</td>
</tr>
<tr>
<td>16</td>
<td>Cluster</td>
<td>300</td>
<td>0.5</td>
<td>13</td>
<td>0.80</td>
<td>0.85</td>
</tr>
</tbody>
</table>

### 3.7 Conclusion

The present study fills a knowledge gap with respect to the measurement error associated with ILI-reported lengths of metal-loss corrosion defects on oil and gas pipelines. The measurement error associated with the ILI-reported length for a given defect depends on whether there is clustering error involved in the defect. Therefore, a given ILI-reported defect is categorized as a Type I defect (without clustering error) or a Type II defect (with clustering error). A log-logistic model is developed to evaluate the probability of a target defect being a Type I defect, i.e. $P_{ID}$, as a function of the shortest distance between the target defect and its surrounding defects based on the ILI-reported and field-measured data for a total of 522 corrosion defects found on 237 pipe joints in 28 pipelines currently in service in Canada. The probabilistic characteristics of length measurement errors for Type I and Type II defects are evaluated separately. The probability
distribution of the length measurement error for a given defect with a probability of $P_{ID}$ being a Type I defect is evaluated as the weighted average of those corresponding to Type I and Type II defects. The proposed framework is predicated on the specific defect interaction rule adopted, i.e. the ASME B31.4 rule or $3t_n \times 3t_n$ rule.

The implications of the proposed measurement error framework for the reliability analysis of corroded pipelines are investigated using a realistic pipeline example containing a single corrosion defect. Various scenarios in terms of the ILI-reported defect depth and length, as well as $P_{ID}$ values are considered. It is observed that for relatively deep and long defects, the reliability analysis results obtained by using the proposed framework are markedly different from those obtained by using the length measurement error derived from typical ILI tool specifications.

Reference


NACE SP0102. (2010). “Standard practice: In-line inspection of pipelines.” Item no. 21094, Houston, TX, USA.


4 Quantification of Measurement Errors Associated with the Effective Portion of the Corrosion Defects reported by the In-line Inspections

4.1 Introduction

Metal-loss corrosion is a major threat to the structural integrity of oil and gas pipelines. To assess the condition of a corroded pipeline, in-line inspection (ILI) tools are used regularly to identify and measure corrosion defects. Based on the ILI information, fitness-for-service (FFS) assessments of corrosion defects are performed by integrity engineers to evaluate the burst pressure capacities of the pipeline at corrosion defects and determine appropriate, if any, maintenance actions. Among many FFS assessment models available in the literature, the RSTRENG model (Kiefner and Vieth 1989) is widely used in the pipeline industry and has been shown to be one of the most accurate models for predicting the burst pressure of corroded pipelines (Kiefner and Vieth 1990; Cosham et al. 2007; Zhou and Huang 2012; Mokhtari and Melchers 2018). To apply the RSTRENG model, the three-dimensional defect profile is first projected onto a two-dimensional plane using the “river-bottom” approach (see Figure 4.1). The river-bottom defect profile is then divided into a series of sub-defects, each sub-defect enclosing a contiguous portion of the overall profile. The burst pressure capacity of the pipeline is defined as the minimum value of burst pressures corresponding to individual sub-defects. The sub-defect resulting in the minimum burst pressure is further defined as the effective portion of the overall defect profile, with corresponding length and area defined as the effective length and effective area of the defect profile, respectively (Figure 2.1). Furthermore, the ratio of the effective area to effective length is defined as the effective depth of the defect profile. It follows that the effective depth is the average depth of the effective portion of the defect profile.
The corrosion defect dimensions measured by ILI involve measurement errors, which should be considered in the FFS assessment of defects. Studies have been carried out to investigate the measurement errors associated with the simple characteristics of the defect geometry such as the maximum defect depth (Caleyo et al. 2007; Nessim et al. 2008; Al-Amin et al. 2012) and length (Chapter 3). However, measurement errors associated with the sizes of the effective portion of ILI-reported corrosion defects are unavailable in the literature. Therefore, the objective of the present study is to quantify measurement errors associated with the effective length and effective depth of ILI-reported corrosion defects to facilitate the use of the RSTRENG model in the FFS assessment of corrosion defects. The study follows the methodology described in Chapter 3 by classifying ILI-reported defects into two different types, namely Type I and Type II defects, which are defects without and with clustering errors, respectively. The dataset described in Chapter 3 is used to quantify measurement errors associated with the effective length and depth for Type I and Type II defects, respectively. The application of the developed measurement error models in the reliability analysis of corroded pipelines is then illustrated through a realistic example.

The rest of the chapter is organized as follows. Section 4.2 describes in detail the RSTRENG model; Section 4.3 describes the corrosion data used to develop the measurement error models for the effective lengths and effective depths of Type I and Type II defects as well as the measurement error models developed; Section 4.4 illustrates the application of the proposed measurement error models in the reliability analysis of a corroded pipe joint, followed by concluding remarks in Section 4.5.
4.2 RSTRENG model

To evaluate the burst pressure capacity of a pipe section at a corrosion defect using the RSTRENG model, the entire river bottom defect profile is divided into \( n \) subsections or subdefects (Figure 4.1). For the \( i \)th subdefect, the burst pressure \( P_{bl} \) is calculated as follows:

\[
P_{bl} = \xi \frac{2t(\sigma_y+68.95)}{D} \left( \frac{A_i}{l_i} \right) \left( 1-\frac{l_i}{M_i} \right) \quad i = 1, 2, \ldots, n
\]  

(4.1)

\[
M_i = \left\{ \begin{array}{ll}
\sqrt{1 + 0.6275 \frac{l_i^2}{Dt} - 0.003375 \left( \frac{l_i}{Dt} \right)^4}, & \frac{l_i^2}{Dt} \leq 50 \\
3.3 + 0.032 \frac{l_i^2}{Dt}, & \frac{l_i^2}{Dt} > 50
\end{array} \right.
\]  

(4.2)

where \( D, t, \) and \( \sigma_y \) in Eq. (4.1) are the pipe outside diameter, wall thickness, and yield strength, respectively; \( \sigma_y + 68.95 \) (MPa) is an empirical equation employed to derive the so-called flow stress; \( M \) is the Folias factor; \( \xi \) is the model errors associated with the RSTRENG model, and \( l_i \) and \( A_i \) are the length and area of the \( i \)th subdefect, respectively. Equations (4.1) and (4.2) are applicable if the maximum defect depth is less than or equal to 80% of the pipe wall thickness.

The parameter \( A_i \) in Eq. (4.1) can be expressed as \( A_i = l_id_{avg_i} \), where \( d_{avg_i} \) is the average depth of the \( i \)th subdefect. The RSTRENG burst pressure capacity at a corrosion defect, \( P_b \), is given by \( P_b = \min\{P_{bi}\} \quad (i = 1, 2, \ldots, n) \). For the purpose of illustration, assume that the \((n - 1)\)th subdefect in Figure 4.2 leads to the minimum burst pressure, \( P_b \). Consequently, \( l_{eff} = l_{n-1} \) and \( A_{eff} = A_{n-1} \). Furthermore, the effective depth \( d_{eff} = A_{eff}/l_{eff} \). It follows that \( P_b \) can be expressed as,
\[ P_b = \xi \frac{2t(\sigma_y + 68.95)}{D} \left[ \frac{1-d_{eff}}{t} \right] \left[ \frac{1-d_{eff}}{Mt} \right] \]

\[ M = \begin{cases} 
1 + 0.6275 \frac{l_{eff}^2}{Dt} - 0.003375 \frac{l_{eff}^4}{(Dt)^2}, & l_{eff}^2 \leq 50 \\
3.3 + 0.032 \frac{l_{eff}^2}{Dt}, & l_{eff}^2 > 50 
\end{cases} \]

---

**Figure 4.1 Evaluation of effective portion of a corrosion defect**

### 4.3 Measurement Error Models for Effective length and Depth

#### 4.3.1 Corrosion Defect Data

The corrosion defect data analyzed in this study are collected from 209 steel pipe joints of 24 pipelines currently in service in Canada. The length of a typical pipe joint varies from 12 to 24 m. The nominal diameter \((D_n)\), wall thickness \((t_n)\), and the steel grades of the pipe joints vary from 324 to 762 mm, 3.18 to 12.7 mm, and X42 to X70, respectively. One ILI was performed on each
of the 209 pipe joints between 2011 and 2016. These pipe joints were subsequently subjected to
corrosion mitigation actions between 2013 and 2017. The difference between the times of ILI and
corrosion mitigation action is months to 3 years. The growth of corrosion defects between the
times of ILI and corrosion mitigation is assumed to be negligible. During the corrosion mitigation,
the corrosion defects on the pipe joints are measured in the ditch by laser scanning devices. The
present study considers that the field-measured defect sizes obtained from the laser scanning
device are error free and equal to the actual sizes of the defect (Al-Amin et al. 2012). The
RSTRENG model is employed by the corrosion mitigation contractor to evaluate the burst pressure
capacities at the corrosion defects based on the field-measured defect geometry; the evaluated burst
pressures, together with the corresponding effective lengths and depths of the defects, are reported
in the corrosion mitigation field reports submitted to the pipeline operators. On the other hand, the
ILI reports also document the effective lengths and effective depths of the corrosion defects.
Therefore, by comparing the field reports and ILI reports for the same corrosion defects, a dataset
can be established to quantify the measurement errors associated with the ILI-based effective
length and depth of the corrosion defect.

