Failure prediction and availability-based maintenance planning of gas transmission pipelines

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ABSTRACT

Failure prediction and availability-based maintenance planning of gas transmission pipelines

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As the most frequent failure source, external corrosion has led to more than 1700 failures in gas transmission pipelines in US since 1996, causing a property damage of approximately $189M. Such numbers highlight the importance of maintaining gas transmission pipelines in safe conditions to postpone corrosion failures. As the most widely applied method of corrosion monitoring technique, in-line inspection is expensive and time-consuming due to requiring high frequencies. On the other hand, the recent efforts directed towards developing failure prediction or maintenance planning models for oil and gas pipelines seem to have some limitations. As such, most of the failure prediction models are based on limited number of inspection or historical records or are limited in application due to their subjectivity. Furthermore, in the domain of maintenance planning, the current procedures are merely based on considering the associated costs and safety thresholds in the decision-making process. Such methodologies do not address the importance of pipeline availability and continuation of operation as a critical asset in the selection of the maintenance strategy.

This research has two main objectives. As the first objective, the proposed research aims to develop historical data-based failure prediction models for gas transmission pipelines by considering geo-environmental features. As the second objective, this research aims to propose a reliability-centered availability-based maintenance planning framework that considers the criticality of pipeline operation.

For these objectives, a detailed literature review was carried out on current methodologies to predict failures in oil and gas pipelines and maintain them. As the most important limitations, current failure prediction models do not consider geographical and environmental properties of pipelines to predict failures. On the other hand, in maintenance planning scope, none of current practices highlight importance of pipeline operation and availability in making the proper decision. In addition, these methodologies are often subjective, i.e. they are merely applicable to limited pipelines. To overcome these limitations the mentioned objectives of this research were defined and failure and maintenance data were collected from accessible historical records and reports. The failure prediction models were developed from best-subset and multiple regression analyses on the historical failure data and were then validated. On the other hand, the maintenance planning framework was developed from a coupled cost and availability-based maintenance planning procedure on different maintenance scenarios. For each scenario, a discrete event simulation was carried out through MATLAB programming. Such simulation was performed on the pipeline reliability profile obtained from a Monte Carlo simulation and consideration of improvement in availability per unit cost as the decision criteria. Monte Carlo simulation was carried out to consider wide range of design parameters for development of the reliability profile.

The developed failure prediction models were able to satisfactory predict time of corrosion failures in gas transmission pipelines for Great Plains and South East Regions of the U.S. These models were validated with mean absolute error (MAE) and root mean square error (RMSE) of 0.12 and 0.04, for Great Plains, and 0.11 and 0.07, for South East regional classifications, respectively. The proposed maintenance planning framework reveals that for a case study of a 24-inch pipeline, considering an availability-cost indicator, the second maintenance scenario, with interventions at the service life of 30.1 and 40.5 years is more effective. This order is followed by the first scenario with interventions at service life of 33.3 and 42.2 years, and finally the third scenario with intervention at service life of 24.2 years, respectively.

The developed failure prediction models can assist decision makers and pipeline operators to predict the expected time of corrosion failure in gas transmission pipelines in the selected regions by considering geo-environmental and pipeline design parameters. In addition, for maintenance planning of oil and gas pipelines, this research proposes a novel methodology that considers oil and gas pipelines as critical assets for which continued operation is of high importance. Such consideration provides a compensation between the costs incurred and pipeline availability to avoid over/under maintenance.

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To my beloved father, who will always be in my heart.

LIST OF PUBLICATIONS

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- Zakikhani, K. Zayed T., Abdrabou, B., Senouci, A. (2019). "Modeling failure of oil pipelines," Journal of Performance of constructed facilities, ASCE, 34(1), 04019088.
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- Mohammadi, A., Zakikhani, K. Zayed, T. (2019). "Simulation of Rubble-mound Breakwater Construction Productivity "7th International Construction CSCE Conference, Laval, Quebec.

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LIST OF ABBREVIATIONS AND SYMBOLS

A_i: Actual value

AVP: Average validity percentage

C: Associated costs

COV: Depth of cover

Cp: Mallow's

DIAM: Pipe diameter

d_0: The measured depth of a defect at time T_0 (the time of the last inspection)

d(T): Time-dependent depth of the defect

E_i: Estimated value

*f(t): P*robability distribution function

F^*: F test

i: inflation rate (5%)

INCP: Pressure at the time of the incident

IQR: The interquartile range

L: Section length

L_0: The measured length of a defect at time T_0

L(T): The axial length of the defect projected on the longitudinal axis

M: Folias (bulging) factor

MAE: Mean absolute error

MAOP: maximum allowable pressure

MSE: Mean squared error

MSR: Mean square regression error

MTTF: Mean time to failure

MTTR: Mean time to repair

n: number of observations or number of interest periods (years)

P: Number of the parameters or present cost value *p:* number of independent variables

P_f: Failure pressure

P-value: Probability of obtaining a value of F^* through referring to an F-distribution with p numerator degree of freedom and n-p-1 denominator degrees of freedom.

Q_i: ith quarter

RMSE: Root mean square error

RSS: Residual sum of squares

R_i: Primary reliability level

R_{ii}: Secondary reliability level

R_t: Reliability level at time t

R^2: The coefficient of determination

Sd_t: Defect size at each time

SMYS: Specified minimum yield strength

t: Time

T: Elapsed time

T_0: The time of the last inspection

THK: Wall thickness

TSS: Total sum of squares

UTS: Ultimate tensile strength

Va: The axial corrosion rate

Vr: The radial corrosion rate

X: Independent variable

x_i: Value of the predictor variable in the ith trial

Y: Dependent variable

y_i: Value of the response variable in the "ith" trial

$\overline{y}$: Mean value of response variable

$\hat{y}_I$: Estimated values of response variable

α *and* β: Regression parameters or as shape and scale parameters

$\Delta\alpha$: Changes of availability

ε_i : Random error

CHAPTER 1. INTRODUCTION

1.1 RESEARCH MOTIVATION AND PROBLEM STATEMENT

The oil and gas industry play a key role in the national economy in Canada. Only in 2010, oil and gas extraction accounted for half of the growth domestic product (GDP) in the energy sector, i.e. $42.1 billion. Though oil and gas pipelines are recognized as one of the safest means of transporting petroleum products, a considerable number of failures have occurred in these facilities. According to the statistics, over 3000 failures occurred in gas transmission pipelines located in U.S. since 1986 leading to more than $1bn of property damage. These numbers highlight the importance of maintaining such facilities in proper conditions to prevent failures.

As the most accurate method for condition monitoring of pipelines, in-line inspection is considered as expensive and time-consuming due to required high frequencies. Therefore, more research has been directed towards developing models that can forecast failure parameters. Such a model can help pipeline operators reduce the costs associated with frequent inspections and to take a maintenance decision before an accident takes place. A review of the state of the arts revealed that most of the developed models are based on limited historical or inspection data which question the applicability of such methods as a comprehensive model. In addition, in some procedures, lack of generalization due to the subjectivity of the proposed models and ignoring geo-environmental attributes limit their application. These points highlight the importance of developing a failure prediction model that relies on a comprehensive historical data with information on different pipeline attributes and aspects.

In addition to the current limitations of failure prediction models for oil and gas pipelines, some limitations are identified regarding maintenance planning procedures of such facilities. Most of the maintenance planning procedures developed for oil and gas pipelines concentrate on the selection of a maintenance alternative solely based on reliability/condition levels and the associated costs without considering uncertainties in pipeline parameters. In most of these researches, the importance of pipeline availability due to a possible shutdown during maintenance has not been considered. Such consideration is of high importance due to the criticality of petroleum pipeline operation and its impact on the national economy. As another limitation, most of the maintenance planning methods developed are merely applicable to pipelines with specific characteristics due to their reliance on in-line inspection; therefore, they are limited in application.

The mentioned research gaps motivated the author to develop an integrated failure prediction model and maintenance planning procedure for gas transmission pipelines.

1.2 RESEARCH OBJECTIVES

This research has two main objectives, first, this research aims to develop historical data-based corrosion failure prediction models for gas transmission pipelines. Second, this research aims to propose a novel methodology in maintaining these assets by considering criticality of pipeline operation and availability. These objectives can be broken down into the following sub-objectives.

1.2.1 Review of oil and gas pipelines safety

Such review composes of i) identification of different types of failure and the corresponding contributing parameters, ii) review of developed failure prediction models and maintenance planning procedures for oil and gas pipelines, iii) review of different maintenance alternatives for these assets, iv) gap analysis on the developed failure prediction and maintenance planning procedures.

1.2.2 Development of historical data-based corrosion failure prediction models

After assessing the current research gaps in the developed failure prediction models of oil and gas pipelines and highlighting corrosion failure as the most frequent and most costly failure source, this research aims to failure prediction models for such failures in gas transmission pipelines. Such models are based on historical data and consider geo-environmental parameters next to conventional design ones to predict time of failure.

1.2.3 Development of an availability-based reliability-centered maintenance planning framework

Upon highlighting current research gaps in the domain of maintenance planning of oil and gas pipelines, this research aims to develop a maintenance framework that assesses these assets as critical for which continuation of operation is of high importance. In comparison with conventional methods, such framework considers the associated costs, reliability levels and pipeline availability as decision criteria through an availability-cost index.

1.3 RESEARCH METHODOLOGY

In general, the proposed research methodology is composed of three main phases. The first step involves review of the state of art in the domain of oil and gas pipelines safety. The second step corresponds to development of data-based subjective prediction models. Finally, the third step corresponds to development of an availability-based reliability-centered maintenance planning framework. The details on pursued research methodology are presented in chapter 3.

1.3.1 State of the art review

As the first step of the proposed research methodology, a detailed review on the state of art in oil and gas pipeline safety is performed to highlight current gaps as presented in chapter 2. More specifically, this chapter covers the following topics,

- Detailed review on the developed failure prediction models which presents a comprehensive, classified review and analysis of the existing literature on such models developed for oil and gas pipelines.
- Identification of different failure types, more specifically, in this part, the contributing design parameters to external corrosion failure in oil and gas pipelines are highlighted.
- Review on the maintenance planning methods developed for oil and gas pipelines;
- Review of the available maintenance alternatives for gas transmission pipelines;
- Review on the principals of reliability-centered availability-based maintenance planning procedure.

1.3.2 Data collection

After highlighting the research gaps in developed failure prediction and maintenance planning models of oil and gas pipelines, historical data was collected. The collected data comprise of the historical failure records on gas transmission pipelines. In this step, due to the data collected on high frequency and property damage costs associated with external corrosion failures, the direction of this research was furthered confined to such failures. In addition, maintenance data to repair such assets was collected by going through published reports. Maintenance data include the time required to perform a maintenance action in addition to the maintenance costs.

1.3.3 Development of corrosion failure prediction model

As the third step of the proposed research, corrosion failure prediction models are developed to estimate the time of failure in gas transmission pipelines. Such models are based on consideration of both conventional design and geo-environmental parameters obtained from the literature review, next to the collected failure and climatological records. Based on such data, best subset and multiple regression analysis are employed to exploit the collected data and generate prediction models for two selected climatological regions in the U.S. The details on these prediction models are presented in chapter 5.

1.3.4 Development of availability-based reliability-centered maintenance framework

As the third step of the proposed research methodology, a framework for availability-based reliability-centered maintenance planning of gas transmission pipelines is proposed. In this step, first the limitations on the available maintenance planning procedures are highlighted. Then, the corresponding maintenance time and cost data for a case study of gas transmission pipeline are collected. In the third step, according to the developed failure prediction model, the reliability profile of a typical gas transmission pipeline was obtained. Finally, an availability-based reliability-centered maintenance planning framework is proposed through discrete event simulation considering different maintenance scenarios. The details on the proposed framework are discussed in detail in chapter 4.

1.4 THESIS LAYOUT

This research proposal is comprised of five main chapters, including:

Chapter 1 covers the introduction to the problem, research motivation and the objectives pursued in the proposed research,

Chapter 2, covers a detailed literature review on oil and gas pipelines safety,

Chapter 3, presents the methodology pursued,

Chapter 4, presents details on collected data,

Chapter 5 presents the details on model implementation. These models include historical data-based failure prediction models in addition to the developed maintenance planning framework.

Chapter 6, highlights conclusions and contributions of the research and provides some recommendations for future work.

CHAPTER 2. LITERATURE REVIEW

Oil and gas pipelines are important assets of a society, transporting millions of dollars of wealth. Though pipelines are recognized as one of the safest means of transportation of oil and gas compared to rail and road transportation, the statistics show an increasing trend in the occurrence of incidents. According to U.S. Department of transportation (US DOT 2016a), around 10,000 failures have occurred in U.S. since 2002 leading to considerable safety, environmental and economic consequences. Table 2-1 reports the statistics regarding the number of failures and property damages due to oil and gas pipelines malfunctioning (US DOT 2016a). These numbers highlight the importance of adopting failure prediction and maintenance planning procedures to establish timely prevention and intervention strategies.

Table 2-1 Records of Oil and gas pipeline failures since 2002

Pipeline commodity	No. of failures	Damage ($)
Gas	3,569	$1,358,067,990
Oil	5,528	$1,793,863,357
Total	9,217	$3,151,931,347

Different sources may threaten pipeline integrity such as corrosion, natural hazards and third-party activities. To minimize such threats, pipeline integrity programs are widely practiced. This program is composed of three main phases including defect detection, prediction and maintenance management (Xie and Tian 2018). Defect detection requires extensive in-line inspection (ILI) and monitoring of pipeline conditions. In this sense, anomalies (e.g. metal loss, dents, gouges and girth weld quality), length, width and location of the anomaly are reported by using smart devices such as magnetic flux and ultrasonic tools (Baker 2008). However, these techniques are considered as time-consuming and expensive due to the necessity of performing frequent inspections with high-resolution tools to obtain accurate results and minimize the associated uncertainties. In the second step of integrity programs, defect prediction is carried out involving the development and implementation of failure prediction models based on historical data, experimental tests, or inspection results obtained from the first step (Xie and Tian 2018). In doing so, there has been a growing attention towards developing models that can ameliorate prediction of failure attributes of oil and gas pipelines. Such models could predict one or several parameters including risk, time of failure, probability of failure (POF) or reliability, consequence, source, pressure at the time of failure, rate of failure and mode of failure. These models may be based on inspection, experimental, and historical records or use physical methods such as finite element analysis to predict failure. Considering the variety of the proposed models, there is a need to conduct a comprehensive literature review to distinguish these techniques in a classified manner, discuss their advantages in the prediction of failure parameters, and highlight their gaps to present avenues for future research. In addition, the current code-based failure prediction methodologies practiced in the industry need to be discussed identifying their limitations. Such a review could pave the path to connect the research and practice on failure prediction for oil and gas pipelines by informing the researchers and practitioners about the state-of-the-art contributions and developments in this area.