The B31.4 interaction rule (i.e. $3t_n \times 3t_n$) rule is used in both ILI and field reports to identify
interacting corrosion anomalies. According to this rule, if the $3t_n \times 3t_n$ boxes drawn around two
adjacent corrosion anomalies intersect, then the corrosion anomalies are part of a cluster (e.g.
corrosion anomalies 1 and 2 are part of a cluster in Figure 4.2). On the other hand, a corrosion
anomaly that does not belong to any cluster according to the $3t_n \times 3t_n$ rule is defined as a DMA
(e.g. corrosion anomaly 3 is a DMA in Figure 4.2). Since individual corrosion anomalies are
characterized by ILI as boxes, the river-bottom depth profile of a cluster obtained based on the ILI
information resembles a step function (see Figure 4.2). Let $l_{ILI}$ and $d_{max-ILI}$ denote the length and
maximum depth, respectively, of a defect measured by ILI, and \( l_{\text{eff-ILI}} \) and \( d_{\text{eff-ILI}} \) denote the effective length and depth, respectively, of the defect based on the ILI information. As the rectangular depth profile of the DMA characterized by ILI implies that the effective portion of the profile is its entire length (Figure 4.2), for DMA, \( l_{\text{eff-ILI}} = l_{\text{ILI}} \) and \( d_{\text{eff-ILI}} = d_{\text{max-ILI}} \).

**Figure 4.2. Schematic representation of ILI and Laser scanned corrosion defect along with their river bottom profile**

As described in Chapter 3 of this thesis, a DMA/cluster without clustering error is defined as a Type I DMA/cluster, and DMA and clusters with clustering errors are combined and defined as Type II defects. The dataset of 522 corrosion defects with both ILI and field-measurement information described in Chapter 3 is also used in the present study. For unknown reasons, the
field measurement-based effective lengths and depths for 180 corrosion defects are missing in the field reports. As a result, a total of 342 corrosion defects including DMA and clusters are considered. Among the 342 defects, there are 70 Type I DMA, 105 Type I clusters, and 167 Type II defects (including 5 DMAs and 162 clusters).

4.3.2 Measurement Error Models

The measurement error associated with the ILI-based effective length is quantified by defining three random variables: $\alpha_1 = \frac{l_{\text{eff}}}{l_{\text{eff-ILI}}}$ for Type I DMA, $\alpha_2 = \frac{l_{\text{eff}}}{l_{\text{eff-ILI}}}$ for Type I cluster, and $\alpha_3 = \frac{l_{\text{eff}}}{l_{\text{eff-ILI}}}$ for Type II defects. Similarly, the measurement error associated with the ILI-based effective depth is quantified by defining three random variables: $\delta_1 = \frac{d_{\text{eff}}}{d_{\text{eff-ILI}}}$ for Type I DMA, $\delta_2 = \frac{d_{\text{eff}}}{d_{\text{eff-ILI}}}$ for Type I cluster, and $\delta_3 = \frac{d_{\text{eff}}}{d_{\text{eff-ILI}}}$ for Type II defects. The probabilistic characteristics of $\alpha_1$ and $\delta_1$, $\alpha_2$ and $\delta_2$, and $\alpha_3$ and $\delta_3$ (Table 4.1) are obtained from the corresponding values of $l_{\text{eff}}$ and $l_{\text{eff-ILI}}$, and $d_{\text{eff}}$ and $d_{\text{eff-ILI}}$ associated with 70 Type I DMA, 105 Type I clusters, and 167 Type II defects, respectively, collected in this study. The empirical cumulative distribution function (CDF) is evaluated by arranging the data into an ascending order and assigning the plotting positions (Fuglem et al. 2013) for the $i$-th ($i = 1, 2, \ldots$) data point as $i/71$ for $\alpha_1$ and $\delta_1$, $i/106$ for $\alpha_2$, and $\delta_2$, and $i/168$ for $\alpha_3$ and $\delta_3$. The Kolmogorov-Smirnov test (Ang and Tang 1975) suggests that the lognormal distribution is the best-fit distribution for all six variables among a suite of candidates such as the gamma and exponential distributions. The fitted distributions, together with the empirical CDF, are plotted in the lognormal probability paper (Ang and Tang 1975) in Figure 4.3, where $F(\bullet)$ and $\Phi^{-1}(\bullet)$ denote the CDF of the lognormal distribution and inverse of the standard normal distribution function, respectively.
As indicated in Table 4.1, the mean and standard deviation of $\alpha_3$ are markedly greater than those of $\alpha_1$ and $\alpha_2$. Similar observations are obtained with respect to measurement errors associated with $d_{ILI\text{-eff}}$. It is also observed that the mean value of $\delta_1$ is less than unity, which means that the $d_{eff}$ is on average less than $d_{eff\text{-ILI}}$ for Type I DMA. This can be explained by the fact that $d_{eff\text{-ILI}} = d_{max\text{-ILI}}$ for a DMA as a result of ILI characterizing the DMA as a box (i.e. having a rectangular profile). The values of $\alpha_j$ and $\delta_j$ ($j = 1, 2, 3$) are plotted versus each other along with their Pearson correlation coefficients in Figure 4.3, which suggests that there is a negligibly small negative correlation between $\alpha_j$ and $\delta_j$ ($j = 1, 2, 3$).
Figure 4.3. The empirical CDF and CDF of fitted lognormal distributions plotted in the lognormal probability paper for (a) $\alpha_1$, (b) $\alpha_2$, (c) $\alpha_3$, (d) $\delta_1$, (e) $\delta_2$, and (f) $\delta_3$

Table 4.1 Basic statistics of effective length and depth measurement error

<table>
<thead>
<tr>
<th>Measurement error model for</th>
<th>Measurement error</th>
<th>Symbol</th>
<th>Mean</th>
<th>Standard deviation</th>
<th>Best-fit distribution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Effective length</td>
<td>Type I DMA</td>
<td>$\alpha_1$</td>
<td>1.14</td>
<td>0.79</td>
<td>Lognormal</td>
</tr>
<tr>
<td></td>
<td>Type I cluster</td>
<td>$\alpha_2$</td>
<td>1.00</td>
<td>0.29</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Type II defects</td>
<td>$\alpha_3$</td>
<td>1.63</td>
<td>1.36</td>
<td></td>
</tr>
<tr>
<td>Effective depth</td>
<td>Type I DMA</td>
<td>$\delta_1$</td>
<td>0.67</td>
<td>0.26</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Type I cluster</td>
<td>$\delta_2$</td>
<td>0.89</td>
<td>0.36</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Type II defects</td>
<td>$\delta_3$</td>
<td>1.06</td>
<td>0.44</td>
<td></td>
</tr>
</tbody>
</table>
Figure 4.4. Relationship between (a) $\alpha_1$ and $\delta_1$, (b) $\alpha_2$ and $\delta_2$, and (c) $\alpha_3$ and $\delta_3$

It should be noted that $\alpha_1$, $\alpha_2$, $\alpha_3$, $\delta_1$, $\delta_2$, and $\delta_3$ are applicable if a DMA or a cluster is known (or assigned) to be a Type I or Type II defect. A methodology has been proposed in Chapter 3 to evaluate the probability of a given target defect (i.e. an ILI-reported defect) being a Type I defect, denoted by $P_{ID}$, using the following log-logistic function:

$$P_{ID} = \frac{e^{-7.56+3.50 \ln(\frac{s}{10})}}{1+e^{-7.56+3.50 \ln(\frac{s}{10})}}$$

(4.5)

where $s$ is the shortest distance between the target defect and its surrounding corrosion anomalies.

For a given target DMA with a probability of $P_{ID}$ being a Type I defect (i.e. a probability of (1-
\( P_{ID} \) being a Type II defect), the probability distribution of the measurement error associated with \( l_{\text{eff-ILI}} \) of the DMA, \( \alpha_{DMA} \), can be evaluated as:

\[
F_{DMA}(\alpha_{DMA}) = P_{ID}F_1(\alpha_{DMA}) + (1 - P_{ID})F_3(\alpha_{DMA}) 
\]

(4.6)

where \( F_{DMA}(\bullet) \), \( F_1(\bullet) \) and \( F_3(\bullet) \) are CDF of \( \alpha_{DMA} \), \( \alpha_1 \), and \( \alpha_3 \), respectively. The actual effective length of the target DMA then equals \( \alpha_{DMA}l_{\text{eff-ILI}} \). Similarly, the probability distribution of the measurement error associated with \( l_{\text{eff-ILI}} \) for a given target cluster, \( \alpha_{CL} \), is given by

\[
F_{CL}(\alpha_{CL}) = P_{ID}F_2(\alpha_{CL}) + (1 - P_{ID})F_3(\alpha_{CL}) 
\]

(4.7)

where \( F_{CL}(\bullet) \) and \( F_2(\bullet) \) are CDF of \( \alpha_{CL} \) and \( \alpha_2 \), respectively. The actual effective length of the target cluster equals \( \alpha_{CL}l_{\text{eff-ILI}} \). Similarly, Eqs. (8) and (9) below express the measurement errors (\( \delta_{DMA} \) and \( \delta_{CL} \)) associated with \( d_{\text{eff-ILI}} \) for a given target DMA and cluster, respectively.

\[
G_{DMA}(\delta_{DMA}) = P_{ID}G_1(\delta_{DMA}) + (1 - P_{ID})G_3(\delta_{DMA}) 
\]

(4.8)

\[
G_{CL}(\delta_{CL}) = P_{ID}G_2(\delta_{CL}) + (1 - P_{ID})G_3(\delta_{CL}) 
\]

(4.9)

where \( G_{DMA}(\bullet) \), \( G_{CL}(\bullet) \), \( G_1(\bullet) \), \( G_2(\bullet) \) and \( G_3(\bullet) \) are CDF of \( \delta_{DMA} \), \( \delta_{CL} \), \( \delta_1 \), \( \delta_2 \) and \( \delta_3 \), respectively, and the corresponding actual effective depth for the target DMA and cluster equals \( \delta_{DMA}d_{\text{eff-ILI}} \) and \( \delta_{CL}d_{\text{eff-ILI}} \), respectively. It must be emphasized that measurement error models described above are predicated on the ASME B31.4 interaction rule, i.e. the \( 3t_n \times 3t_n \) interaction rule.
4.4 Application in Reliability Analysis