This chapter covers a detailed state of the arts review on oil and gas pipeline More specifically, this chapter presents the following,

i) Classification of oil and gas pipelines;

ii) Identification of various failure sources and their contributing factors;

iii) Review of developed failure prediction models for oil and gas pipeline: This review organizes, classifies and analyzes previous contributions in this domain and highlights the gaps associated with different failure prediction modes;

iv) Review of maintenance options in oil and gas pipelines: This review summarizes and analyzes different alternatives available in practice to maintain oil and gas pipelines;

2.1 CLASSIFICATION OF OIL AND GAS PIPELINES

Followed by hydroelectricity, crude oil and natural gas count for the highest energy commodity production in Canada with global production percentages of 4.8% and 4.7% respectively (National Energy Board 2017a). Oil and gas pipelines are the majority of petroleum transportation operating systems through Canada with an estimated of 825,000 km of transmission, gathering and distribution lines (Natural Resources Canada 2014). These pipelines include all parts of those physical facilities through which gas, hazardous liquid, or carbon dioxide moves in transportation (US DOT 2016e). According to statistics Canada, in 2015, over 91% of oil exports from Canada to US was conducted through pipelines (Statistics Canada 2017). Canada's pipeline network is comprised of four main pipeline systems including gathering, feeder, transmission and distribution pipelines.

Gathering pipelines: These pipelines transfer natural gas or oil from wellhead to oil batteries or natural gas processing facilities (National Energy Board 2017b). In oil pipelines, petroleum is transported from a production facility which has no more than 8 5/8 inches (219.1 mm) in diameter (US DOT 2016a).

Feeder pipelines: These pipeline systems transport crude oil, natural gas and other products such as natural gas liquids (NGLs) from batteries, processing facilities, and storage tanks to transmission pipelines (National Energy Board 2017b).

Transmission pipelines: As a major part of a network, these pipelines transport crude oil and natural gas within provinces and across provincial or international boundaries (National Energy Board 2017b). In general, natural gas transmission pipeline transports gas from a gathering line or storage facility to a distribution center, storage facility, or large-volume customer that is not downstream from a distribution center (US DOT 2016a).

Distribution pipelines: These pipelines are usually operated by local distribution companies or provincial cooperatives and transport natural gas to homes, businesses, and various industries. Figure 2-1 illustrates a schematic view of the Canadian petroleum pipeline system including gathering, feeder, transmission and distribution pipelines for oil and gas production.

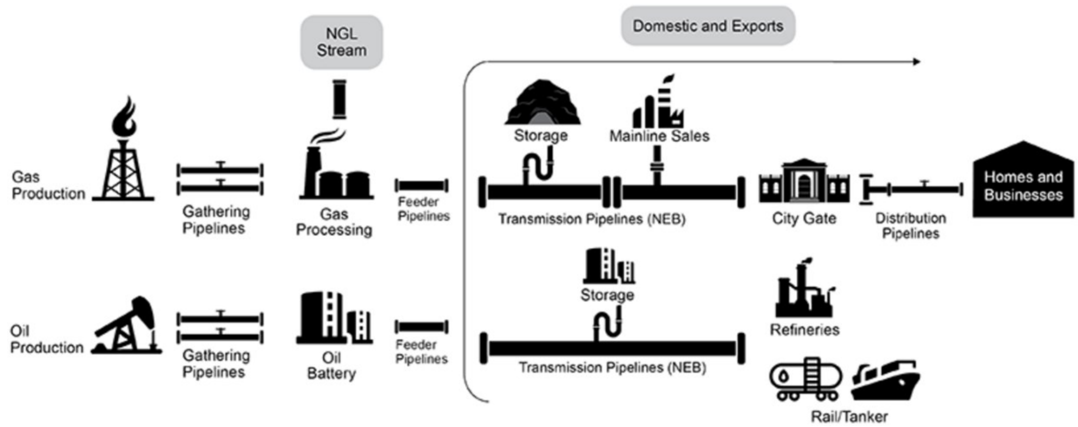


Figure 2-1 Schematic view of Canadian oil and gas production (National Energy Board 2016)

2.2 CLASSIFICATION OF FAILURE SOURCES

The most common classification of oil and gas pipeline failures is according to the failure source as presented in Figure 2-2. These failure sources include manufacturing/material and weld failure, natural force damage, equipment failure, excavation failure, other outside force damage, incorrect operation and corrosion (Davis et al. 2010; US DOT 2016a; EGIG 2015) (Figure 2-2).

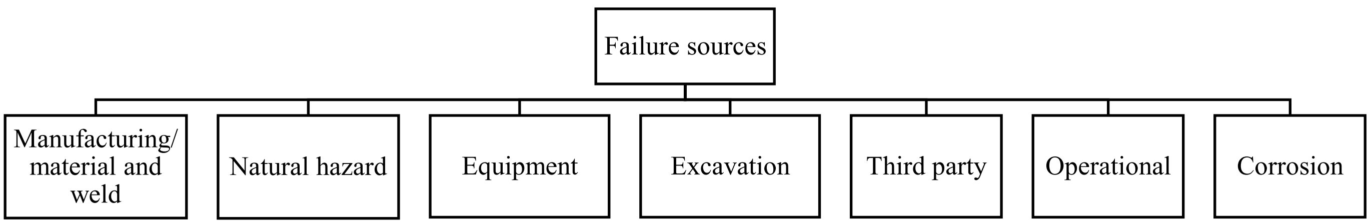


Figure 2-2 Failure sources in oil and gas pipelines

2.2.1 Material/weld failures

This type of failure corresponds to all failures resulting from material, weld and manufacturing deficiencies during construction phase (Davis et al. 2010; US DOT 2016a). Material/weld failure usually leads to development of dents and gouges which can lead to either immediate, delayed or no failures and are detectable through application of in-line inspections (Senouci, El-Abbasy et al. 2014).

Material failure: In pipelines, material failure usually occurs due to existence of impurities and oxides in steel material, metallurgical defects, trap and expansion of gas within steel, and inappropriate material specification leading to incomplete bonding in steel plate or billet (US DOT 2016e; Davis et al. 2010). Such problems can lead to laminations, blisters and scabs.

Manufacturing process: During production of a pipeline, hard spots may be generated. This type of defect can occur during localized cooling of plate material in rolling process as well as due to generation of indentations formed by expanders and mandrels for seamless pipelines. Hard spots are susceptible to generation of cracks which will grow over time leading to failure (US DOT 2016e).

Weld failure: The following factors may contribute to weld failure in oil and gas pipelines (US DOT 2016e).

Burnt pipe edges: In this case, edge of steel plate is heated too high and is susceptible to cracking (US DOT 2016e).

Incomplete fusion: When the edges of lap and flash welded pipe are not heated enough, impurities may remain in the seam leading to poor bonding of the edges (US DOT 2016e).

Hook cracks: This type of crack occurs in a weld zone with curves and hooks. Hook cracks usually occur due to some types of early electric resistance welding (ERW) processes (US DOT 2016e).

Cold Welds: While using cold welds, either inadequate heat or pressure can result to poor bonding in the edges (US DOT 2016e).

Weld metal cracks: Weld metal cracks can sometimes be formed if the plate edges are moved before they are cooled completely (US DOT 2016e).

2.2.2 Natural hazard

This type of failure is caused by natural events such as earth movement, landslides, earthquakes, heavy rains, flooding, winds, tornadoes, hurricanes, lighting, temperature extremes etc. Natural force damage does not happen often; however, it may lead to catastrophic consequences due to the potential for extreme large forces. To mitigate natural hazards, geotechnical and meteorological conditions of the site shall be assessed. In addition, ongoing risk assessment is needed to identify all the possible natural hazards. For some types of natural force damage which may be anticipated, some mechanisms may be designed. For example, for earth movement hazard, valves may be installed to mitigate the threat on either side of a fault (US DOT 2016f).

2.2.3 Equipment failure

This failure type involves pipe pumps, compressors, valves, meters, tanks and other components and often leads to product release and environmental pollution. In order to prevent equipment failure, it is required to inspect the equipment periodically. Also, mitigative measures are necessary for leak predicted areas. For example, facility housing pumps should be equipped with alarms that warn buildup of hydrocarbons. Also risk assessments are needed to identify failure modes, likelihoods and consequences (US DOT 2016b).

2.2.4 Excavation failure

This failure is an accidental type associated with different forms of excavation including digging, grading, trenching, boring etc. The excavation operation may happen due to different reasons such as road and highway maintenance, general construction and farming activities. Due to excavation, a buried pipeline may get damaged leading to dents, scraps, cuts, punctures and damage to external coating. This type of damage usually occurs undeliberate when the location of the pipe is not determined properly. The failures occurred due to excavation damage may have two modes, either immediate failure of pipeline or future failures due to damage to coating and pipe deformation (US DOT 2016c). To avoid this type of damage, in U.S., a legislation has been assigned that it is obligatory to call government centers prior to digging. Also, pipeline operators should increase excavation awareness and training prior to initiation of excavation (US DOT 2016c).

2.2.5 Third party damage

Third party damages include intentional or accidental actions representing damages by others in pipeline vicinity and not related to management. This type of failure includes the damages by outside forces due to events other than excavation activity and natural forces, such as vehicle accidents and vandalism. This type of damage occurs relatively rarely with different magnitude of consequences. However aboveground pipelines near highways or large population areas are the most probable (US DOT 2016g). To prevent this type of failure, it is recommended to secure facility and protect it from public access by precautions such as staff, surveillance cameras, and crash guards. Also risk assessment can provide some estimates for failure probability and its consequences (US DOT 2016g).

2.2.6 Operational failure

Operation failures result from operational errors and safeguarding deficiencies due to system malfunction and excessive pressure. This failure type deals with human actions by company or operator personnel and relies on workers actions. Some examples of incorrect operation include leaving the wrong valve open, overfilling the tank, over pressuring a piece of equipment, mismarking an underground pipeline prior to excavation work, not following proper measures, using improper equipment techniques. Personnel knowledge and expertise should be enhanced to avoid failures due to incorrect operation. This can be achieved through training, qualification programs (US DOT 2016d).

2.2.7 Corrosion

Pipeline corrosion is defined as deterioration of metal over time due to interaction of pipe with the environment and can be classified as internal, external or stress corrosion cracking (Bersani et al. 2010; Davis et al. 2010). Corrosion is a time-dependent failure leading to wall metal loss and can be classified as either internal, external or stress corrosion cracking (Bersani et al. 2010).

External corrosion: External corrosion causes more than 90% of corrosion-related failures in distribution pipeline. In external corrosion, the environment is considered as water or moist soil for onshore pipelines and seawater for offshore pipelines (Fessler 2008). In general, external corrosion can be categorized into three groups including differential cell, microbiologically influenced corrosion and stray current corrosion (Beavers and Thompson 2006). Differential cell corrosion takes place when parts of a pipe are over-exposed to different oxygen concentrations leading to the generation of cells. Different parameters can lead to this type of corrosion including differential aeration cell, soil properties such as PH value, temperature, soil type, moisture content, resistivity, redox potential, cover, galvanic corrosion, surface films and relative size of anodic and cathodic areas (Beavers and Thompson 2006; Ismail and El-Shamy 2009; Orazem 2014).

Microbiologically influenced corrosion (MIC) corresponds to the activity of microorganisms including bacteria, archaea and fungi to promote corrosion by converting the metal oxide to a less protective layer (Little and Lee 2014). Varieties of these bacteria include aerobic (surviving in presence of oxygen) and anaerobic (surviving in the absence of oxygen), facultative anaerobic (prefer aerobic conditions but can live under anaerobic conditions too).

Stray current corrosion corresponds to traveling of stray current along the pipe to other areas and its returning to the power source. In this type of corrosion, the extent of metal loss is proportional to the current leaking from the pipe. Examples of direct current include foreign pipelines not properly bonded to the intended pipeline in direct current sources such as railroads and mining operations (Beavers and Thompson 2006; Zhu et al. 2011).

Internal corrosion: This corrosion type takes place when an electrolyte is available and completes the corrosion cell. Natural gas is prone to internal corrosion due to the presence of contaminants such as water, carbon dioxide, and hydrogen sulfide and the possibility of reaction with condensed water. Different mitigation methods of internal corrosion include dehydration, inhibitors, coatings, buffering, cleaning pigs and biocides (Fessler 2008).

Stress corrosion cracking (SCC): SCC leads to cracking of material due to combined actions of corrosion and tensile stresses (Senouci, Elabbasy et al. 2014). In this type of corrosion failure, colonies of longitudinal surface cracks form in the pipe and link up to join long-shallow flaws (Beavers and Thompson 2006).

The most effective method of external and SCC corrosion prevention is to use high-performance coatings applied to an abrasive surface cleaned to white or near white metal surface finish in conjunction with cathodic protection (NACE International 2000). According to RP-0169 coating isolates external surface of underground or submerged pipeline to reduce cathodic protection requirement and improve protective current distribution (NACE International 2013). Some of the roles of coating include, effective electrical insulation, effective moisture barrier, good adhesion to pipe surface (Fessler 2008).

Another effective method for external corrosion prevention is cathodic protection. Through altering the electrical potential field around the pipe and applying a negative potential, pipe acts as a cathode leading to reduction in corrosion rate (Beavers and Thompson 2006). Cathodic protection is often used in conjunction with coating and leads to corrosion control. The two primary types of cathodic protection include sacrificial (galvanic) anode and impressed-current (Beavers and Thompson 2006). Galvanic anode (is either made of zinc or magnesium) utilizes an anode material connected to pipe steel. This changes the pipe to cathode in circuit leading to mitigation of corrosion. Impressed-current cathodic protection applies an outside power supply to control voltage between the pipe and the anode (Beavers and Thompson 2006).

Besides cathodic protection and coating, placing a metallic pipe within another pipeline with nondestructive filler in its annular space is another preventive method which is suitable for short sections of pipeline such as those which pass under streams and rivers (Fessler 2008).