4.4.1 Probability of Burst of the Corroded Pipelines

The application of the above-described measurement error models for $l_{\text{effILI}}$ and $d_{\text{effILI}}$ in the reliability analysis of corroded pipelines based on the RSTRENG model is illustrated in this section. The failure condition is defined as the internal operating pressure of the pipeline exceeding its burst pressure capacity at a given corrosion defect. The corresponding limit state function $g$ is expressed as follows:

$$g = r_p - P$$

(4.10)

where $r_p$ is the burst pressure capacity of the pipeline at the defect evaluated using the RSTRENG model; $P$ is the internal pressure of the pipeline, and $g \leq 0$ represents the failure (i.e. burst) condition. Let $X$ define the vector of basic random variables involved in the limit state function such as the measurement errors associated with $l_{\text{effILI}}$ and $d_{\text{effILI}}$, the pipe yield strength, and operating pressure. Furthermore, let $f_X(x)$ denote the joint probability density function (PDF) of $X$. The probability of failure, $P_f$, is given by

$$P_f = \int_{g \leq 0} f_X(x) dx$$

(4.11)

The first-order reliability method (FORM) (Melchers 1999b) is employed in this study to evaluate the integral in Eq. (4.11). It follows that $P_f \approx \Phi(-\beta)$, where $\Phi(\bullet)$ is the CDF of the standard normal distribution function, and $\beta$ is the reliability index representing the shortest distance between the origin and limit state surface in the standard normal space. The value of $\beta$ is obtained through a constrained optimization analysis in the FORM with the constraint being $g \leq 0$ in the standard normal space.
4.4.2 Analysis Cases and Input of the Reliability Analysis

The numerical example considered is a natural gas transmission pipeline with a nominal pipe outside diameter \((D_n)\) of 762 mm, a pipe steel grade of X42, a maximum operating pressure (MOP) of 6.0 MPa, and a nominal pipe wall thicknesses \((t_n)\) of 9.9 mm. It is assumed that the pipeline contains a single corrosion defect reported by ILI. The defect is assumed to be a DMA or cluster with different values of \(l_{eff-ILI}, d_{eff-ILI}\) and \(P_{ID}\). In total, 24 different scenarios are considered in the reliability analysis as summarized in Table 4.2.

**Table 4.2 Summary of analysis scenarios**

<table>
<thead>
<tr>
<th>Analysis scenarios</th>
<th>Defect Type</th>
<th>(l_{eff-ILI} (\text{mm}))</th>
<th>(\frac{d_{eff-ILI}}{t_n})</th>
<th>(s/t_n)</th>
<th>(P_{ID})</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>DMA</td>
<td>15</td>
<td>0.2</td>
<td>7</td>
<td>0.32</td>
</tr>
<tr>
<td>2</td>
<td>DMA</td>
<td>15</td>
<td>0.2</td>
<td>13</td>
<td>0.80</td>
</tr>
<tr>
<td>3</td>
<td>DMA</td>
<td>40</td>
<td>0.2</td>
<td>7</td>
<td>0.32</td>
</tr>
<tr>
<td>4</td>
<td>DMA</td>
<td>40</td>
<td>0.2</td>
<td>13</td>
<td>0.80</td>
</tr>
<tr>
<td>5</td>
<td>DMA</td>
<td>15</td>
<td>0.4</td>
<td>7</td>
<td>0.32</td>
</tr>
<tr>
<td>6</td>
<td>DMA</td>
<td>15</td>
<td>0.4</td>
<td>13</td>
<td>0.80</td>
</tr>
<tr>
<td>7</td>
<td>DMA</td>
<td>40</td>
<td>0.4</td>
<td>7</td>
<td>0.32</td>
</tr>
<tr>
<td>8</td>
<td>DMA</td>
<td>40</td>
<td>0.4</td>
<td>13</td>
<td>0.80</td>
</tr>
<tr>
<td>9</td>
<td>DMA</td>
<td>15</td>
<td>0.6</td>
<td>7</td>
<td>0.32</td>
</tr>
<tr>
<td>10</td>
<td>DMA</td>
<td>15</td>
<td>0.6</td>
<td>13</td>
<td>0.80</td>
</tr>
<tr>
<td>11</td>
<td>DMA</td>
<td>40</td>
<td>0.6</td>
<td>7</td>
<td>0.32</td>
</tr>
<tr>
<td>12</td>
<td>DMA</td>
<td>40</td>
<td>0.6</td>
<td>13</td>
<td>0.80</td>
</tr>
<tr>
<td>13</td>
<td>Cluster</td>
<td>100</td>
<td>0.2</td>
<td>7</td>
<td>0.32</td>
</tr>
<tr>
<td>14</td>
<td>Cluster</td>
<td>200</td>
<td>0.2</td>
<td>13</td>
<td>0.80</td>
</tr>
<tr>
<td>15</td>
<td>Cluster</td>
<td>100</td>
<td>0.2</td>
<td>7</td>
<td>0.32</td>
</tr>
<tr>
<td>16</td>
<td>Cluster</td>
<td>200</td>
<td>0.2</td>
<td>13</td>
<td>0.80</td>
</tr>
<tr>
<td>17</td>
<td>Cluster</td>
<td>100</td>
<td>0.4</td>
<td>7</td>
<td>0.32</td>
</tr>
<tr>
<td>18</td>
<td>Cluster</td>
<td>200</td>
<td>0.4</td>
<td>13</td>
<td>0.80</td>
</tr>
<tr>
<td>19</td>
<td>Cluster</td>
<td>100</td>
<td>0.4</td>
<td>7</td>
<td>0.32</td>
</tr>
<tr>
<td>20</td>
<td>Cluster</td>
<td>200</td>
<td>0.4</td>
<td>13</td>
<td>0.80</td>
</tr>
<tr>
<td>21</td>
<td>Cluster</td>
<td>100</td>
<td>0.6</td>
<td>7</td>
<td>0.32</td>
</tr>
<tr>
<td>22</td>
<td>Cluster</td>
<td>200</td>
<td>0.6</td>
<td>13</td>
<td>0.80</td>
</tr>
<tr>
<td>23</td>
<td>Cluster</td>
<td>100</td>
<td>0.6</td>
<td>7</td>
<td>0.32</td>
</tr>
<tr>
<td>24</td>
<td>Cluster</td>
<td>200</td>
<td>0.6</td>
<td>13</td>
<td>0.80</td>
</tr>
</tbody>
</table>
In terms of the measurement error associated with $l_{\text{eff-ILI}}$ and $d_{\text{eff-ILI}}$, two cases (Case I and Case II) are considered in this study. In Case I, the measurement errors of $l_{\text{eff-ILI}}$ and $d_{\text{eff-ILI}}$ are assumed based on typical ILI tool specifications, whereas the measurement error models proposed in this study are employed in Case II. It is noted that ILI tool specifications are generally stated such that measurement errors associated with $d_{\text{max-ILI}}$ and $l_{\text{ILI}}$, as opposed to $d_{\text{eff-ILI}}$ and $l_{\text{eff-ILI}}$, are inferred. However, measurement errors associated with $d_{\text{max-ILI}}$ and $l_{\text{ILI}}$ as inferred from the ILI tool specifications have been applied to $d_{\text{eff-ILI}}$ and $l_{\text{eff-ILI}}$, respectively, as a first approximation in practice (Adianto et al. 2018). Such a practice is adopted in this study. Therefore, two additive measurement errors, $\varepsilon_l$ and $\varepsilon_d$, are defined in Case I such that $l_{\text{eff}} = l_{\text{eff-ILI}} + \varepsilon_l$ and $d_{\text{eff}} = d_{\text{eff-ILI}} + \varepsilon_d$, where $\varepsilon_l$ and $\varepsilon_d$ are both zero-mean normal variates with the standard deviations equal to 7.8 mm and 7.8% $t_n$, respectively. It should also be noted that $\varepsilon_l$ and $\varepsilon_d$ are the same for both DMAs and clusters. The measurement errors considered in Case II are according to Table 1; that is, $l_{\text{eff}} = \alpha_{\text{DMA}} l_{\text{eff-ILI}}$ and $d_{\text{eff}} = \delta_{\text{DMA}} d_{\text{eff-ILI}}$ for DMA, and $l_{\text{eff}} = \alpha_{\text{CL}} l_{\text{eff-ILI}}$ and $d_{\text{eff}} = \delta_{\text{CL}} d_{\text{eff-ILI}}$ for clusters. The probability distributions of $\alpha_{\text{DMA}}$, $\delta_{\text{DMA}}$, $\alpha_{\text{CL}}$, and $\delta_{\text{CL}}$ are given by Eqs. (4.6)-(4.9). Furthermore, the probabilistic characteristics of the rest of the variables used in reliability analysis are summarized in Table 4.3.
Table 4.3 Probabilistic characteristics of random variables in the reliability analysis