Figure 2-3 presents a summary of the contributing factors for the identified failure sources.

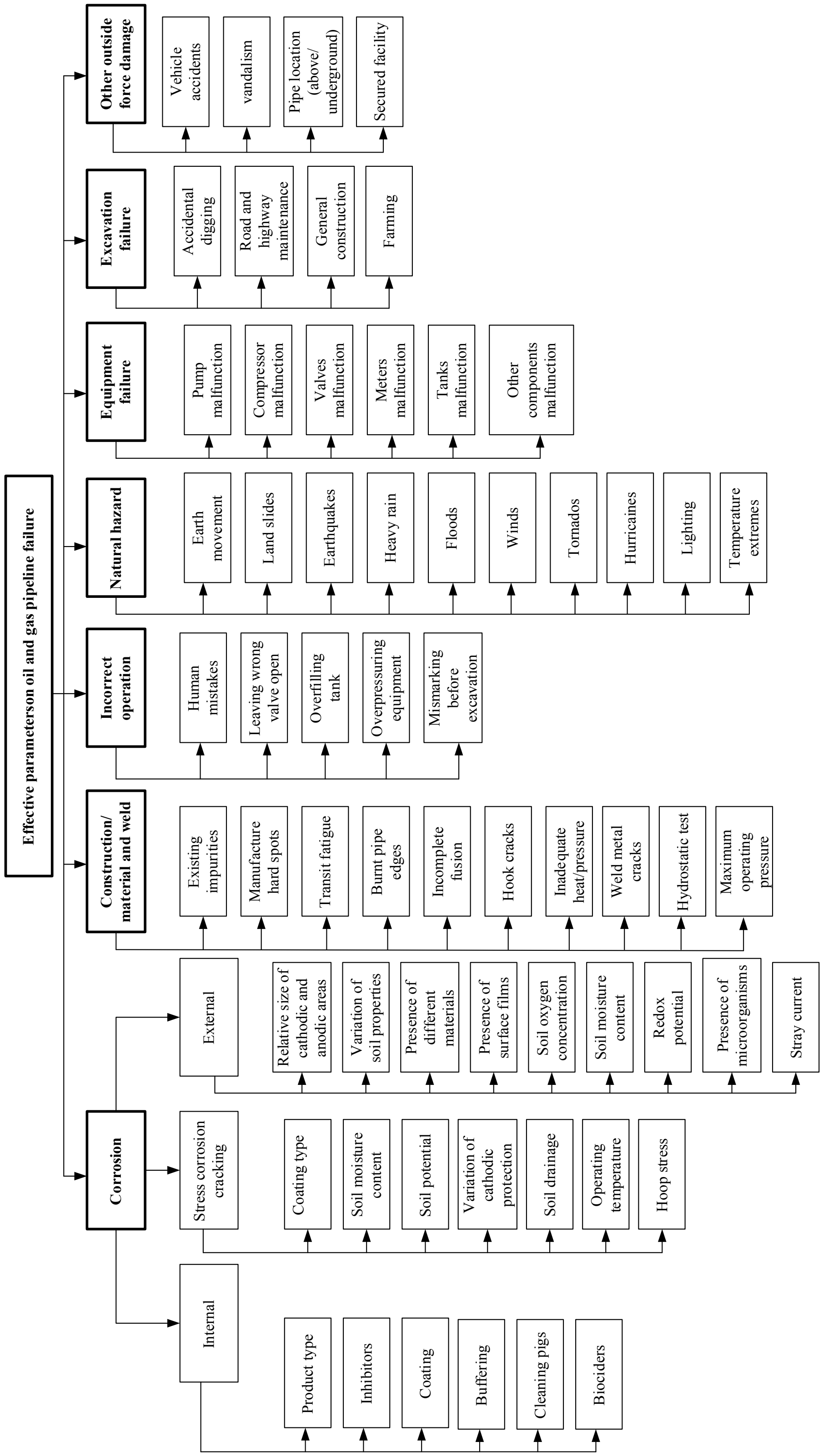


Figure 2-3 Contributing factors on pipeline failures

2.3 FAILURE PREDICTION MODELS

In this section, a comprehensive, classified review and analysis of the existing literature on failure prediction models developed for oil and gas pipelines are presented. In review of the literature, first a pool of related publications is collected. The selected publications are then meticulously analyzed and classified based on topic, predicted parameter and the applied techniques. Then, a detailed discussion and gap analysis of the reviewed methodologies is provided in line with the identified failure parameters. In addition, the current code-based methods practiced in the industry for assessment of pipelines are discussed and analyzed, highlighting their limitations.

In summary, in this section, research and practice in failure prediction for oil and gas pipelines are distinguished and their shortcomings for advocating some future research directions are discovered.

2.3.1 Background

To conduct a detailed review of developed models for oil and gas pipeline safety, a structured methodology is followed. This methodology consists of three main phases. In the first step, the papers focusing on model development for oil and gas pipeline safety are identified. In the second phase, the selected papers are classified according to different criteria. In the third phase, research and code-base methods are analyzed and discussed according to their classifications. Figure 2-4 presents a summary of the framework adopted in this study. The details of the above-mentioned phases are provided as follows:

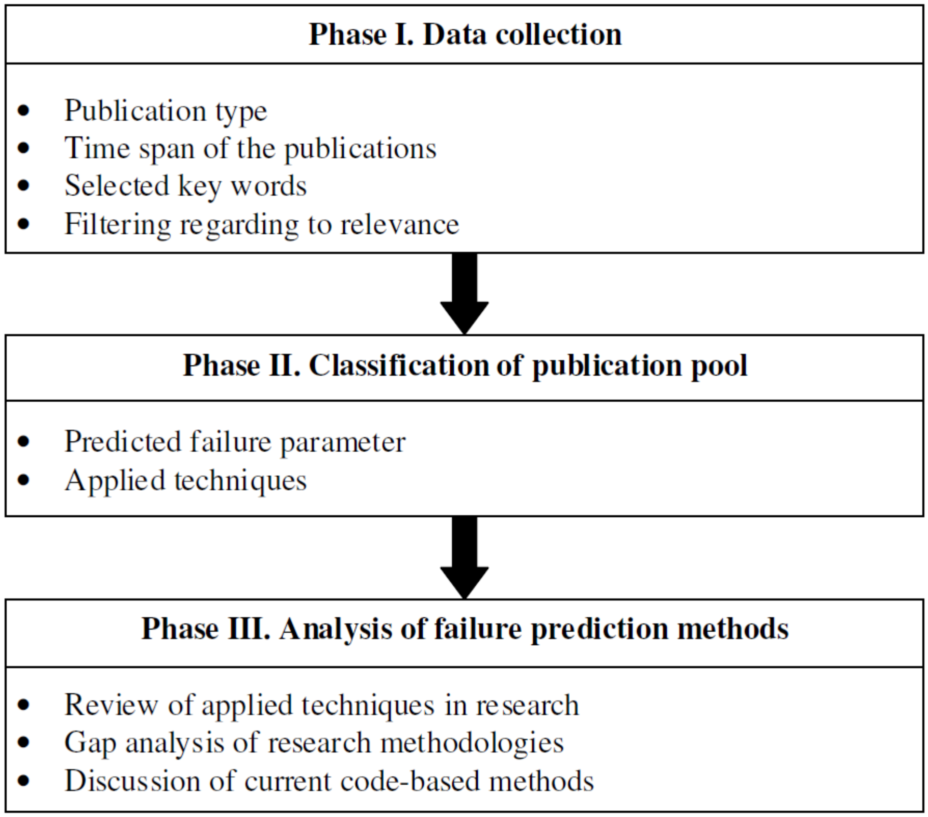


Figure 2-4 Methodology for prediction models review

Phase I: In this phase, a search was performed by keywords which were accessible through web-search facilities. Keywords of “pipeline”, “oil”, “gas”, “model”, “prediction” and “assessment” were chosen within titles and abstracts in the search tool. After extracting the resulting publications and squinting abstracts, they were further assessed individually regarding their relevance to oil and gas pipeline safety. This step led to a final selection of more than one hundred journal publications and conference proceedings that propose assessment models to defer oil and gas pipeline failure. It should be mentioned that in the collection and classification of the literature, the focus is first directed towards academic journal publications and conference proceedings. Then, an overview of practical contributions (including industry reports, standards, etc.) is provided. This approach facilitates the investigation of the gaps and limitations from both research and practical perspectives.

Phase II: A framework for classifying the selected publications is then explored. After gathering the related journal publications and conference proceedings, they were classified according to different criteria including predicted failure parameters and the applied techniques. Figure 2-5 illustrates taxonomy of failure prediction parameters in the reviewed research including risk, time of failure, probability of failure (POF) or reliability, consequence, source, pressure at the time of failure, rate of failure and mode of failure. This step provides answers to questions such as, what failure parameters are predicted, and which techniques are applied.

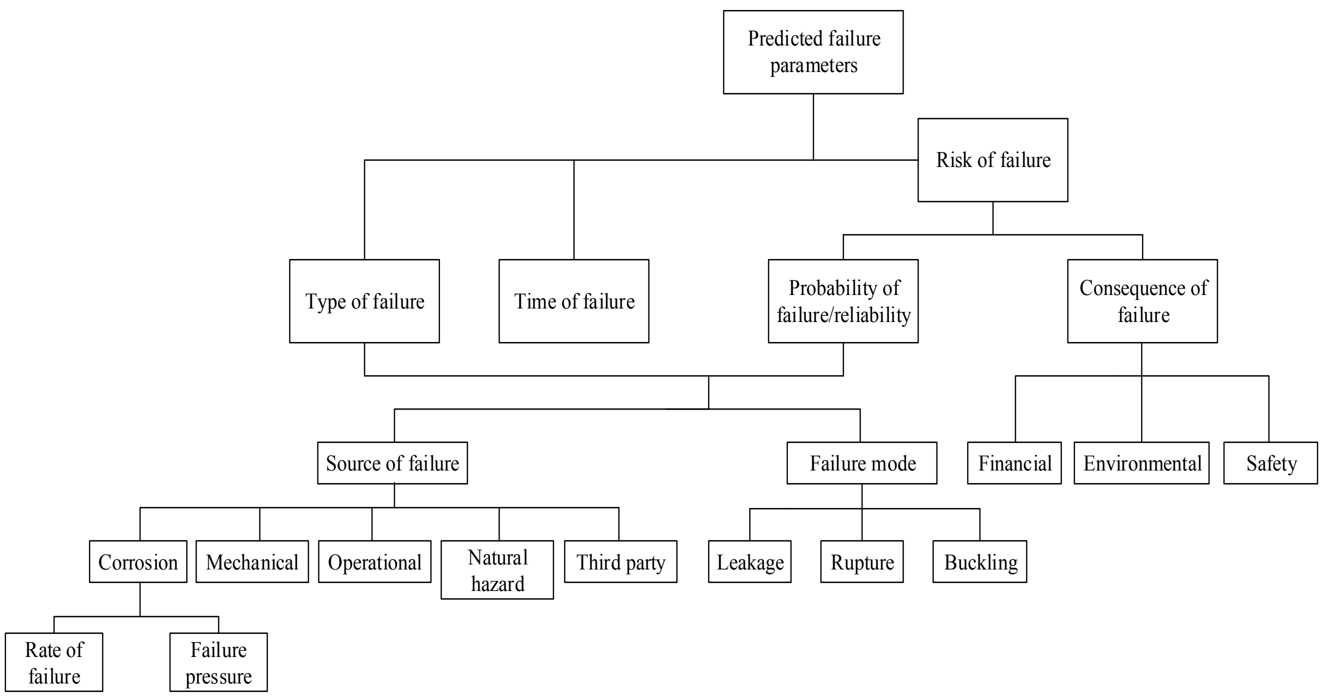


Figure 2-5 A taxonomy of failure prediction parameters

Phase III: Due to the vast number of contributions in the development of safety models for oil and gas pipelines, a more focused analysis is provided for the models proposed to predict the failure parameters shortlisted from the previous phase. To predict these failure parameters in oil and gas pipelines, different methods have been investigated in the literature. The most common types of these methods include fuzzy technique, analytic hierarchy process (AHP), bow tie analysis, fault trees, event trees, neural networks, Monte Carlo simulation, regression analysis and Bayesian network. Table 2-2 presents a summary of the predicted failure parameter and the applied techniques for the reviewed researches published in the past five years.

Table 2-2 Summary of the recent literature

Literature	Predicted parameter							Approach															
	Risk	POF/reliability	Consequence	Rate of failure	Type of failure	Failure pressure	Time of failure	Numerical	Empirical/ Experimental	Expert opinion	Fault/fault tree	Bayesian	AHP	Fuzzy	Monte Carlo/simulation	Matrix-based	Index-based	Bow-tie	Entropy method	NPP/NHPP	Neural network	SVM	Regression
Aljaroudi et al. (2014)		Y+							Y														
Aljaroudi et al. (2015)	Y								Y														
Aljaroudi et al. (2016)	Y								Y														
Bonvicini et al. (2015)	Y										Y						Y						
Cobanoglu et al. (2014)		Y																		Y			
Dundulis et al. (2016)		Y						Y				Y			Y								
Engelhardt et al. (2013)				Y											Y								
Guan et al. (2016)		Y										Y											
Guo et al. (2016)	Y									Y			Y	Y					Y				
Hasan (2016)		Y											Y										
Ismail et al. (2015)		Y													Y								
Jamshidi et al. (2013)	Y													Y			Y						
Kabir et al. (2016)		Y								Y	Y	Y	Y	Y									
Kaewpradap et al. (2017)				Y											Y								
Kamsu-Foguem (2016)	Y															Y							
Khaleghi et al. (2014)	Y									Y				Y			Y						
Li et al. (2016a)		Y								Y	Y		Y	Y									

Literature	Predicted parameter							Approach																
	Risk	POF/reliability	Consequence	Rate of failure	Type of failure	Failure pressure	Time of failure	Numerical	Empirical/ Experimental	Expert opinion	Fault/fault tree	Bayesian	AHP	Fuzzy	Monte Carlo/simulation	Matrix-based	Index-based	Bow-tie	Entropy method	NPP/NHPP	Neural network	SVM	Regression
Li et al. (2016b)	Y											Y						Y					
Liao et al. (2012)				Y																	Y		
Liu et al. (2018)		Y													Y								
Lu et al. (2014)	Y									Y				Y		Y							
Lu et al. (2015)	Y													Y			Y	Y					
Luo et al. (2013)				Y																		Y	
Ma et al. (2013a)						Y		Y	Y														
Ma et al. (2013b)	Y								Y														
Oliveira et al. (2016)		Y							Y														
Omidvar and Kivi (2016)		Y						Y			Y												
Ossai et al. (2015)		Y						Y	Y														
Parvizsedghy and Zayed (2013a)							Y																Y
Parvizsedghy and Zayed (2013b)			Y																		Y		
Parvizsedghy and Zayed (2015a)			Y											Y				Y					Y
Parvizsedghy and Zayed (2015b)							Y																Y
Senouci et al. (2014a)					Y																Y		Y
Senouci et al. (2014b)					Y									Y									
Tajallipour et al. (2014)	Y															Y							
Weiguo et al. (2014)		Y						Y															
Wen et al. (2014)		Y													Y								

Literature	Predicted parameter							Approach															
	Risk	POF/reliability	Consequence	Rate of failure	Type of failure	Failure pressure	Time of failure	Numerical	Empirical/ Experimental	Expert opinion	Fault/fault tree	Bayesian	AHP	Fuzzy	Monte Carlo/simulation	Matrix-based	Index-based	Bow-tie	Entropy method	NPP/NHPP	Neural network	SVM	Regression
Witek (2016)		Y							Y														
Zhang et al. (2014a)				Y								Y			Y								
Zhang et al. (2014b)			Y														Y						
Zhou et al. (2014)	Y																Y						

+Y stands for Yes.