<table>
<thead>
<tr>
<th>Variable</th>
<th>Distribution</th>
<th>Mean</th>
<th>COV (%)</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>( t/l_n^a )</td>
<td>Normal</td>
<td>1.0</td>
<td>1.5</td>
<td>CSA (2015)</td>
</tr>
<tr>
<td>( \sigma_y/SMYS^b )</td>
<td>Lognormal</td>
<td>1.1</td>
<td>3.5</td>
<td></td>
</tr>
<tr>
<td>( D/D_n^c )</td>
<td>Deterministic</td>
<td>1.0</td>
<td>0</td>
<td>Jiao et al. (1995)</td>
</tr>
<tr>
<td>( P/P_o^d )</td>
<td>Gumbel</td>
<td>1.0</td>
<td>3.0</td>
<td></td>
</tr>
<tr>
<td>( \delta_d % t_m^a )</td>
<td>Normal</td>
<td>0</td>
<td>7.8*</td>
<td>Stephens and Nessim (2006)</td>
</tr>
<tr>
<td>( \alpha_1 )</td>
<td>Lognormal</td>
<td>1.14</td>
<td>69.3</td>
<td></td>
</tr>
<tr>
<td>( \alpha_2 )</td>
<td>Lognormal</td>
<td>1.00</td>
<td>29.0</td>
<td></td>
</tr>
<tr>
<td>( \alpha_3 )</td>
<td>Lognormal</td>
<td>1.63</td>
<td>83.4</td>
<td></td>
</tr>
<tr>
<td>( \delta_1 )</td>
<td>Lognormal</td>
<td>0.67</td>
<td>38.8</td>
<td></td>
</tr>
<tr>
<td>( \delta_2 )</td>
<td>Lognormal</td>
<td>0.89</td>
<td>40.4</td>
<td></td>
</tr>
<tr>
<td>( \delta_3 )</td>
<td>Lognormal</td>
<td>1.06</td>
<td>41.5</td>
<td></td>
</tr>
<tr>
<td>( \alpha_l ) (mm)</td>
<td>Normal</td>
<td>0</td>
<td>7.8*</td>
<td>Zhou and Huang (2012)</td>
</tr>
<tr>
<td>( \xi^e )</td>
<td>Normal</td>
<td>1.067</td>
<td>16.5</td>
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</tbody>
</table>

* The values are standard deviation

* Based on Annex O of CSA Z662-15 (CSA 2015b), \( t/l_n \) follows a normal distribution with the mean ranging from 1.0 to 1.01 and COV ranging from 1.0 to 1.7%. present study considered normally distributed \( t/l_n \) with mean and COV equal to 1 and 1.5%, respectively

* Based on Annex O of CSA Z662-15 (CSA 2015b), both normal and lognormal distribution can be used for \( \sigma_y/SMYS \) with mean 1.1 and COV ranging from 3-3.5%. present study considered \( \sigma_y/SMYS \) follows a lognormal distribution with mean and COV equal to 1 and 3.5%, respectively

* Based on Annex O of CSA Z662-15 (CSA 2015b), \( D/D_n \) with no uncertainty and the present study assumed \( D/D_n \) is deterministic

* Based on Jiao et al. (1995), \( P/P_o \) follows a Gumbel distribution with mean between 1.03 and 1.07, and a COV between 1 and 2%. Present study used \( P/P_o \) follows a Gumbel distribution with mean and COV equal to 1 and 3%, respectively

* Based on Zhou and Huang (2012), model error for RSTRENG burst pressure capacity model, \( \xi \) follows a normal distribution with mean and COV equal to 1.067 and 16.5%, respectively, and used in the present study
4.4.3 Analysis Results and Discussion

Results of the reliability analysis for different scenarios listed in Table 2 are presented in Figure 4.5, where Figure 4.5(a) is for DMA and Figure 4.5(b) is for cluster. Regardless of DMA or cluster, it is observed that the reliability index $\beta$ corresponding to Case II with $s/t_n = 7$ is always lower (i.e. the probability of failure is higher) than those corresponding to Case I and Case II with $s/t_n = 13$. This is because a relatively small value of $s/t_n$ leads to a low value of $P_{ID}$, which subsequently results in higher uncertainties associated with $l_{eff(ILI)}$ and $d_{eff(ILI)}$. It is also observed that for relatively deep and/or long DMAs (i.e. scenarios 5 through 12), the $\beta$ values corresponding to Case II (irrespective of the value of $s/t_n$) are significantly lower than those corresponding to Case I. For clusters, the magnitude of the difference between the $\beta$ values corresponding to Case I and Case II is more scenario-specific. For example, there are marked differences between the $\beta$ values corresponding to Case I and Case II (irrespective of the value of $s/t_n$) for scenarios 21 and 22 in which $l_{eff(ILI)} = 100$ mm and $d_{eff(ILI)} = 0.6t_n$. However, for scenario 24 ($l_{eff(ILI)} = 200$mm, and $d_{eff(ILI)} = 0.6t_n)$ in Case I and Case II with $s/t_n = 13$ (Figure 4.5(b)), the $\beta$ values corresponding to Case I and Case II with $s/t_n = 13$ are almost the same, whereas the $\beta$ value corresponding to Case II with $s/t_n = 7$ is somewhat lower than those for Case I. These results suggest that the failure probability of deep and long clusters such as that considered in scenario 24 is not highly sensitive to the measurement errors associated with $l_{eff(ILI)}$ and $d_{eff(ILI)}$. Finally, it is noted that for relatively shallow and short defects such as the DMAs considered in scenarios 1 and 2 (in which $l_{eff(ILI)} = 15$ mm and $d_{eff(ILI)} = 0.2t_n$) and the clusters considered in scenarios 13 and 14 (in which $l_{eff(ILI)} = 100$ mm, and $d_{eff(ILI)} = 0.2t_n$), the $\beta$ values for Case I and Case II (irrespective of $s/t_n$) are comparable. This indicates that for relatively shallow and short (around 15 mm for DMAs and 100 mm for clusters) defects, the proposed measurement error model for $l_{eff(ILI)}$ and $d_{eff(ILI)}$ has negligible effects.
on the reliability analysis of corrosion defects compared with the measurement error model derived from the ILI tool specifications.

Figure 4.5. Reliability index, $\beta$ for different analysis scenarios for (a) DMA, and (b) Cluster
4.5 Conclusion

The present study evaluates the measurement errors associated with the ILI-based effective length and effective depth for a corrosion defect, as defined in the context of the RSTRENG model for evaluating the burst pressure capacity of corroded pipelines. The measurement errors are quantified based on the ILI and field measurements for 481 corrosion defects found on 209 pipe joints from 24 pipelines currently in service in Canada. The development of the measurement error model follows a strategy similar to that described in Chapter 3. That is, the probability distribution of the measurement error associated with $l_{eff\text{-}ILI}$ ($d_{eff\text{-}ILI}$) is the weighted average of those corresponding to Type I (i.e. defects containing no clustering error) and Type II (i.e. defects containing clustering error) defects, respectively, with the weighting factor being $P_{ID}$ and $(1 - P_{ID})$, respectively. The evaluation of $P_{ID}$ has been described in Chapter 3.

The application of the proposed measurement error model in reliability analysis using RSTRENG burst pressure capacity models is illustrated using a realistic pipeline example containing a single corrosion defect. Various scenarios in terms of the ILI-reported effective defect length and effective depth, as well as $P_{ID}$ values are considered. In addition, two cases are considered in the reliability analysis, whereas Case I represents the reliability analysis incorporating the ILI tool specification-based measurement error models, and Case II represents the reliability analysis incorporating the proposed measurement error models. Results of the reliability analysis show that, because of higher measurement uncertainties associated with $l_{eff\text{-}ILI}$ and $d_{eff\text{-}ILI}$ in Case II, the reliability index (i.e. $\beta$) corresponding to Case II is always lower (i.e. probability of failure is higher) than that corresponding to Case I. It is also observed from the results that for relatively shallow ($d_{eff\text{-}ILI}/t_n$ equal to about 0.2) and short defects (around 15 mm for DMAs and 100 mm for clusters), the $\beta$ values for Case I and Case II are comparable. For deeper
and/or longer DMAs, the $\beta$ values corresponding to Case II are significantly lower than those corresponding to Case I. For deeper and longer clusters, the difference between the $\beta$ values for Case I and Case II is sensitive to the specific values of $l_{\text{eff-ILI}}$, $d_{\text{eff-ILI}}$ and $P_{\text{ID}}$ involved in the analysis.

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5 Effects of In-line Inspection Sizing Uncertainties on System Reliability of Corroded Pipelines

5.1 Introduction

One of the major threats to the structural integrity of oil and gas pipelines is metal-loss corrosion as indicated by the historical pipeline incident data (Lam and Zhou 2016b). High-resolution in-line inspection (ILI) tools are used by the pipeline operators to periodically detect and size corrosion defects on pipelines. The corrosion defect sizes reported by ILI involve measurement uncertainties (Al-Amin et al. 2012). In addition, there are uncertainties associated with such parameters as the pipe geometric and mechanical parameters that are relevant to the burst pressure capacity of corroded pipelines. The reliability-based method provides an effective framework to incorporate all the aforementioned uncertainties in assessing the structural integrity of corroded pipeline and determining appropriate maintenance actions. This method has been more and more adopted by pipeline operators (Zhou et al. 2006; Kariyawasam and Peterson 2008).