The next section provides a more detailed overview of the prediction models, techniques used, and their advantages and shortcomings. This will be followed by a review of the practical implications of failure prediction for oil and gas pipelines and the existing practices in the industry.

2.3.2 Practical implications

In this section, a review of failure prediction measures applied in industry is provided, highlighting their applications as well as limitations. For risk assessment of oil and gas pipelines, quantitative risk assessment procedures are specified in standards codes (ASME B31.8 2018; PD 8010 2015) with special attention directed towards external failures (i.e. not related to design and operation of pipelines) cited as the most significant failure sources. Accordingly, for individual and societal risks, tolerable risk levels are specified (Goodfellow, G. et al. 2014; Nessim et al. 2009). These risk levels are dependent upon parameters including location type, wall thickness, population density, maximum stress and proximity of population to the studied pipeline (Goodfellow, G. and Haswell 2006). In the corresponding equations, the fracture equations employed as criteria for such failures are considered semi-empirical and conservative (Seevam et al. 2008; Lyons et al. 2008; Cosham et al. 2008). In addition, the occurrence of dent damage is supposed to be only dependent upon the force applied by indenter not the pipeline itself (Goodfellow, Graham et al. 2018).

Regarding to assessment of the remaining strength of pipelines, this parameter is evaluated according to specified design codes for metal loss due to corrosion. These design codes are NG-18 equation (Kiefner, F. et al. 1973), DNV-RP-F101 (LPC) (D.N. Veritas 2004; D.N. Veritas 1999), SHELL92 (Ritchie and Last 1995a), ASME B31G (A.N.S. Institute 1991), modified B31G (Kiefner, J. and Vieth 1989), RSTRENG (Kiefner, J. and Vieth 1989), CPS (Cronin and Pick 2000), and SAFE (Kim et al. 2013; Wang et al. 1998). These evaluation techniques used in these codes are different from one another in defect shape and bulging factors and are mainly based on are deterministic and experimental approaches with simplified assumptions for metal loss with two main limit states for the depth of corrosion and failure pressure (Xie and Tian 2018; Timashev and Bushinskaya 2016; Noor et al. 2010; Aljaroudi et al. 2014). In corrosion assessment, a threshold for the depth of corrosion defect is considered relative to pipe wall thickness, while in failure pressure approach, the difference between operating and failure pressures is used (Aljaroudi et al. 2014). In comparison with data from actual pipelines with corrosion failure, such methodologies tend to provide considerably conservative results leading to economic loss and under maintenance of the pipes, mainly due to ignoring the probabilistic nature of corrosion (Ma et al. 2011; Kim et al. 2013). In this sense, the use of probabilistic measures that take into account the randomness of pipeline parameters (geometry, material, loading, defect parameters) could provide more realistic estimations (Timashev and Bushinskaya 2016; Aljaroudi et al. 2014).

Regarding consequence modeling, by comparing the results obtained from industry methods such as DNV PHAST with actual pipeline accidents, (Pettitt et al. 2014) concluded that industry techniques are conservative in the estimation of thermal radiation and fatal injuries. These limitations highlight the importance of integrating procedures that take into account the random nature of pipeline failure into current industry codes and methodologies in assessing risk and consequence of failure. In industry, maintenance measures and interventions applied to oil and gas pipelines are mostly in accordance with scheduled in-line inspections. Due to the conservative nature of current design codes, such scheduled maintenance procedures lead to under/over maintenance of pipeline components which eventually have a negative impact on a pipeline uptime.

In this regard, adopting an availability-based maintenance planning, as practiced in the power industry (Bose et al., 2012), would be beneficial due to criticality of oil and gas pipeline availability and importance of their operation on the economy. This maintenance procedure is a branch of reliability-centered maintenance planning and is applied for maintenance planning of critical facilities such as power plants for which the availability of the system is critical. The objective of performing availability-based maintenance scheduling is to provide a maintenance plan, which results in high availability and a high level of safety (Zhang, T. et al. 2002). In this method, the components with bigger effects in system availability are selected to be maintained more frequently and the ones with less impact on the system availability will be maintained less frequently (Pourhosseini and Nasiri 2017), helping to avoid over/under maintenance of components by considering their availability priorities. In this domain, availability is defined as a function of mean time to repair, *MTTR*, and mean time to failure, *MTTF* (i.e. *MTTF/[MTTF+MTTR]*) (Zhang, T. et al. 2002). The first step in this method is to develop a comprehensive failure prediction model that considers the probabilistic nature of pipeline failure for different sources (in contrast with current design codes). Based upon the developed prediction models, the reliability profiles can be obtained, and maintenance planning can be performed as directed by the expected improvements in the availability of pipelines. The proposed availability-based approach, and its link to failure prediction models of pipelines, is presented in Figure 2-6.

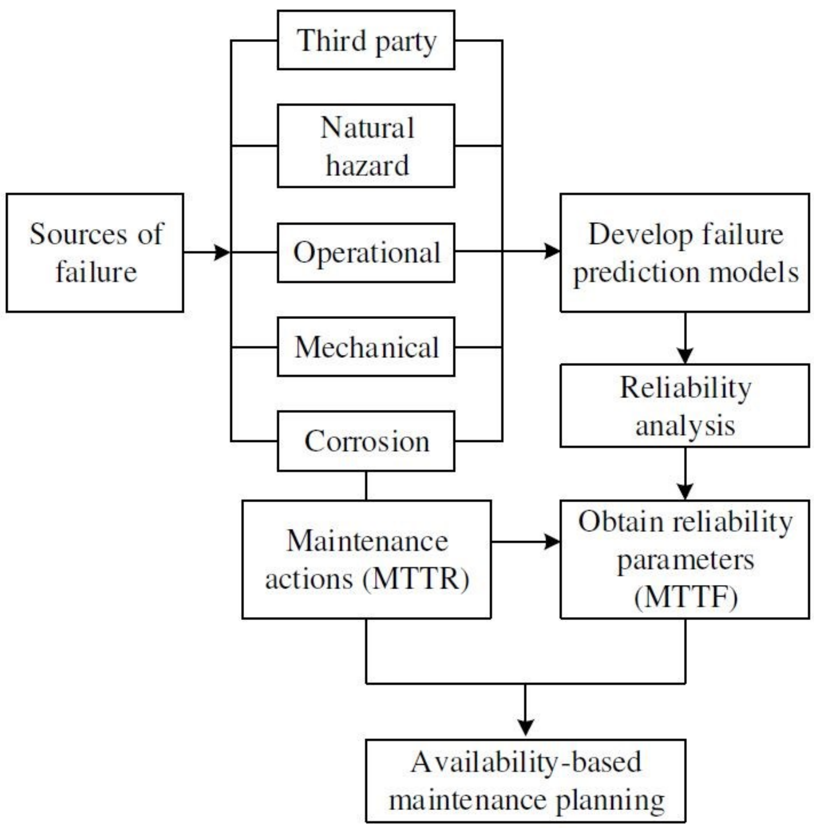


Figure 2-6 Proposed framework for availability-based maintenance planning

2.4 CORROSION FAILURE PREDICTION MODELS

Since concentration of this research is on corrosion failures, in this section, the developed corrosion failure prediction models are specifically highlighted. These models can predict various corrosion failure parameters such as probability and rate of failure, cause, and risk of failure as well as the consequence of corrosion failure or its rate. The developed models may be either based on available in-line inspection data, empirical equations, numerical finite element modeling or reported historical data on pipeline corrosion failures (Zakikhani et al. 2019). As one of these parameters, the probability of corrosion failure was estimated by (Li et al. 2009) and (Witek 2016) by referring to empirical equations for burst pressure and application of a Monte Carlo simulation. Similarly, (Wen et al. 2014) estimated the probability of failure using Monte Carlo simulation from limit state functions for several types of failure including corrosion, equipment impact, and weld defect. In addition, (Dundulis et al. 2016) integrated the Bayesian method with hoop stress values obtained from Monte Carlo simulation and finite element analysis to estimate the probability of failure in gas pipelines due to corrosion.

Regarding reliability analysis, compared to different failure sources in petroleum pipelines, corrosion is the most highlighted. Through iterative numerical analysis, (Weiguo et al. 2014) predicted the remaining life of buried gas pipelines under corrosion and cyclic loads. Similarly, (Kucheryavyi and Mil'kov 2011) performed reliability assessment towards corrosion failure in a defective gas pipeline based on mechanical equations on pipeline strength. Through application of a Monte Carlo simulation and principals of reliability analysis, (Teixeira et al. 2008) and (Ossai, Chinedu I. et al. 2015) proposed two methodologies to assess the reliability of oil and gas pipelines. (Teixeira et al. 2008) performed a first-order reliability analysis on burst pressure results from numerical and experimental analysis. By considering maximum corrosion pit depth, (Ossai, Chinedu I. et al. 2015) applied a Monte Carlo simulation in conjunction with Weibull probability to assess pipeline reliability. In addition to reliability and probability analysis, (Liao et al. 2012), (Caleyo et al. 2009) and (Papavinasam et al. 2010) predicted corrosion rate parameter. This failure parameter was obtained through the application of a backpropagation neural network, Monte Carlo simulation and empirical equations respectively.

2.5 MAINTENANCE ALTERNATIVES FOR OIL AND GAS PIPELINES

There are different repair options available for pipelines including, a) permanent repairs of onshore nonleaking defects, b) permanent repairs of onshore leaks, c) permanent offshore repairs, and, d) temporary onshore repairs (Jaske et al. 2006). Since in this research, the proposed maintenance planning concentrates towards external corrosion defects for underground pipelines, in this section the repair options for nonleaking external corrosion defects are highlighted. For such failures in underground pipelines, first the repair site is excavated, and the general condition of the pipeline coating is inspected. Then, to expose the exterior of the pipe, coating will be removed. If the defect or anomaly is on the exterior surface of the pipe, then the pipeline will be cleaned. In addition, through performance of in-line inspections, dimensional data (depth, location on pipe, width and length) are derived to decide on the repair type to be considered (US DOT 2012).

According to ASME (ASME B31.8S 2015), acceptable repair methods for defects due to external corrosion include, recoating, direct deposition weld, type B pressurized sleeving, type A reinforcement sleeving, composite sleeving, epoxy filled sleeving, mechanical leak clamp and replacement. On the other hand, according to (Palmer-Jones et al. 2005), for external defects, repair methods include weld repair, Type A and B sleeves and composite repairs. According to a survey conducted by (Jaske et al. 2006) among different repair techniques, the most typical ones include, application of type A and B sleeves, composite wraps, and welded patch or half soles.

2.5.1 Recoating

This type of rehabilitation technique is applicable to localized damaged areas which do not require a replacement and may be possible without production outage (CAPP 2018). Replacement of coating acts as an electoral insulator and moisture barrier with a good adhesion to the pipe surface (Palmer-Jones et al. 2005). The new coating may be of different types such as fusion bonded epoxy, three-layer polyethylene or tape wrap. In this repair type, the existing coating is removed through high pressure water jetting, surfaces are cleaned and prepared by sand blast or other equivalent treatments. Finally, application of coating material and curing is followed (Jaske et al. 2006; Palmer-Jones et al. 2005). As the most widely applied coating replacement, application of tapes (PVC or PE) is popular. However, as one of the limitations of this rehabilitation type, it's normally not suitable for pipelines with an operating temperature of 50 ^{0}C or more and may not conform to the corroded surface (Palmer-Jones et al. 2005).

2.5.2 Pipe replacement

This option is usually considered with extensive damage or deterioration is observed on the pipeline (AEA Technology Consulting 2001). In some cases, pipeline repair is performed by replacing a section of pipeline with new externally coated pipe (CAPP 2018). As the most economic repair solution, this replacement can either be a complete section (weld to weld) or a smaller cut out section through utilization of couplings or connector (AEA Technology

Consulting 2001; US DOT 2012). In case of pipe removal, shutdown or isolation of the affected segment through depressurization is inevitable to cut out a cylinder (Jaske et al. 2006).

2.5.3 Hot tapping

This method can be applied to an in-service pipeline. Application of this repair type may require reduction in pipeline pressure and resistance to stresses. In addition, the entire defect should be included in the removal by hole-cutting saw (Jaske et al. 2006).

2.5.4 Full-encirclement sleeving

Considered as the most common repair type, this repair method is not applicable to repair of offshore pipelines since it involves welding (US DOT 2012; Jaske et al. 2006). The sleeve may be of steel (type A or B) or composite material considered (US DOT 2012). As type A, it is used for non-leaking defects and can be installed on the pipe without welding to the pipe, making it a favorable option (Jaske et al. 2006). In type B sleeving, the sleeves are fillet welded to the carrier pipe. This method can be used for leaking or strengthening circumferential defects (Jaske et al. 2006). As composite wrap sleeving, the material type is normally of fiberglass or carbon fiber-based in some case with the same configuration of type A steel sleeving which is normally applied with an adhesive (US DOT 2012; Jaske et al. 2006; ASME B31.8S 2015). Compared to traditional repair practices such as pipeline replacement or full-encirclement steel split sleeves, this repair type is less expensive and time consuming. As another type of full-encirclement sleeving, epoxy filled shells contain a standoff distance from the pipe and are centered by bolts while side seams are welded and filled with epoxy (Jaske et al.

2006). Similar to type B sleeving, this repair type can be implemented for repair of cracks and girth weld defects (Palmer-Jones et al. 2005).

2.5.5 Weld deposition

In this kind of repair, the defect is eliminated through welding to restore the pipeline as an alternative to sleeving and is usually applied when application of a full encirclement is not possible due to fittings or bends (US DOT 2012). This method is popular since it is fast, direct and relatively inexpensive. However, there are two risks associated with this method, including risk of pipe wall penetration due to welding arc and hydrogen cracking due to accelerated cooling rate of the weld (Jaske et al. 2006).

2.5.6 Mechanical clamps

Mechanical clamps can be classified into two groups including bolt-on clamps and leak clamps. For bolt on clamps, a full circumferential clamp is used with bolted connection between the two halves (US DOT 2012). These clamps are usually heavy and thick and can be installed similar to Type A or B sleeves to contain full pressure of the pipeline, and are equipped with elastomeric seals to contain pressure in case of leaking (Jaske et al. 2006). Compared to bolt on clamps, a leak clamp is considered as a temporary option and is composed of relatively light metal bands with a single bolt to repair external corrosion pits (Jaske et al. 2006).

2.5.7 Patches and half soles

As one of the simplest forms of repair, a patch usually covers a portion of pipe surface while a half soles covers half of pipeline circumference. This repair type involves welding in regions far away from the defect area with sufficient thickness (AEA Technology Consulting 2001) . However, these repair types are sensitive to fabrication defects and are not recommended for pipelines with high pressures (Jaske et al. 2006).

In this research, the maintenance alternatives considered for maintenance of gas transmission pipelines include, replacement, composite wraps and type B reinforcement sleeving.

2.6 MAINTENANCE PLANNING MODELS FOR OIL AND GAS PIPELINES

Performing in-line inspections are considered as time demanding and expensive (Parvizsedghy and Zayed 2015a). On the other hand, regarding the suggested intervals for these inspections, the maintenance standards usually propose instructions without considering pipeline condition (Li et al. 2017). In recent years, more focus has been directed towards developing maintenance planning models based on data analysis (Dey et al. 2004). Most of these methods are considered as condition-based methodologies in which maintenance planning is scheduled regarding the deterioration profile or reliability level of the pipeline. Parvizsedghy et al. (Parvizsedghy et al. 2015) developed a maintenance planning framework based on condition thresholds for each maintenance action in addition to life cycle cost analysis (LCC). The LCC considers the uncertainties associated with operational costs and economic parameters through a Monte Carlo simulation and fuzzy approach. In two other similar studies, Sahraoui et al. (Sahraoui et al. 2017) and Gomes et al. (Gomes et al. 2013) proposed reliability-based maintenance planning strategies for corrosion failures on gas pipelines. For this objective, by referring to the available mechanical equations for the stresses acting on a pipeline and the yield strength of the steel material, the thresholds for reliability analysis were defined. In these studies, the decision criteria for inspection intervals are based on the total associated costs (i.e. the cost of repair, inspection and failure).

Li et al. (Li et al. 2017) proposed a maintenance strategy for subsea pipelines by determining the optimal maintenance intervals from the required failure probability and its distribution. However, this research is based on some pre-assumptions for the corrosion distribution rather than real field data. Through a parametric study, Zhang and Zhou (Zhang, S. and Zhou 2014) estimated the optimal inspection time of natural gas pipelines prone to corrosion failures based on pre-assumptions on the distribution of failure growth rate and the total number of defects. By considering the burst pressure of the pipeline as the limit state function and the expected cost as the decision criteria, the inspection interval is selected.

As one of the few studies to address pipeline availability during maintenance due to corrosion failure, Ossai et al. (Ossai, C. et al. 2016) determined different lifecycle phases of a pipeline. By considering several inspection scenarios and based on the survival function of the pipeline at different life cycle phases and availability of the pipeline, the probability of failure is calculated for the future. This model predicts defect growth rate and the appropriate maintenance strategy based on the defined thresholds for maintenance actions and defect growth rates. Accordingly, the costs of the maintenance plan are estimated based on the strategy selected. In the cited research, availability is not deployed as a decision criterion for pipeline maintenance planning.

2.7 GAP ANALYSIS

The review of state of art on developed failure prediction models reveals that despite large contributions in this domain, several limitations are remaining including: subjectivity due to reliance on models on expert judgment, need to expensive inspection/experiments, limited historical data, and inclusion of a limited number of failure types or consequences. In more detail, these limitations are classified and discussed as follows:

(i) Regarding failure risk and consequence assessment of oil and gas pipelines, the majority of the studies did not consider multiple consequences. The reviewed studies evaluated risk concerning only one or two specific consequences (individual, societal or monetary).

(ii) Most studies considered few failure types and did not differentiate between failure sources. Failures due to corrosion are considered as the most highlighted failure type in the reviewed publications. Most studies predicted the failure of oil and gas pipelines by considering only one failure type. Some studies ((Parvizsedghy and Zayed 2015b; Parvizsedghy and Zayed 2013) developed prediction models for time of failure; however, they did not consider any differentiation between failure types.

(iii) Applicability and generalization of some of the reviewed publications are limited since they are based on limited inspection or experimental data or they are proposed for a particular case study. Most studies developed failure prediction models based on inspection and experimental results from a particular case study.

(iv) Some of the models developed from available historical data are not considered as comprehensive models due to their reliance on limited historical data records. (Bertolini and Bevilacqua 2006), (Senouci, Elabbasy et al. 2014; Senouci, El-Abbasy et al. 2014), (Bersani et al. 2010), (Cobanoglu et al. 2014), (Luo et al. 2013) and (Zhou et al. 2016) developed failure prediction models from different available historical data with a limited number of records.

(v) The use of subjective approaches such as conducting expert surveys, which highly depend on human judgments and experience, can be considered as another limitation. Several studies developed failure prediction models solely based on expert judgments in the absence of historical data.

(vi) The current code-based procedures, widely practiced in industry, mainly consider corrosion and third-party activities in pipeline failure prediction. This is an oversimplification that leads to conservative predictions (underestimation) of failures that could lead to higher economic loss.

The review of current code-based procedures practiced in the industry for failure prediction of oil and gas pipelines revealed that such methodologies are mainly limited to corrosion and third-party failures. In addition, these procedures are oversimplified and conservative when it comes to failure prediction. This highlights the current gap between research and practice in oil and gas pipeline failure prediction. On the other hand, in the domain of corrosion failure prediction, the review of the developed methodologies reveals that though this failure type is the most frequently studied failure source, several research gaps are remaining. Numerous design and environmental parameters are effective on corrosion failure (Figure 2-3), however, most of these researches are merely based on empirical equations and are a function of design parameters, ignoring environmental factors. On the other hand, the application of some of these models may be limited since they are solely based on experimental tests or in-line inspections rather than pipeline historical data.

In addition, the state-of-the-art review on maintenance planning of oil and gas pipelines highlights some research gaps in this field that need to be addressed. Some of these methodologies rely on performing in-line inspections or are based on simplified assumptions for failure distribution to obtain pipeline deterioration curve or probability of failure. Such methodologies are limited in application due to their dependency on parameters of specific pipelines. In addition, in most of these studies, the impact of maintenance actions on the availability of a pipeline is ignored. In other words, these studies consider maintenance costs and condition or reliability thresholds as decision criteria for maintenance planning. Such approaches are ignoring the effect of mean time to repair on availability of a pipeline as a critical facility. Through a coupled cost and availability-based maintenance planning procedure, the logistics behind mean time to repair are considered in determining the maintenance time in addition to the associated costs. Performing a maintenance action before the proposed schedule will lead to over maintenance due to a marginal improvement in availability compared to considerable maintenance costs. On the other hand, performing a maintenance action after this time will lead to under maintenance due to compromising availability for cost efficiency.

CHAPTER 3. METHODOLOGY

In this chapter, mainly the methodologies pursued to develop the failure prediction models and maintenance planning framework are highlighted in detail. In general, this research is composed of three main phases including conducting detailed literature review as presented in the previous chapter, data collection, and the model development. In addition, model development is comped of two main phases. In the first phase, time-based failure prediction models for external corrosion of gas transmission pipelines are developed. Then in the second phase, a new maintenance planning framework is developed through an availability-based reliability-centered maintenance planning procedure. Development of such models are based on the analyzed research gaps in this domain and the collected failure records and maintenance data.

3.1 OVERVIEW

As presented in Figure 3-1, the general research methodology starts with a comprehensive review on failure sources in oil and gas pipelines and developed prediction models. Next, a review of the developed maintenance planning methods for these assets is conducted. In addition, the research gaps in developed prediction models and maintenance planning procedures of petroleum pipelines are identified. The details of this review are presented in chapters 2 and 5. Then, based upon the highlighted research gaps in this domain, a framework was proposed to develop time-based corrosion failure prediction models and an availability-based reliability-centered maintenance planning framework for gas transmission pipelines. To develop such prediction models, the corresponding failure and geo-environmental data for gas transmission pipelines were collected. Also, for the proposed maintenance planning framework, the corresponding cost and time maintenance data for such pipelines were gathered. The details of such data collection are discussed in detail in chapter 4.

In the third phase, based on the proposed methodology, two main models were developed. These models include corrosion failure prediction model for gas transmission pipelines and the availability-based reliability-centered maintenance planning method for these assets. In this chapter, the methodology pursued to develop such models are highlighted.

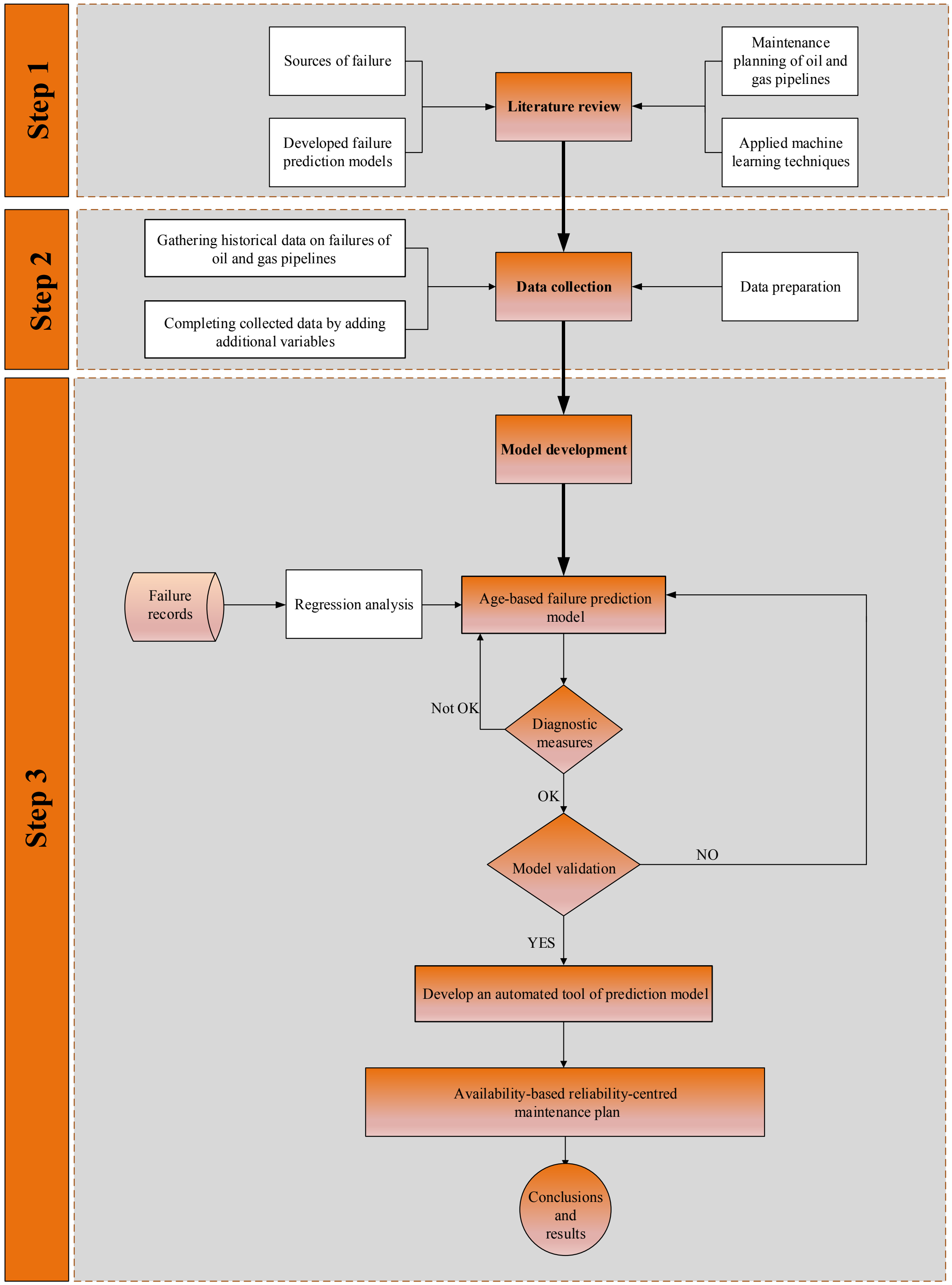


Figure 3-1 General methodology of the proposed research

3.2 FAILURE PREDICTION MODEL

Based on research gap analysis on the developed failure prediction models, this research aims at developing corrosion failure prediction models for gas transmission pipelines. Such models are developed through consideration of both conventional design and geo-environmental parameters which are often ignored. This objective is fulfilled through the application of multiple linear or best subset regression analysis on the highlighted variables. For this objective, the accessible experimental equations were also reviewed to extract the conventional corrosion failure parameters. To develop the failure prediction models, the predictor and response variables were first processed and prepared. In addition, to facilitate interpretation of results and correlation between variables, the data were standardized. Then regression analysis was performed on the training dataset that corresponded to 80% of the data which were randomly selected. Development of failure prediction models was done through trial and error rather than a straightforward procedure. Through a step by step procedure, the model with the most satisfactory diagnostic measures was selected to be validated and be determined as the final model. Chapter 5 presents the step-by step procedure to develop such models. Figure 3-1 (step 3) presents the overall methodology to followed for the development of the time of failure prediction model.