ILI tools may report simple geometric characteristics of corrosion defects only, i.e. the maximum defect depth and defect length (see Fig. 2.1). In this case, the B31G Modified model (Kiefner and Vieth 1989) is widely used to deterministically evaluate the burst pressure capacity of a pipeline at an ILI-reported corrosion defect as a function of the maximum defect depth and defect length, in addition to the pipe geometric and material properties. Certain ILI tools may be able to report the so-called river-bottom profiles of corrosion defects. In this case, the RSTRENG model (Kiefner and Vieth 1989) is widely used to predict the burst pressure capacities $s$ of corroded pipelines, whereby the burst pressure at the corrosion defect is a function of the effective depth and effective length of the defect profile. There is a significant amount of literature on the quantification of the measurement error associated with the ILI-reported maximum defect depth
(Bhatia et al. 1998; Caley et al. 2007; Al-Amin et al. 2012), but little literature on the measurement errors associated with the ILI-reported defect length, effective length and effective depth. In Chapter 3 of this thesis, a measurement error model for the ILI-reported defect length is proposed, and measurement error models for the ILI-based effective depth and length are proposed in Chapter 4. The implications of the above-mentioned measurement error models for the reliability of a pipeline containing a single corrosion defect have been investigated and described in Chapters 3 and 4. However, a corroded pipeline section almost always contains multiple (as opposed to a single) corrosion defects. Since failure at any defect implies failure of the pipeline section, it is a series system with the system components being the corrosion defects. It follows that the reliability analysis of the pipeline section is a system reliability problem. The system reliability analysis must take into account the fact that failures at different defects are correlated events. The correlation may arise from the spatial correlations of the pipe geometric and material properties, and internal pressures at different defects. Furthermore, the measurement errors associated with ILI-reported sizes of different defects may be correlated. Ignoring the potential correlation between different defects leads to conservative estimates of the system failure probability. However, overly conservative estimates of the failure probability may lead to unnecessary corrosion mitigation actions, which translate to significant cost penalties to the pipeline operators.

The objective of the present study is to investigate the implications of the measurement error models proposed in Chapters 3 and 4 for the system reliability of corroded pipelines. To this end, the system reliability of a corroded pipe joint (containing multiple corrosion defects) that is a part of a natural gas transmission pipeline currently in service in Canada is analyzed. The sensitivity of
the system reliability to the correlation between random variables associated with different corrosion defects is also investigated.

The rest of this chapter is organized as follows. Section 5.2 describes the B31G Modified and RSTRENG models as well as methodology for carrying out the system reliability analysis of a corroded pipe joint; Section 5.3 describes the input of the reliability analysis that includes a detail description of the pipe joint used in the case study along with the probabilistic characteristics of the input variables of the pipe joint. Section 5.4 presents the analysis results and discussions followed by concluding remarks in Section 5.5.

5.2 Reliability Analysis of Corroded Pipe Joint

5.2.1 Burst Pressure Capacity Models

Let $P_b$ denote the burst pressure capacity of a pipe joint at a corrosion defect. Then $P_b$ can be evaluated using the B31G Modified and RSTRENG model as follows.

**B31G Modified**

$$P_b = \xi_1 \left[ \frac{2t}{D} \left( \frac{\sigma_f + 68.95}{D} \right) \left[ \frac{1 - 0.85d_{\text{max}}}{t} \right] \right], \quad \frac{d_{\text{max}}}{t} \leq 0.8 \quad (5.1)$$

$$M = \begin{cases} \sqrt{1 + 0.6275 \left( \frac{l^2}{Dt} \right) - 0.003375 \left( \frac{l^4}{(Dt)^2} \right)} & \frac{l^2}{Dt} \leq 50 \\ 3.3 + 0.032 \left( \frac{l^2}{Dt} \right) & \frac{l^2}{Dt} > 50 \end{cases} \quad (5.2)$$

**RSTRENG**

$$P_b = \min\{P_{bi}\} \quad i = 1, 2, \ldots, n, \quad (5.3)$$

$$P_{bi} = \xi_2 \frac{2t(\sigma_f + 68.95)}{D} \left[ \frac{1 - A_i}{A_i} \right] \left[ \frac{1 - A_i}{M_i} \right] \quad (5.4)$$
where \( d_{\text{max}} \) and \( l \) denote the maximum depth and length of the corrosion defect, respectively; \( D \) and \( t \) are the pipe outside diameter and wall thickness, respectively; \( \sigma_y \) and \( \sigma_y + 68.95 \) (MPa) are the pipe yield strength and flow stress, respectively; \( M \) is the Folias factor, and \( \xi_1 \) and \( \xi_2 \) are the model errors associated with the B31G Modified and RSTRENG models, respectively.

To apply the RSTRENG model, one needs to generate \( n \) sub-defects based on the defect profile, each sub-defect being a contiguous portion of the overall defect. The area and length of the \( i \)-th (\( i = 1, 2, \ldots, n \)) sub-defect are denoted by \( A_i \) and \( l_i \), respectively, and the corresponding Folias factor \( M_i \) is evaluated by replacing \( l \) with \( l_i \) in Eq. (5.2). The sub-defect that has the lowest burst pressure is defined as the effective portion of the overall defect, with the corresponding area length and average depth defined as the effective area (\( A_{\text{eff}} \)), effective length (\( l_{\text{eff}} \)) and effective depth (\( d_{\text{eff}} = A_{\text{eff}} / l_{\text{eff}} \)) of the defect, respectively. Consequently, Eqs. (5.3) and (5.4) can be replaced by the following equation:

\[
P_b = \xi_2 \frac{2t(\sigma_y + 68.95)}{D} \frac{1 - \frac{d_{\text{eff}}}{l}}{1 - \frac{d_{\text{eff}}}{M_{\text{eff}}}} \tag{5.5}
\]

where \( M_{\text{eff}} \) is evaluated by using Eq. (5.2) and replacing \( l \) by \( l_{\text{eff}} \).

### 5.2.2 Probability of Burst of the Corroded Pipe Joint

A pipe joint containing \( r \) corrosion defects can be considered as a system with \( r \) components. The limit state function at the \( j \)-th (\( j = 1, 2, \ldots, r \)) defect, \( g_j \), is given by,

\[
g_j = P_{b_{\text{eff}}} - P_j \tag{5.6}
\]
where $P_{bj}$ is the burst pressure capacity of the pipe joint at the $j$-th defect and can be evaluated using the B31G Modified or RSTRENG model as shown in Eqs. (5.1) – (5.5), and $P_j$ denotes the internal pressure at the $j$-th defect. Failure at the $j$-th defect is defined as $g_j \leq 0$. Let $X_j$ denote a vector of $m_j$ random variables (such as the measurement errors, pipe wall thickness, and yield strength) that need to be considered for $g_j(x_j)$; $x_j$ denotes the values of $X_j$. To evaluate the failure probability of the pipe joint, let $X$ denote the union of all $X_j$ ($j = 1, 2, \ldots, r$), representing a vector of $m$ random variables that needs to be considered for the system. For systems containing a large number of components, it follows that $m$ can be much larger than $m_j$. The multidimensional integral to evaluate the failure probability, $P_f$, of the system is,

$$P_f = \int_{\bigcup g_j(x_j) \leq 0} f_X(x) \, dx \tag{5.7}$$

where $\bigcup g_j(x_j) \leq 0$ ($j = 1, 2, \ldots, r$) denotes the union of $g_j \leq 0$. The first-order reliability method (FORM) (Madsen et al. 2006) is employed in this study to evaluate the integral in Eq. (5.7). To this end, $P_f$ is given by (Melchers 1999b).

$$P_f = 1 - \Phi_r(\beta^s, \Sigma) \tag{5.8}$$

where $\Phi_r(\cdot, \cdot)$ is the $r$-dimensional standard normal distribution function; $\beta^s = [\beta_1, \beta_2, \ldots, \beta_r]$ is the vector of $r$ reliability indices obtained from the FORM corresponding to the $r$ components (i.e. defects) of the system, and $\Sigma$ is the correlation matrix of the $r$-dimensional standard normal distribution function with the diagonal elements equal to unity and off-diagonal elements denoted by $\rho_{jk}$ ($j, k = 1, 2, \ldots, r$). The variable $\rho_{jk}$ represents the correlation between the limit state functions, $g_j(x_j)$ and $g_k(x_k)$ (Der Kiureghian 2005; Madsen et al. 2006).
Key to the evaluation of $P_f$ from Eq. (5.8) is to compute $\rho_{jk}$ ($j, k = 1, 2, \ldots, r$) and the $r$-dimensional normal probability distribution function given $\beta^s$ and $\Sigma$. The value of $\rho_{jk}$ can be evaluated as $(u^*(j))^T(u^*(k))/(\beta_j\beta_k)$ (Madsen et al. 2006; Zhou et al. 2017), where $u^*(j)$ and $u^*(k)$ are two $m$-dimensional vectors representing values of the $m$ random variables (i.e., those involved in the entire system) in the standard normal space at the so-called design points associated with $\beta_j$ and $\beta_k$, respectively, obtained from the FORM (Zhou et al. 2017). The conventional approach to obtain $u^*(j)$ and $u^*(k)$ is to involve all $m$ random variables in the standard normal space in the FORM, which is essentially a constrained optimization analysis (Der Kiureghian 2005; see also Chapter 2), for evaluating $\beta_j$ and $\beta_k$, although the limit state functions $g_j(x_j)$ and $g_k(x_k)$ only involve $m_j$ and $m_k$ random variables, respectively, in the physical space (rather than the standard normal space). For systems involving a large number of components, $m$ is often much larger than $m_j$ and $m_k$. Therefore, the computational efficiency and robustness of the conventional approach for evaluating $u^*(j)$ and $u^*(k)$ (as well as $\beta_j$ and $\beta_k$) decreases significantly for systems with many components. Such a deficiency is resolved by a methodology recently proposed by Zhou et al. (2017). The essence of Zhou et al.’s methodology is that the FORM analysis for obtaining $\beta_j$ ($j = 1, 2, \ldots, r$) can be performed in the $m_j$-dimensional normal space, as opposed to the $m$-dimensional normal space involved in the conventional approach. The $m_j$-dimensional design point obtained from the FORM analysis is then mapped to the corresponding $m$-dimensional design point $u^*(j)$ through a simple operation of the correlation matrix of the $m$ random variables involved in the system. Zhou et al.’s methodology is employed in the present study. The computation of $\Phi_r(\beta^s, \Sigma)$ is straightforward as long as $r$ is not too large: the built-in function, mvncdf, in MATLAB R can accurately evaluate $\Phi_r(\beta^s, \Sigma)$ for $r \leq 25$. This function is employed
in the present study, as the number of defects considered for the example pipe joint is less than 25. Note that for analyses involving \( r > 25 \), a computationally efficient methodology based on the equivalent component concept recently proposed by Gong and Zhou (2017) can be used to compute \( \Phi_r(\mathbf{\beta}^\ast, \Sigma) \).