Different corrosion assessment methods have been developed based on experimental testing and numerical studies such as ASME B31 G (ASME B31G-2009 2009), modified B31G (Kiefner, F. and Vieth 1989), SHELL 92 (Ritchie and Last 1995b), and SAFE (Wang et al. 1998). These methods are based on estimates for burst pressure leading to pipeline failure. As one of these assessment methods, SHELL 92 is based on a rectangular shape assumption for corrosion defect and empirical factors to consider nonlinearity of pipeline material (Cosham and Hopkins 2003).

In addition, the application of this method leads to the highest probability of failure and the expected number of repair actions. According to this method, the burst pressure of a pipeline is considered as a function of pipeline design parameters (diameter, thickness, ultimate tensile strength) and Folias empirical factor (Klever et al. 1995; Li et al. 2009):

$$p_f = \frac{1.8UTS.THK}{DIAM}\left(\frac{1-\frac{d(T)}{t}}{1-\frac{d(t)}{t}M^{-1}}\right)$$

Equation 3-1

$$M = \sqrt{1 + 0.805\frac{L(T)^2}{DIAM.THK}}$$

Equation 3-2

Assuming a quasi-steady corrosion process,

$$d(T) = d_0 + V_r(T - T_0)$$

Equation 3-3

$$L(T) = L_0 + V_a(T - T_0)$$

Equation 3-4

Finally, Equation 3-1 is converted to the following equation as,

$$p_f = \frac{1.8UTS.THK}{DIAM}\left(\frac{1-\frac{d_0 + V_r(T - T_0)}{t}}{1-\frac{d_0 + V_r(T - T_0)}{t}M^{-1}}\right)$$

Equation 3-5

In the equations above;

UTS corresponds to ultimate tensile strength

p_f corresponds to failure pressure

$DIAM$ corresponds to pipe diameter

THK corresponds to wall thickness

$d(T)$ corresponds to time-dependent depth of the defect

T corresponds to elapsed time

M corresponds to Folias (bulging) factor

$L(T)$ corresponds to the axial length of the defect projected on the longitudinal axis

V_r corresponds to the radial corrosion rate

V_a corresponds to the axial corrosion rate

d_0 corresponds to the measured depth of a defect at time T_0

L_0 corresponds to corresponds to the measured length of a defect at time

T_0 correspond to the time of the last inspection

According to this equation, pipeline corrosion failure occurs when the operating pressure goes beyond the failure pressure.

3.2.1 Multiple regression analysis

Predictive models used in data mining are divided into two main categories, i.e. classification (discrimination) and predictive (or regression). The objective of both operations is to estimate the value of the dependent (target, response or explained) variable as a function of a certain number of other variables (explanatory, control or exogenous variables) (Tuffery 2011). For predictive models, if the dependent variable is quantitative or qualitative, the technique will be categorized as prediction or classification respectively. Regression analysis is a statistical method that utilizes the relationship between two or more variables to predict a dependent variable from independent ones (Senouci, Elabbasy et al. 2014). In the simplest form, a simple linear regression is expressed as Equation 3-6 where a continuous dependent variable Y relates to a continuous independent variable X (Ledolter and Hogg 1992). In the framework of this research, the independent variables were identified based on the literature review on the variables that affect degredation.

$$y_i = \alpha + \beta x_i + \varepsilon_i$$

Equation 3-6

It is assumed that the values of $x_1, x_2, \ldots, x_n$ of X are controlled and the corresponding values of $y_1, y_2, \ldots, y_n$ of Y are observed. In this equation, y_i is the value of the response variable in the "ith" trial, α and β are the regression parameters, x_i is the value of the predictor variable in the ith trial and ε_i is the random error. In a more general form of multiple regression, a multiple linear regression is applied to the case of several independent variables of X_i to obtain the dependent variable of Y as (Tuffery 2011);

$$Y = \beta_0 + \beta_1 X_1 + \cdots + \beta_p X_p + \varepsilon$$

Equation 3-7

3.2.2 Best subset regression analysis

In this research, for failure prediction model, first an automated best subset regression analysis was performed on the selected predictor variables. Best subset regression analysis facilitates modeling and exploring datasets in which many potential predictors are available. In this method, based on Mallow's C_p (which shall be close to the number of variables plus one), the model that presents the testing database more efficiently, is selected and its corresponding diagnostic measures are extracted. In this research, if the diagnostic measures of the selected subset were not satisfactory, the subsequent scenario was implemented until satisfactory diagnostic measures are obtained.

Mallow's C_p is considered as an estimate of total variation in the predicted estimate and yields to useful information on the size of the bias in a model. The difference between the population regression line and the average predicted regression line is the bias (Equation 3-8).

$$B_i = E(\hat{y}_i) - E(y_i)$$

Equation 3-8

An underspecified model is a model in which important predictors are missing and yields to biased regression coefficients. Mallow's C_p is the summation of two variance components; i.e. random sampling variation and the variance associated with the bias and is obtained from Equation 3-9, where p is the number of the parameters in the model,

$$C_p = \mathrm{p} + \frac{\left(\mathrm{MSE}_p - \mathrm{MSE}_{all}\right)(n - \mathrm{p})}{\mathrm{MSE}_{all}}$$

Equation 3-9

where

$$MSE = \frac{\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2}{n - p - 1}$$

Equation 3-10

Regarding to this equation, it is concluded that:

- When the C_p value is near p, the bias is small.
- Subset models with small C_p values have a small total (standardized) variance of prediction.

• When the C_p is much greater than p, the bias is substantial

Mallow's C_p also addresses the issue of overfitting. In case of overfitting, model selection statistics such as the residual sum of squares always get smaller as more variables are added into the model. However, Mallow's C_p is based on a sample data for which mean squared prediction error (MSPE) is set as population target.

3.2.3 Data processing and preparation

After the selection of the corresponding important variables in failure prediction of oil and gas pipelines, data preparation and processing were performed prior to model development. For this objective, first, the aberrant values (outliers) are detected and considered as missing. Outlier is an value resulting from an incorrect measurement or input error. In the next step, to handle the missing values for independent variables, through SPSS software, an automatic multiple imputation procedure was performed to interpret the patterns of missingness and to replace missing values with plausible estimates according to variable constraints. SPSS applies an automatic imputation that chooses the most suitable imputation method (monotone or fully conditional specification) based on data characterization. For this objective, the variables with missing or incorrect values are specified with their corresponding constraints. In addition, the time of failure is specified as the response when imputing missing values. After imputation, the software provides several imputed datasets for different imputation iteration. These imputed values are then united through mean values to be replaced in the dataset.

Regarding to the patterns of missingness, the data are monotone in case of presence of a pattern among missing values. For this data type, a monotone imputation method is usually applied. In monotone imputation, the model creates multiple imputations by imputing missing values sequentially over the variables taken one at a time. On the other hand, when the data have an arbitrary missing pattern (monotone or nonmonotone), a fully conditional specification (FCS) multiple imputation method is applied. In this method, the model specifies a univariate model for each variable. Then based on the imputed dataset, each variable with missing values is imputed iteratively. Then the imputed missing value is used in imputation of other variables until all missing data is imputated (IBM 2012).

In addition to dealing with missing values, the outliers were detected and omitted from analysis. These outliers were identified through constructing a box plot graph in Minitab software. To detect outliers in a box plot, interquartile ranges are calculated. The interquartile range (IQR) is the distance between Q3 – Q1 which contains the middle 50% of the data. Any data point more than 1.5 interquartile ranges (IQRs) below the first quartile (Q1 – (1.5 * IQR)) or above the third quartile (Q3 + (1.5 * IQR)) are considered as an outlier. Also, to facilitate interpretation of the developed models and due to differences in units of measurement, the data were standardized by rescaling the values between minimum and maximum ranges.

3.2.4 Diagnostic measures

After regression model was developed, several diagnostics measures are applied to test the efficiency of the model. These diagnostics include the coefficient of determination of R-Sq, adjusted R-Sq, mean square error (S or MSE), Mallow's C_p and residual analysis.

The coefficient of determination (R^2): As one of the diagnostic measures in regression model, R^2 presents the relative reduction of response error (Equation 3-11 to Equation 3-13). R^2 represents the proportion of variation in y (about its mean) "explained" by the multiple linear regression model with several predictors and can vary between 0 and 1. The more this measure gets close to 1 the better the data fits into the developed model.

$$R^2 = \frac{RSS}{TSS}$$

Equation 3-11

where,

$$TSS = \sum_{i=1}^{n} \left(y_i - \overline{y}\right)^2$$

Equation 3-12

and,

$$RSS = \sum_{i=1}^{n} \left(\hat{y}_i - \overline{y}\right)^2$$

Equation 3-13

Adjusted R-Sq: Though R-Sq is one of the important diagnostic measures, caution shall be made in considering this measure. For multiple linear regression, R-Sq always increases (or stays the same) when more predictors are added to a multiple linear regression model. It happens even when the predictors added are unrelated to the response variable (PSU 2017). An alternative measure, for multiple linear regression adjusted R-Sq is used for diagnostic measures (Equation 3-14 and Equation 3-15);

$$adjusted\ R^2 = 1 - \frac{(1 - R^2)(n - 1)}{n - p - 1} = 1 - \left(\frac{n - 1}{SSTO}\right) MSE$$

Equation 3-14

where

$$MSE = \frac{\sum_{i=1}^{n} \left(y_i - \hat{y}_i\right)^2}{n - p - 1}$$

Equation 3-15

Mean square error (S or MSE): Mean square error (S or MSE) quantifies how far away our predicted responses are from our observed responses and is desired to be small. By comparing Equation 3-14 with Equation 3-15, adjusted R^2 is a function of the mean square error (MSE).

Null hypothesis test: The diagnostic measures of Mallow's C_p, R-sq and R-sq (adj) were considered as the preliminary model selection criteria. However, the implementation of null hypothesis testing is necessary to determine whether a relationship between the response and explanatory variables indeed exists. For this objective, P-value (statistical significance) is a measure to interpret the results of regression analysis and tests the null hypothesis for each term. For a multiple linear regression model with the general form below as hypothesis we have,

$$Y = \beta_0 + \beta_1 X_1 + \cdots + \beta_p X_p + \varepsilon$$

Equation 3-16

null hypothesis: H_0: $\beta_1 = \beta_2 = \ldots = \beta_p = 0$

against the alternative hypothesis: H_0: $\beta_1 \neq \beta_2 \neq \ldots \neq \beta_p \neq 0$

In the analysis of variance table (ANOVA), a low p-value (< α=significance level) indicates that the null hypothesis can be rejected, where the coefficient of that term is not equal to zero. On the other hand, a large p-value indicates that the term is not significant. The significance level of α is used as a probability cutoff for making decisions about the null hypothesis where is assumed as 5%. P-value can be obtained from F-test which is a function of mean square regression (MSR) and mean square error (MSE).

$$F^* = \frac{MSR}{MSE}$$

Equation 3-17

For a multiple regression with *n* number of observations and *p* number of independent variables;

$$MSR = \frac{\sum_{i=1}^{n}(\hat{y}_i - \bar{y})^2}{p}$$

Equation 3-18

$$MSE = \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n-p-1}$$

Equation 3-19

Where $\hat{y}_1$,$\bar{y}$ and y_1 are estimated, mean and actual values of response variable respectively.

P-value is defined as the probability of obtaining a value of F^* through referring to an F-distribution with p numerator degree of freedom and $n - p - 1$ denominator degrees of freedom.

Residual analysis: Another criterion that should be fulfilled in model implementation is to verify that model error is random which implies that explanatory information is not present in the error. On the other hand, a satisfactory model shall have a normal probability plot which implies the normal distribution of the residuals that is an assumption in regression analysis.

3.2.5 Model validation

After model implementation and examination of the diagnostic measures, the developed model was validated to test its predictive effectiveness. For this objective, some mathematical validation procedures are conducted on the results obtained from the model for the testing dataset. The testing dataset corresponds to the remaining 20% randomly selected data. These mathematical validation procedures include average validity percentage (AVP), root mean square error (RMSE) and mean absolute error (MAE) as obtained from (Equation 3-20 to Equation 3-23).

$$AIP = \sum_{i=1}^{n} \left|1 - \left(\frac{E_i}{A_i}\right)\right| \times \frac{100}{n}$$

Equation 3-20

$$AVP = 100 - AIP$$

Equation 3-21

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(A_i - E_i)^2}{n}}$$

Equation 3-22

$$MAE = \frac{\sum_{i=1}^{n}|A_i - E_i|}{n}$$

Equation 3-23

$RMSE$ and MAE are used as statistical procedures to test model performance. While MAE gives the same weight to all errors, the $RMSE$ penalizes variance as it gives errors with larger absolute values more weight than errors with smaller absolute values.

3.3 MAINTENANCE PLANNING FRAMEWORK (PHASE II)

Figure 3-2 presents the proposed framework for availability-based reliability-centered maintenance planning of gas transmission pipelines. First, a state-of-the-art review was conducted on maintenance strategies of petroleum pipelines and their corresponding limitations as described in chapter 5. Then, failure records, data corresponding to the required repair timing and the associated costs for different maintenance actions were collected with respect to the developed failure prediction models as discussed in chapter 4. In phase III, based on the developed failure prediction model, and use of Monte Carlo simulation, the reliability profile of a gas transmission pipeline was obtained. Finally, in phase IV, an availability-based maintenance plan (schedule) is proposed (Figure 3-3). This schedule is based upon implementing discrete event simulation on different maintenance scenarios with respect to pipeline reliability profile and consideration of improvement in availability per unit cost as decision criteria. The costs associated with pipeline maintenance planning were derived from future estimates obtained from life cycle cost analysis. In the following section, the proposed methodology is discussed in detail.