5.3 Input of the Reliability Analysis

5.3.1 Attributes of Pipe Joint

To demonstrate the application of the proposed measurement error models in the system reliability analysis, a pipe joint that is a part of an in-service pipeline in Canada is used. The pipe joint is 12.4 m long with a nominal outside diameter \((D_n)\) of 508 mm, a nominal pipe wall thickness \((t_n)\) 7.14 mm, a nominal operating pressure \((P_o)\) of 5.66 MPa, and a steel grade of X52 (specified minimum yield strength (SMYS) = 359 MPa). An ILI conducted in 2013 found a significant number of corrosion anomalies, 306 in total, in the pipe joint. By applying the ASME B31.4 interaction rule (i.e. \(3t_n \times 3t_n\) interaction rule, see Chapter 3), the 306 corrosion anomalies are further categorized as 158 individual anomalies (denoted as DMAs in this study) and 39 clusters. The maximum defect depths, defect lengths ad effective defect depths and lengths for the DMAs and clusters are provided in the ILI report. A schematic view of the 197 DMAs and clusters in the pipe joint is shown in the Figure 5.1, where Figure 5.1(a) shows the corrosion defects within a 6.53 m-long portion of the pipe joint, i.e. between the upstream girth weld (UGW) and 6.53 m downstream of UGW, and Figure 5.1(b) depicts the corrosion defects within the remaining portion of the pipe joint, i.e. between 6.53 and 12.4 m downstream of UGW. In the pipeline industry, corrosion defects with maximum defect depths less than or equal to 20% of \(t_n\) are typically considered to have a negligible impact on the burst pressure capacity of the pipeline (Kiefner and Vieth 1989), regardless of the defect length. This practice is adopted in the present study to limit
the total number of corrosion defects considered in the reliability analysis. To this end, 22 corrosion defects out of a total 197 defects on the pipe joint are reported by ILI tool to have maximum defect depths great than 20% of $t_n$; therefore, these 22 defects are included in the reliability analysis. Among them, 14 and 8 defects are DMAs and clusters, respectively. The geometric characteristics of the 22 defects as reported by ILI are summarized in Table 5.1.
Figure 5.1 Schematic representation of ILI reported corrosion defects in a pipe joint (a) 0-6.53m, and (b) 6.53m-12.4m of a 12.4m pipe joint
Table 5.1 Detail measurements of the DMAs of the pipe joint

<table>
<thead>
<tr>
<th>Individual defect identifier</th>
<th>ILI information</th>
<th></th>
<th></th>
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<th></th>
</tr>
</thead>
<tbody>
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<td></td>
<td>Maximum defect depth, $d_{\text{max}-\text{ILI}}$ (% of $t_n$)</td>
<td>Defect length, $l_{\text{ILI}}$ (mm)</td>
<td>Effective defect depth, $d_{\text{eff-ILI}}$ (% of $t_n$)</td>
<td>Effective defect length, $l_{\text{eff-ILI}}$ (mm)</td>
<td>$s^*/t_n$</td>
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<td>21.9</td>
<td>18.2</td>
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</table>

$s^*$ = Shortest distance to the surrounding anomalies

5.3.2 Analysis Cases and Probabilistic Characteristics of Random Variables

Two scenarios are considered in the system reliability analysis in terms of the burst capacity model employed: The B31G Modified model is employed in Scenario 1, and the RSTRENG model is employed in Scenario 2. For the B31G Modified model, two cases (Case I and Case II) are
considered in this study in terms of the measurement error associated with $l_{ILI}$. In Case I, the measurement error implied by the typical vendor specification of the ILI tool is applied. For the ILI-reported defect length, the typical tool specification states that $l_{ILI}$ is within ±10 mm of the actual defect length ($l$) 80% of the time (Stephens and Nessim 2006). This implies that $l = l_{ILI} + \varepsilon$, where $\varepsilon$ is a normal variate with a zero mean and a standard deviation equal to 7.8 mm (Stephens and Nessim 2006). In Case II, the measurement error model proposed in Chapter 3 is applied. The probability of a given target defect (i.e., an ILI-reported defect) being a Type I defect, denoted by $P_{ID}$, is evaluated using the log-logistic function in Eq. (5.9) (see Chapter 3), and the calculated $P_{ID}$ values for 22 corrosion defects for the case study are shown in Table 5.1.

$$P_{ID} = \frac{e^{-7.56+3.50 \ln\left(\frac{\varepsilon}{\varepsilon_{n}}\right)}}{1+e^{-7.56+3.50 \ln\left(\frac{\varepsilon}{\varepsilon_{n}}\right)}}$$

(5.9)

For a given target DMA with a probability of $P_{ID}$ being a Type I defect (i.e., a probability of $(1-P_{ID})$ being a Type II defect), the probability distribution of the measurement error associated with $l_{ILI}$ of the DMA ($\alpha_{DMA}$) and cluster ($\alpha_{CL}$) can be evaluated as:

$$F_{DMA}(\varepsilon_{DMA}) = P_{ID}F_1(\varepsilon_{DMA}) + (1 - P_{ID})F_3(\varepsilon_{DMA})$$

(5.10)

$$F_{CL}(\varepsilon_{CL}) = P_{ID}F_2(\varepsilon_{CL}) + (1 - P_{ID})F_3(\varepsilon_{CL})$$

(5.11)

where $F_{DMA}(\bullet)$, $F_1(\bullet)$, $F_3(\bullet)$, $F_{CL}(\bullet)$ and $F_2(\bullet)$ are CDF of $\alpha_{DMA}$, $\alpha_1$, $\alpha_3$, $\alpha_{CL}$ and $\alpha_2$, respectively and the probability distributions of $\alpha_1$, $\alpha_2$, and $\alpha_3$ are given in Table 5.2. The actual defect length, $l$ can be evaluated as, $l = \varepsilon_{DMA}l_{ILI}$ for DMA and $l = \varepsilon_{CL}l_{ILI}$ for clusters.

For the RSTRENG model, two cases (Case I and Case II) are also considered in terms of the measurement error associated with $l_{eff-ILI}$ and $d_{eff-ILI}$. Case I involves the measurement errors of $l_{eff-ILI}$ and $d_{eff-ILI}$ derived from typical ILI tool specifications (Adianto et al. 2018), where $l_{eff} = l_{eff-ILI} +$
and $d_{\text{eff}} = d_{\text{eff-ILI}} + \varepsilon_{d}$. The additive error $\varepsilon_{\ell}$ is the same as described previously for Case I for the B31G Modified model and $\varepsilon_{d}$ is assumed to be a normal variate with a zero mean and a standard deviation of $7.8\% t_n$ (Stephens and Nessim 2006; DNV-RP-F101 2010b). On the other hand, for Case II the measurement error models proposed in Chapter 4 in this study are employed. It should be noted that $\varepsilon_{\ell}$ and $\varepsilon_{d}$ are the same for both DMAs and clusters for the B31G Modified and RSTRENG models. The measurement errors considered in Case II are according to Table 5.2; that is, $l_{\text{eff}} = \alpha_{\text{DMA}} l_{\text{eff-ILI}}$ and $d_{\text{eff}} = \delta_{\text{DMA}} d_{\text{eff-ILI}}$ for DMA, and $l_{\text{eff}} = \alpha_{\text{CL}} l_{\text{eff-ILI}}$ and $d_{\text{eff}} = \delta_{\text{CL}} d_{\text{eff-ILI}}$ for clusters. The probability distributions of $\alpha_{\text{DMA}}, \delta_{\text{DMA}}, \alpha_{\text{CL}}$ and $\delta_{\text{CL}}$ are given by the following equations.

\[
F_{\text{DMA}}(\alpha_{\text{DMA}}) = P_{\text{ID}} F_{1}(\alpha_{\text{DMA}}) + (1 - P_{\text{ID}}) F_{3}(\alpha_{\text{DMA}}) \tag{5.12}
\]

\[
F_{\text{CL}}(\alpha_{\text{CL}}) = P_{\text{ID}} F_{2}(\alpha_{\text{CL}}) + (1 - P_{\text{ID}}) F_{3}(\alpha_{\text{CL}}) \tag{5.13}
\]

\[
G_{\text{DMA}}(\delta_{\text{DMA}}) = P_{\text{ID}} G_{1}(\delta_{\text{DMA}}) + (1 - P_{\text{ID}}) G_{3}(\delta_{\text{DMA}}) \tag{5.14}
\]

\[
G_{\text{CL}}(\delta_{\text{CL}}) = P_{\text{ID}} G_{2}(\delta_{\text{CL}}) + (1 - P_{\text{ID}}) G_{3}(\delta_{\text{CL}}) \tag{5.15}
\]

where $F_{\text{DMA}}(\bullet), F_{\text{CL}}(\bullet), F_{1}(\bullet), F_{2}(\bullet)$ and $F_{3}(\bullet)$ are CDF of $\alpha_{\text{DMA}}, \alpha_{\text{CL}}, \alpha_{1}, \alpha_{2}$, and $\alpha_{3}$, respectively; and $G_{\text{DMA}}(\bullet), G_{\text{CL}}(\bullet), G_{1}(\bullet), G_{2}(\bullet)$ and $G_{3}(\bullet)$ are CDF of $\delta_{\text{DMA}}, \delta_{\text{CL}}, \delta_{1}, \delta_{2}$ and $\delta_{3}$, respectively. The probability distributions of $\alpha_{1}, \alpha_{2}, \alpha_{3}, \delta_{1}, \delta_{2}$ and $\delta_{3}$ are given in Table 5.2.