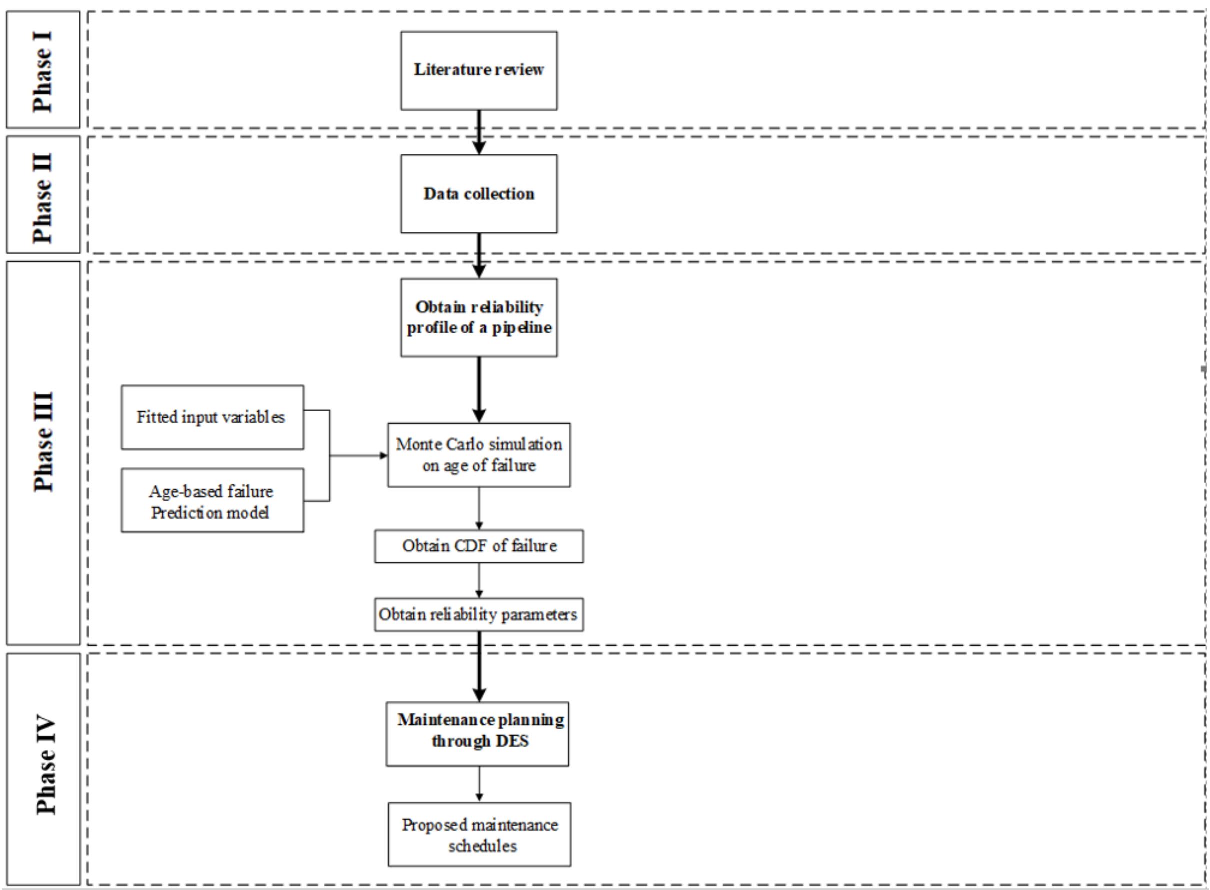


Figure 3-2 Research methodology for maintenance planning framework

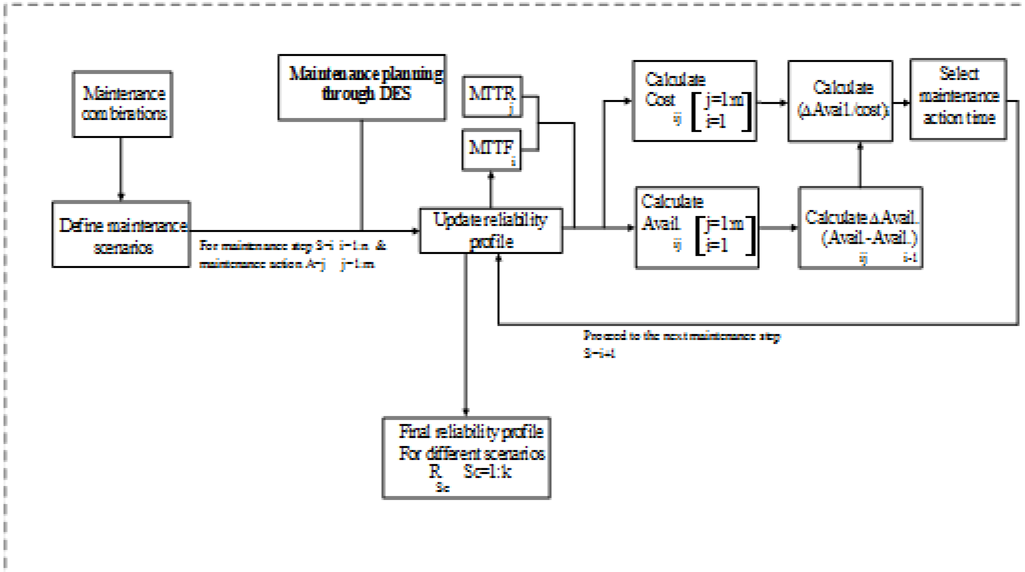


Figure 3-3 Details of discrete event simulation

3.3.1 Principals of reliability-centered availability-based maintenance planning

Reliability-centered maintenance (RCM) is a methodology in the application of a maintenance tool that provides two important pieces of information; criticality of equipment and the most appropriate maintenance operation to apply (Organ et al. 1997). In RCM, it is assumed that the inherent reliability of the equipment is a function of design and build quality (Rausand and Vatn 2008). This technique was designed to create a balance between the costs and benefits to select the most effective maintenance plan and is based on the principles of reliability engineering. In a reliability-centered preventive maintenance procedure, it is expected to improve the lifespan of system components in the system, reduce system failure and increase its mean time to failure (MTTF) (Ramakumar 1993; Pourhosseini 2016). In this procedure, preventive maintenance schedules are assigned depending on the specified reliability levels. RCM assumes that a system carries 100% reliability at the beginning point of operation and decreases over time with a probabilistic distribution (Altuger and Chassapis 2009). For this objective, first the reliability function of the pipeline is obtained to take advantage of the accessible failure data. Second, an availability-based maintenance technique is considered to identify maintenance scenarios to minimize system failures and increase reliability and availability.

Availability of a component is defined as the rate of up-time to the accumulation of up-time plus downtime. Availability is an indication of the probability of up-time of a component or a system and is a measure to assess how often a system is alive (Pourhosseini 2016; Barringer 1997). System availability can be quantified by the mean time to failure (MTTF), and the mean time to repair (MTTR) (Zhang, T. et al. 2002).

$$a_{i,j,k} = \frac{MTTF_{i,j,k}}{MTTF_{i,j,k} + MTTR}$$

Equation 3-24

Where $i,$ j and k reflect the number of systems, number of components and maintenance intervals. $MTTF$ is obtained based on the reliability analysis principles of each component in a system. In addition, $MTTR$ is based on the average time to repair the components to be maintained.

In the case of having access to the database of failures of a component in a system, the mean time to failure ($MTTF$) can be obtained from the cumulative distribution function, i.e. $F(t)$ and probability distribution function (PDF) (Ramakumar 1993);

$$F(t) = \int_0^t f(x)dx \qquad t \geq 0$$

Equation 3-25

Reliability is defined as the likelihood (probability) that a component will perform its intended function without failure for a specified period. The relationship between cumulative distribution function of failures and reliability is as follows,

$$R(t) + F(t) = 1$$

Equation 3-26

In many cases, the probability distribution function, i.e. *f(t)*, typically follows typical distributions such as normal, exponential, Weibull, etc. For a Weibull distribution (Billinton and Allan 1992),

$$f(t) = \frac{\beta t^{\beta-1}}{\alpha^{\beta}} \exp\left[-\left(\frac{t}{\alpha}\right)^{\beta}\right]$$

Equation 3-27

$$R(t) = \int_{t}^{\infty} f(t)dt = \exp\left[-\left(\frac{t}{\alpha}\right)^{\beta}\right]$$

Equation 3-28

where β and α are defined as shape and scale parameters respectively.

$MTTF$ which is defined as the average time that an item will function before it fails is obtained from (Ramakumar 1993; Billinton and Allan 1992);

$$MTTF = \int_{0}^{\infty} tf(t)dt = \int_{0}^{\infty} R(t)dt$$

Equation 3-29

For availability-based maintenance planning of gas transmission pipelines, first the reliability profile of a gas pipeline was obtained through performing a Monte Carlo simulation with

Companion by Minitab software on the collected failure records and the failure prediction model developed for Great Plains (chapter 5). Through Monte Carlo, the uncertainties associated with external corrosion failure are considered. Such simulation considers wide range of design parameters for development of the reliability profile that were potentially missing in the historical data. For such simulation, first the best-fitting distribution is extracted from the software (based on the probability plots and p-values) for each predictor variable in the model (normal or Weibull). Then by feeding the prediction model into the simulation and generation of random values for each predictor (considering its distribution), the response variable (time of failure) is extracted (more than 10,000 alterations).

3.3.2 Availability-based maintenance planning for gas transmission pipelines

To perform an availability-based maintenance planning procedure, a discrete event simulation was performed on three maintenance scenarios for gas transmission pipelines. Each scenario consists of one or more maintenance actions, i.e. composite wrap, reinforcement sleeves or replacement as presented in Table 3-1. The objective of this simulation is to determine the optimum time to carry a maintenance action based on both availability improvement and the associated costs which are linked together through an availability-cost indicator $\left(\frac{\Delta\alpha}{C}\right)$. $\Delta\alpha$ Corresponds to the improvement in availability after and before a maintenance action while C corresponds to the future cost associated with a maintenance action. Such an indicator is defined to prevent performing expensive actions with minor improvements in availability. The improvement in availability ($\Delta\alpha$) is obtained from the equation below where i and ii correspond to the time before and after performing a maintenance action.

$$\Delta\alpha = \alpha_{ii} - \alpha_i = \frac{MTTF_{ii}}{MTTF_{ii} + MTTR_{ii}} - \frac{MTTF_i}{MTTF_i + MTTR_i}$$

Equation 3-30

Table 3-1 Maintenance scenarios

Maintenance scenario	Maintenance actions
1	sleeve and replacement
2	wrap and replacement
3	replacement only

The simulation advances in discrete reliability steps of 0.05 starting from 0.9 to 0.1 for each maintenance action according to its corresponding scenario. At each reliability step (R_i), the time corresponding to the reliability level (t_i) is obtained from Equation 3-28. In this research, the secondary reliability level (R_{ii}, after pipeline maintenance), is obtained from two simplified assumptions on improvement of reliability due to a maintenance action for repair and replacement. For repair actions (composite wrap and reinforcement sleeves), it is assumed that the secondary reliability level improvement is equal to 70% of primary reliability drop, while for replacement action this ratio is equal to 90% (Parvizsedghy et al. 2015).

For repair actions (composite wrap and sleeving):

$$R_{ii} = R_i + 0.7 \times (1 - R_i)$$

Equation 3-31

For replacement action:

$$R_{ii} = R_i + 0.9 \times (1 - R_i)$$

Equation 3-32

After obtaining the secondary reliability level (R_{ii}), t_{ii} is obtained from Equation 3-28. Similar to t_i, these values are deployed in Equation 3-29 to obtain $MTTF_i$ and $MTTF_{ii}$ which correspond to the mean time to failure before and after performing a maintenance action.

To obtain pipeline availability from Equation 3-30, it is required to have access to the associated costs and repair duration data for each maintenance action respective to the pipeline age. However, according to the collected data, these values are a function of the defect size. Therefore, it is required to link the size of a defect with the pipeline age. For this objective, as the second assumption in this research, the maintenance planning procedure is intended for a section with a length of L. In addition, the defect size at each time is assumed to be a function of its corresponding its reliability level;

$$Sd_t = L \times (1 - R_t)$$

Equation 3-33

Where Sd_t, L and R_t correspond to defect size, section length, and the reliability level at each time. Through this assumption, reliability (a function of time) will be incorporated in the developed equations associated with the required costs and timing for each maintenance action.

Finally, for each time step, the availability-cost indicator ($\frac{\Delta\alpha}{C}$) is obtained from $MTTF$, $MTTR$ and the associated cost values, which are all a function of the corresponding time. These values are plotted against time and the point corresponding to the maximum $\frac{\Delta\alpha}{C}$ is determined through a polynomial interpolation among these values. Finally, after determination of the optimum maintenance time, the reliability profile is updated according to the pre-assumptions of reliability level improvements (Equation 3-31 and Equation 3-32). For the maintenance scenarios with more than one action, after determining the optimum time for performing the first action, the same procedure is repeated to proceed with determination of the optimum time to perform the second action.

3.3.3 Life cycle costing

The information obtained from the cost data collection corresponds to the present cost value associated with performing each maintenance action. For the decision criteria ($\frac{\Delta\alpha}{C}$), C corresponds to the future cost (F) of maintaining the pipeline system. Future cost value for each maintenance action is obtained from transforming the present maintenance costs (derived from the linear regression analysis on the collected data) to future costs from Equation 3-34 through a life cycle analysis. In this equation P, i and N correspond to present cost value, inflation rate (5%) and the number of interest periods (years) respectively.

$$F_N = P \times (1 + i)^N$$

Equation 3-34

CHAPTER 4. DATA COLLECTION

This chapter presents an introduction to the historical data that were collected to develop the proposed time-based failure prediction and maintenance planning. These data include, failure records, supplementary geographical and environmental data corresponding to the failure data, cost and time maintenance planning data.

4.1 HISTORICAL FAILURE DATA

In general, in oil and gas sector, access to data is difficult due to criticality and confidentiality issues. However, there are several databases open to the public. Some of these databases can be named of pipeline and hazardous materials safety administration (PHMSA) (US DOT 2016a), CONservation of Clean Air and Water in Europe (CONCAWE) (Davis et al. 2010) and European Gas Pipeline Incident Data Group (EGIG) (EGIG 2015). Among these accessible failure records, PHMSA is considered as one of the most comprehensive databases since it reports detailed information on failures of oil and gas pipelines located in the U.S. Some of the reported information can be named as pipeline properties (physical characteristics, location, coating etc.), consequence properties (material lost, monetary damage and safety damages) and incident properties (time, pressure, incident type, etc). In this database, au lieu of linguistic or binary values, data have been reported as numerical values which increases its accuracy (Parvizsedghy 2015). In this section, the details of the collected data from PHMSA database to develop the proposed time-based failure prediction model are presented.