The details of the other variables included in the limit state function, along with their distribution parameters are given in Table 5.2 as well. Random variables representing different physical parameters are assumed to be mutually independent. However, potential correlations among random variables representing the same physical parameter but at different defects are considered in the analysis. To this end, the pipe steel yield strengths ($\sigma_{y}$) at different defects are assumed to be identical. The same assumption applies to the pipeline internal operating pressure ($P$). The wall thicknesses ($t$) at different defects are assumed to be highly correlated with a
correlation coefficient of 0.9. The measurement errors associated with $l_{ILI}$, $l_{eff-ILI}$, $d_{max-ILI}$, and $d_{eff-ILI}$ at different defects are considered correlated as well. Three different correlation coefficients are assumed in this study: 0.2, 0.5, and 0.9 representing low (L), medium (M), high (H) correlations, respectively. It should be pointed out that the correlations between non-normally distributed random variables in the FORM analysis can be dealt with using the Nataf transformation (Der Kiureghian and Liu 1986). Empirical equations that can be used to estimate the equivalent correlation coefficient in the normal space given the correlation coefficient in the non-normal space have been developed by Der Kiureghian and Liu (1986) for commonly used non-normal marginal distributions such as the exponential, gamma and Weibull distributions. However, the equivalent correlation coefficient in the normal space is in general only slightly higher than that in the non-normal space (Der Kiureghian and Liu 1986); for the sake of simplicity, the Nataf transformation is not employed in this study. The correlation coefficients in the non-normal space are directly incorporated in the FORM analysis.
Table 5.2 Probabilistic characteristics of random variables in the reliability analysis

<table>
<thead>
<tr>
<th>Input for Variable</th>
<th>Distribution</th>
<th>Mean</th>
<th>COV (%)</th>
<th>Correlation at different defects</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>$t/t_n$</td>
<td>Normal</td>
<td>1.0</td>
<td>1.5</td>
<td>0.9</td>
<td>CSA (2015)</td>
</tr>
<tr>
<td>$\sigma_y$/SMYS</td>
<td>Lognormal</td>
<td>1.1</td>
<td>3.5</td>
<td>Fully correlated</td>
<td>Jiao et al. (1995)</td>
</tr>
<tr>
<td>$D/D_n$</td>
<td>Deterministic</td>
<td>1.0</td>
<td>0</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>$P/P_o$</td>
<td>Gumbel</td>
<td>1.0</td>
<td>3.0</td>
<td>Fully correlated</td>
<td>Stephens and Nessim (2006)</td>
</tr>
<tr>
<td>$\varepsilon_1$</td>
<td>Normal</td>
<td>0</td>
<td>7.8*</td>
<td>(L, M, H) = (0.2, 0.5, 0.9)</td>
<td>Chapter 3</td>
</tr>
<tr>
<td>$\varepsilon_2$</td>
<td>Lognormal</td>
<td>1.32</td>
<td>65.2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\varepsilon_3$</td>
<td>Lognormal</td>
<td>1.01</td>
<td>29.7</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\xi_1$</td>
<td>Lognormal</td>
<td>2.89</td>
<td>122.8</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\alpha_1$</td>
<td>Lognormal</td>
<td>1.14</td>
<td>69.3</td>
<td></td>
<td>Chapter 4</td>
</tr>
<tr>
<td>$\alpha_2$</td>
<td>Lognormal</td>
<td>1.00</td>
<td>29.0</td>
<td>(L, M, H) = (0.2, 0.5, 0.9)</td>
<td></td>
</tr>
<tr>
<td>$\alpha_3$</td>
<td>Lognormal</td>
<td>1.63</td>
<td>83.4</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\delta_1$</td>
<td>Lognormal</td>
<td>0.67</td>
<td>38.8</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\delta_2$</td>
<td>Lognormal</td>
<td>0.89</td>
<td>40.4</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\delta_3$</td>
<td>Lognormal</td>
<td>1.06</td>
<td>41.5</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\xi_2$</td>
<td>Normal</td>
<td>1.067</td>
<td>16.5</td>
<td>Independent</td>
<td>Zhou and Huang (2012)</td>
</tr>
</tbody>
</table>

* Based on Annex O of CSA Z662-15 (CSA 2015b), $t/t_n$ follows a normal distribution with the mean ranging from 1.0 to 1.01 and COV ranging from 1.0 to 1.7%. Present study considered normally distributed $t/t_n$ with mean and COV equal to 1 and 1.5%, respectively

* Based on Annex O of CSA Z662-15 (CSA 2015b), both normal and lognormal distribution can be used for $\sigma_y$/SMYS with mean 1.1 and COV ranging from 3-3.5%. Present study considered $\sigma_y$/SMYS follows a lognormal distribution with mean and COV equal to 1 and 3.5%, respectively

* Based on Jiao et al. (1995), $P/P_o$ follows a Gumbel distribution with mean between 1.03 and 1.07, and a COV between 1 and 2%. Present study used $P/P_o$ follows a Gumbel distribution with mean and COV equal to 1 and 3%, respectively

* The values denote standard deviation
5.4 Results and Discussion

The probabilities of failure (burst) of the pipe joint corresponding to two scenarios (Scenarios 1 and 2), two cases (Cases I and II), and three assumed spatial correlations for the ILI measurement errors are summarized in Table 5.3. For Scenario 1 (i.e. employing the B31G Modified model), $P_f$ in general decreases only slightly with the increase of the spatial correlation of the ILI measurement error. This suggests that the effect of spatial correlation of the ILI measurement error has a negligible effect on the system failure probability if the B31G Modified model is employed in the analysis. Similar observation is obtained on results corresponding to Scenario 2-Case I. For Scenario 2 (i.e. employing the RSTRENG model) - Case II, the system failure probability is somewhat sensitive to the spatial correlation of the ILI measurement error: $P_f$ doubles if the spatial correlation coefficient decreases from the high value (0.9) to the low value (0.2). For Scenario 1, the system failure probability corresponding to Case II is about four times that corresponding to Case I, as a higher uncertainty in the measurement error associated with $l_{ILI}$ is considered in Case II. For Scenario 2, the system failure probability corresponding to Case II is about 100-250 times that corresponding to Case I, depending on the degree of the spatial correlation, as higher measurement uncertainties associated with $d_{eff-ILI}$ and $l_{eff-ILI}$ are considered in Case II. Given Case I (i.e. employing ILI tool specification-based measurement errors), the system failure probability corresponding to Scenario 1 is about 2.6 times that corresponding to Scenario 2. Given Case II, however, the system failure probability corresponding to Scenario 2 is about 10-23 times that corresponding to Scenario 1. This suggests that the system reliability analysis employing the RSTRENG model is more impacted by the ILI measurement error models developed in this study than that employing the B31G Modified model.
Table 5.3. Results of reliability analysis of the example pipe joint

<table>
<thead>
<tr>
<th>Scenario no</th>
<th>Case no</th>
<th>Correlation at different defects</th>
<th>$P_f$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scenario 1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(B31G Modified)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Case I</td>
<td>L</td>
<td>3.63E-03</td>
<td>8.46E-04</td>
</tr>
<tr>
<td></td>
<td>M</td>
<td>8.46E-04</td>
<td></td>
</tr>
<tr>
<td></td>
<td>H</td>
<td>3.40E-03</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Case II</td>
<td>L</td>
<td>3.23E-04</td>
<td></td>
</tr>
<tr>
<td></td>
<td>M</td>
<td>3.22E-04</td>
<td></td>
</tr>
<tr>
<td></td>
<td>H</td>
<td>3.40E-03</td>
<td></td>
</tr>
<tr>
<td>Scenario 2</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(RSTRENG)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Case I</td>
<td>L</td>
<td>8.19E-02</td>
<td></td>
</tr>
<tr>
<td></td>
<td>M</td>
<td>6.46E-02</td>
<td></td>
</tr>
<tr>
<td></td>
<td>H</td>
<td>3.33E-02</td>
<td></td>
</tr>
<tr>
<td>Case II</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The relative contributions of the 22 corrosion defects to $P_f$ are shown in Figure 2. Let $c_j (j = 1, 2, ..., 22)$ denote the relative contribution of the $j$-th defect to $P_f$, whereby $c_j$ is defined as follows:

$$c_j = \frac{P_{fj}/P_f}{\sum_{j=1}^{22} (P_{fj}/P_f)}$$  \hfill (5.16)

where $P_{fj}$ denotes the estimated probability of failure of the $j$-th corrosion defect. Figure 2 also includes the factor of safety ($FS$) for the 22 corrosion defects. For the $j$-th defect, the factor of safety computed using the B31G Modified model, denoted as $FS_{j-B}$, is defined as,

$$FS_{j-B} = \frac{2t_n(SMYS + 68.95)}{D_n + P_o} \left[ \frac{1 - 0.85d_{max-HL,j}}{t_n} \right] \left[ \frac{1 - 0.85d_{max-HL,j}}{M_f t_n} \right]$$  \hfill (5.17)
where $M_j$ can be evaluated using Eq. (5.2) by replacing $l$ by $l_{ILI,j}$. The factor of safety computed using the RSTRENG model, denoted by $FS_{j,R}$, is defined as,

$$FS_{j-R} = \frac{2t_n(SMY + 68.95)}{D_nP_0} \left[ \frac{0.85d_{eff-ILI,j}}{t_n} \right] \left[ 1 - \frac{0.85d_{eff-ILI,j}}{M_jt_n} \right]$$

where $M_j$ can be evaluated using Eqs. (5.2) by replacing $l$ by $l_{eff-ILI,j}$. The maximum operating pressure, $P_o$, in Eqs. (5.17) and (5.18) is 5.66 MPa for the example pipe joint used in this study. Note that the factors of safety as expressed in Eqs. (5.17) and (5.18) are widely used in the deterministic assessment of corrosion defects in the pipeline industry. Note also that the results in Figures 5.2(a)-5.2(d) correspond to the spatial correlation coefficient equal to 0.5 (i.e. medium or M) at different corrosion defects, as the similar trend of the relative contributions to $P_f$ is observed for the other two correlation cases (i.e. L and H). Figures 5.2(a) and 5.2(c) depict the values of $c_j$ for Scenario 1 (i.e. B31G Modified model) - Case I and Scenario 2 (i.e. RSTRENG model) - Case I, respectively, whereas Figures 5.2(b) and 5.2(d) depict the values of $c_j$ for Scenario 1 - Case II and Scenario 2 – Case II, respectively. Figures 5.2(a) and 5.2(c) indicate that $c_j$ decreases as the factor of safety increases under Case I. On the other hand, Figures 5.2(b) and 5.2(d) indicate that $c_j$ does not depend strongly on the factor of safety under Case II. As Case I employs ILI tool specification-based measurement error models, which involve relatively low uncertainties and do not differentiate between DMA and clusters, there is a clear one-to-one relationship between $c_j$ and $FS_{j,B}$ ($FS_{j,R}$). For Case II, the uncertainty in the ILI measurement error increases with the decrease of $P_{ID}$. As a result, there is no definite relationship between $c_j$ and $FS_j$ for Case II. It can be comprehended from this analysis that the reliability-based corrosion defect assessment provides equivalent results as deterministic defect assessment (i.e. evaluated $FS_j$) for Case I; however, the
reliability-based assessment will lead to markedly different outcomes compared with factor-of-safety-based deterministic assessments.
Corrosion defect ($d_{eff-ILI}/t_n$, $l_{eff-ILI}$)
The present study evaluates the effect of the measurement error models proposed in Chapter 3 and 4 in this thesis, on the system reliability of a pipe joint. To this end, a real pipe joint that is currently in service in Canada is considered for the analysis. The pipe joint contains a significant number of corrosion defects identified by ILI, among which 22 corrosion defects with the maximum defect depth greater than 20\% of wall thickness are considered in the reliability analysis. The detail measurements of all corrosion defects (i.e. Maximum defect depth ($d_{\text{max-ILI}}$), defect length ($l_{\text{ILI}}$), effective defect depth ($d_{\text{eff-ILI}}$), effective defect length ($l_{\text{eff-ILI}}$)) contained in the pipe joint are known from a previous in-line inspection (ILI). Furthermore, the study also evaluates...
the effect of the correlation of the proposed measurement error models at different defects in a pipe joint on system reliability; whereas pipe physical parameters such as, wall thickness, and yield strength, and pipe internal pressure are considered highly correlated, and the measurement errors associated with the ILI measured corrosion defect geometric parameters are correlated by different correlation parameters (i.e. varying from high to low correlations).

The present study demonstrates two cases for the evaluation of system reliability of the pipe joint. Case I employs the ILI tool specification-based measurement error models in the B31G Modified and RSTRENG burst pressure capacity models, and Case II employs the measurement error models proposed in Chapters 3 and 4 in the B31G Modified and RSTRENG models, respectively. The evaluated system probability of failure (burst) of a pipe joint using the B31G Modified model is about two order of magnitude lower than that using the RSTRENG model for Case II, whereas for Case I, the evaluated probability of failure for B31G modified model is approximately two times higher than the RSTRENG. The correlation of measurement errors at different corrosion defects is found to be have insignificant effects on the system failure probability, if the B31G Modified model is employed. On the other hand, the spatial correlation of measurement errors has a somewhat large impact on the system failure probability if the RSTRENG model in conjunction with the proposed measurement error model is employed. In addition to that, the estimated probability of failure of the pipe joint is found always higher for Case II than Case I for both B31G modified and RSTRENG burst pressure capacity models, due to high uncertainty involve in the proposed measurement error models used in Case II. However, RSTRENG model with Case II showed highest probability of pipe system failure among all the other cases considered, as higher uncertainty is involved to both the effective defect depth ($d_{eff-ILI}$), and effective defect length ($l_{eff-ILI}$) as opposed to Case II with B31G modified model.
where high uncertainty is only involve in defect length \( (l_{III}) \). Furthermore, it is observed that, for Case I, the results obtained from the reliability-based corrosion assessment have a one – to – one relationship with the deterministic corrosion assessment; however, no such trend is observed for Case II for both the B31G Modified and RSTRENG models.

References


6 Summary, Conclusions and Recommendations for Future Study

6.1 General

The research conducted and described in this thesis addresses the issues that will improve the current practice and aid in the reliability-based corrosion management program. Firstly, as empirical burst pressure capacity models’ experiences model errors and studies show that RSTRENG and CSA burst pressure capacity models have considerably low model error associated with them, RSTRENG and CSA models are preferable models in reliability-based corrosion assessments. However, these models cannot be used if the detailed geometric corrosion defect measurements are not available though in-line inspections (ILIs). As a result, the study reported in Chapter 2 proposes a methodology that will facilitate the use of RSTRENG and CSA models in reliability-based corrosion assessment while the detailed geometric measurements are not available through ILI. The study evaluates the statistical characteristics of three factors that relates the simplified corrosion measurements (i.e. maximum corrosion defect depth, and corrosion defect length) to the detail geometric measurements (i.e. average defect depth, average defect depth to the effective portion, and effective defect length). The statistical characteristics of proposed three factors are evaluated using 470 external corrosion defects found on an in-service pipeline in Alberta, Canada and measured using the high-resolution tools during field investigation.

Secondly, Chapter 3 proposes a methodology to evaluate the measurement error associated with the ILI measured corrosion defect length as corrosion defect length measurement is an important parameter for empirical burst pressure capacity models and no such studies has not been conducted so far as per researcher’s knowledge. The study proposed a step by step methodology to evaluate the measurement error associated with the ILI measured corrosion defect length, based
on 522 corrosion defects from 237 pipe joints that is a part of 28 currently operating pipelines in Canada and corrosion defects are measured during ILI and field investigations. As clustering error may introduce during an ILI, the field measured, and the ILI measurement corrosion defect length have a poor correlation. As a result, the study proposes a log-logistic model to evaluate the likelihood of absence or presence of clustering error associated with a corrosion defect, where the former denoted as Type I defect and the latter denoted as Type II defect in this study. Consequently, the statistical distributions of measurement error associated with ILI measured corrosion defect length for Type I and Type II defects are evaluated. Finally, the measurement error associated with an ILI measured corrosion defect is the weighted average of the evaluated Type I and Type II measurement error, whereas the weighted factor is the probability of a defect being Type I or Type II defect, evaluated using the proposed log-logistic model.

Thirdly, as ILI reports often document the detailed geometric measurements of a corrosion defect that includes the effective depth and effective length of a corrosion defect, the measurement error associated with effective depth and effective length is evaluated in the chapter 4 with the aid of the methodology proposed in Chapter 3. Measurement error associated with the effective depth and effective length for Type I and Type II defects are evaluated in this chapter based on the same corrosion data sets used in the Chapter 4. The proposed measurement error model for effective depth and effective length is the weighted average of the distributions of Type I and Type II defects. The weighted factor is the likelihood of a corrosion being Type 1 or Type II and can be evaluated by the proposed log-logistic model in chapter 3.

Finally, the implication of the proposed measurement error models for ILI measured corrosion defect length, effective defect length, effective depth was shown by evaluating the probability of
failure of a pipeline (due to pipe burst) using reliability-based corrosion assessment methodology, for different corrosion defect scenarios. The results are compared with the vendor specified measured error in reliability analysis and the comparison shows that the vendor specified measurement error provides lower of probability of failure of a pipe than the probability of failure evaluated using the proposed measurement error models.

6.2 Recommendations for Future Study

The recommendations for the future study are summarized as follows:

1. The proposed methodology in Chapter 3 to evaluate the measurement error associated with the corrosion defect length adopts a log-logistic model to evaluate the likelihood of the Type I and Type II defects. The proposed log-logistic model is valid both for individual defects (i.e. DMAs) and clusters, as the available ILI reported DMA data set is small. The proposed framework should be revised when the new data of DMAs are available, to obtain a more robust measurement error model.

2. The measurement error associated with the ILI measured average corrosion defect depth should be investigated to facilitate the use of CSA model if the detail defect profile is available in ILI reports.

3. The probability of detection (POD) of ILI tools is an essential measure to evaluate the detection capability of the ILI tools. POD curves for detection capability of external metal loss corrosion by ILI tools evaluated from the ILI data, is scarce in the literature and should be investigated.

4. The corrosion growth modeling plays an important role in the pipeline corrosion management, as it enables the engineers to determine the re-inspection interval and develop a staged defect
mitigation plan that meets the safety and resource constraints. Therefore, considerable research has been conducted to develop the corrosion growth model (the growth of the depth of the corrosion in the direction of pipe wall) which is mostly time dependent. These studies sometimes ignored or implicitly considered the environmental condition surrounding the pipelines, and the length of the corrosion defects in the longitudinal direction of the pipe surface. In addition to that there are some background assumptions (i.e. assumed the measurement errors associated with the ILI tools are spatially independent, assumed the function that defines the corrosion detection capability of ILI tools) behind the development of these corrosion growth models. Hence, 1) a verification of the assumptions made in the previous studies to develop the corrosion growth model, 2) development of growth model that will explicitly consider the explanatory variables (or so called local covariates), such as, pipe steel, corrosion protection coating on the pipe surface, soil conditions (i.e. soil type, PH of soil, moisture content of soil etc.), and 3) development of growth model for corrosion length, is needed.
Curriculum Vitae

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