4.2 OVERVIEW OF FAILURE DATABASE

PHMSA database reports the incidents that have occurred in oil and gas pipelines since 1970. According to this database, an incident is an event that resulted in the gas leakage and has led to one or more of the following criteria:

1) "A death, or personal injury necessitating in-patient hospitalization; or"

2) "Property damage, including the product loss cost of 50,000 USD or more",

3) "An event that is significant even though if it does not meet the above criteria" (PHMSAa 2014).

Depending on the type of pipeline and the material transferred, the database is classified into four categories including gas transmission (GT), gas distribution (GD), hazardous liquid (HL) and liquefied natural gas (LNG) pipelines. Except for LNG pipelines, each category covers failures since 1986 to the present at three different time intervals. Figure 4-1 presents the description of the available data fields in this database.

Gas Transmission and Gathering Systems Incident Reports for 2002 - 2009 (PHMSA Form 7100.2 Rev. 01-2002) - Data Dictionary for Flagged Data file

Field Name	Data Type	Field Name Description	Form Location
PRTYR	NUMBER	Year the pipe or component which failed was installed	PART C - ORIGIN OF THE INCIDENT
NPS	NUMBER	Nominal pipe size in inches	PART D - MATERIAL SPECIFICATION
WALLTHK	NUMBER	Wall thickness in inches	PART D - MATERIAL SPECIFICATION
SPEC	VARCHAR2	Specification	PART D - MATERIAL SPECIFICATION
SMYS	NUMBER	Specified Minimum Yield Strength (SMYS)	PART D - MATERIAL SPECIFICATION
SEAM	VARCHAR2	Seam type	PART D - MATERIAL SPECIFICATION
VALVE	VARCHAR2	Valve type	PART D - MATERIAL SPECIFICATION
MANU	VARCHAR2	Pipe or valve manufactured by	PART D - MATERIAL SPECIFICATION
MANYR	NUMBER	Year manufactured	PART D - MATERIAL SPECIFICATION
LOCLK_TEXT	VARCHAR2	Area of incident	PART E - ENVIRONMENT
LOCLKO	VARCHAR2	Text describing Other for LOCLK_TEXT field	PART E - ENVIRONMENT
DEPTH_COV	NUMBER	Depth of cover in inches	PART E - ENVIRONMENT
CAUSE	VARCHAR2	Apparent cause of incident	PART F - APPARENT CAUSE
CAUSE_DETAILS	VARCHAR2	Detailed cause of accident	PART F – APPARENT CAUSE
MAP_CAUSE	VARCHAR2	Cause by PHMSA for 20 year incident trending	Not on the form
MAP_SUBCAUSE	VARCHAR2	SubCause by PHMSA for 20 year incident trending	Not on the form
PIPE_COAT_TEXT	VARCHAR2	Pipe coating	PART F1 - CORROSION
VIS_EXAM_TEXT	VARCHAR2	Visual examination	PART F1 - CORROSION
VIS_EXAMO	VARCHAR2	Text describing Other for VIS_EXAM_TEXT field	PART F1 - CORROSION
COR_CAUSE_TEXT	VARCHAR2	Cause of corrosion	PART F1 - CORROSION

Figure 4-1 Sample reported data in PHMSA database

As the concentration of this research is on gas transmission pipelines, Table 4-1 presents the frequency of failures and the cost of property damage in these assets since the year 1986. As presented in this table, more than 1 billion dollar of property damage has been reported for gas transmission pipelines in this period. Such number highlights the importance of maintaining these assets in proper conditions. It should also be noted that in this database there is not a unit framework for data presentation for different time intervals. This problem leads to devoting more time into exploring and interpreting the reported data.

Table 4-1. Frequency of failure for different pipelines

Type of pipeline	Time interval	No. of failures	Damage ($)	Total no. of failures	Total damage ($)
GT	1986-2001	1288	$484,462,681		
GT	2002-2009	1029	$158,060,438	3569	$1,358,067,990
GT	2010-P	1252	$715,544,871		

4.3 FAILURE DATA ANALYSIS

As previously mentioned, one of the objectives of this research is to develop a time-based failure prediction model based on the reported historical data. To fulfill this objective, the variables corresponding to pipeline failure first need to be extracted from the database. As one of the failure variables, distribution of different failure sources and the property damage costs associated with each source was analyzed. Table 4-2 presents the proportion of these incidents for different failure sources in gas transmission pipelines. According to this figure, for these assets, corrosion failure is ranked as the most frequent failure type, corresponding to approximately a quarter of total number of failures. Followed by corrosion failure, other outside force damage is the next frequent failure type. However, as it is clear from the title, this failure can be derived from different causes. On the other hand, similarly, corrosion failure is identified as the failure source with the highest property damage costs since 1986 leading to more than 410M$ of property damage as presented in Table 4-3. This number corresponds to 30% of the total property damages in these assets during this period. The numbers related to the high frequency and considerable associated costs with corrosion failure, were a motivation to base this research upon this failure source. On the other hand, compared to other failure sources such as excavation damage and natural force damage, corrosion failure is considered as time-dependant, and not random. In other words, the frequency of distribution and the severity of damages due to this failure source accelerate with time.

Table 4-2 Proportion of failure sources in gas transmission pipelines

Failure source	% of occurrence
Corrosion	23
Other outside force damage	19
Equipment failure	14
Material failure of pipe or weld	13
Other incident cause	13
Excavation damage	8
Natural force damage	7
Incorrect operation	3

Table 4-3 Property damage due to different failure sources

Cause	Property damage ($)	% of cost
Corrosion	$410,113,115	30
Other outside force damage	$284,634,401	21
Equipment failure	$99,569,644	7
Material failure of pipe or weld	$200,957,185	15
Other incident cause	$170,148,536	13
Excavation damage	$51,784,839	4
Natural force damage	$84,070,697	6
Incorrect operation	$56,789,572	4
Total	$1,358,067,990	

After selection of corrosion failure as the failure source to be studied in this research, other failure parameters were extracted from the database. PHMSA database provides information on many parameters and attributes of an incident that has taken place in oil and gas pipelines. As a simple classification, the recorded parameters can be categorized into three main groups including system, consequence and incident parameters as summarized in Figure 4-2. According to this figure, system parameters correspond to the physical properties of the system (e.g., installation year, depth of cover, class), design characteristics (e.g. diameter, thickness, maximum operating pressure, yield strength) and the environment in which the system is located (e.g. soil type, soil temperature). Consequence parameters correspond to the consequences that take place due to the failure including safety damages (injuries and death) and monetary damages (e.g. loss, operator and total damages). On the other hand, incident parameters correspond to the ones that are related to the incident itself rather than what happens afterward (e.g. date, pressure, the part that failed source of failure etc.). Since the concentration of this research is on time of failure prediction of gas transmission pipelines, the parameters to be used correspond to system parameters that are known before a failure takes place.

The identified system parameters from the database were then compared to the identified efficient design factors in experimental equations for corrosion failure (Equation 3-1 and Equation 3-5), and the important parameters were extracted accordingly. These design parameters include pipe wall thickness (THK), diameter (DIAM), and pressure at the time of the incident (INCP), maximum allowable pressure (MAOP), specified minimum yield strength (SMYS) and depth of cover (cov) as presented in Table 4-4.

Table 4-4 Variable thresholds

Variable	Minimum	Maximum
TIME (years)	4.00	85
TEMP (cent.)	35.00	86
INCP (psi)	35.0	1200
MAOP (psi)	120.0	1337
DIAM (in)	3.50	36
THK (in)	0.1300	0.5
SMYS (psi)	1050	1200
COV (in)	12.00	99.6

After selection of the corresponding variables to failure prediction of oil and gas pipelines, first, the aberrant values are detected and removed. Aberrant value is an enormous value resulting from incorrect measurement or input error. As an example, according to design specifications, the diameter of a gas transmission pipeline does not go beyond 52 inches. For this reason, the records with diameters exceeding 52 inches are excluded from statistical analysis and are treated as missing values. In the next step, an automatic imputation procedure was performed through SPSS software, in order to obtain estimates for the missing values. Also followed by data imputation, the outlies for the collected data were identified and removed from data analysis. The details of imputation procedure and detection of outliers were previously presented in section 3.2.3 of research methodology.

4.4 SUPPLEMENTARY DATA

In addition to the data collected from PHMSA, in this research, other available databases were also examined to obtain supplementary information. Such examination is tied to the literature review already pursued on effective design parameters on corrosion failure. For this objective, for each recorded failure, two other variables were extracted, i.e. average monthly soil temperature at the date of the incident and geographic location based on the climatological classification.

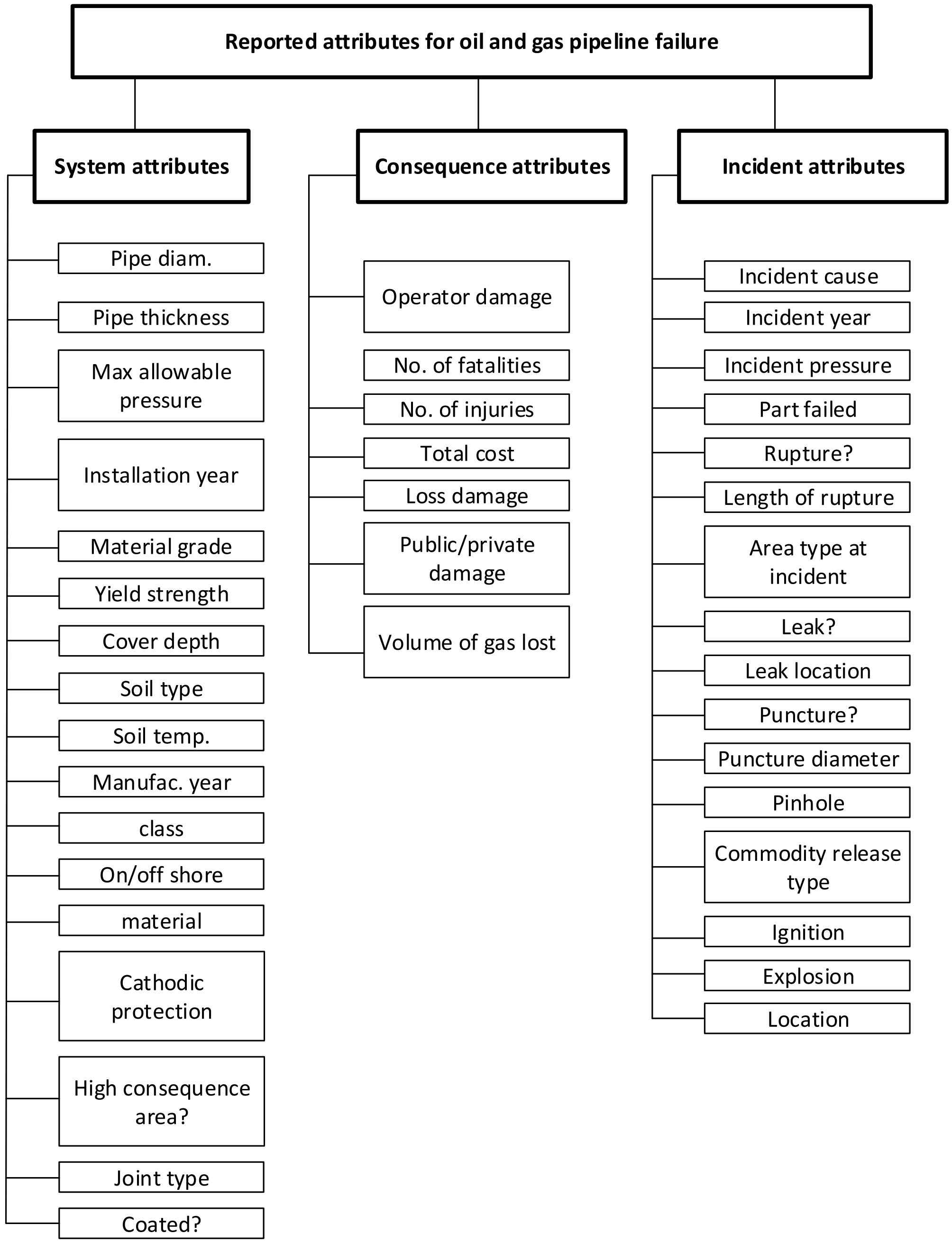


Figure 4-2. Reported variables in PHMSA database

4.4.1 Average monthly soil temperature

According to the literature, soil properties and content are among the parameters than have an impact on soil corrosivity (Bansode et al. 2015). As one of these properties, higher soil temperatures in summer months have led to greater magnitudes of steel pipe corrosion. In other words, changes in soil temperature would lead to changes in soil electrical resistivity (Pritchard et al. 2013; Nie et al. 2009; SeonYeob et al. 2007). In this research, as one of the affective parameters on soil corrosivity, soil temperature record at the time of failure were also extracted from other databases.

To obtain this parameter, the data was collected from national climatic data center (NCDC) (NCDC 2017). In this database, since 1891, for different states in the U.S. and for different stations across each state, the daily soil temperatures are recorded. For simplicity in the context of this research depending on the date and the state of each incident, the average monthly temperature for different soil stations was extracted. As an example, Figure 4-3 presents a sample of the reported soil temperatures in NCDC for Oklahoma State in 2004.

OKLAHOMA
2004

SOIL TEMPERATURES

STATION	DEPTH	EXTREMES	JAN		FEB		MAR		APR		MAY		JUN		JUL		AUG		SEP		OCT		NOV		DEC		ANNUAL	
			AVERAGES	EXTREMES	AVERAGES	EXTREMES	AVERAGES	EXTREMES	AVERAGES	EXTREMES	AVERAGES	EXTREMES	AVERAGES	EXTREMES	AVERAGES	EXTREMES	AVERAGES	EXTREMES	AVERAGES	EXTREMES	AVERAGES	EXTREMES	AVERAGES	EXTREMES	AVERAGES	EXTREMES	AVERAGES	EXTREMES
OKLAHOMA																												
PANHANDLE 01																												
GOODWELL RESEARCH STA	(IN)																											
BARE GROUND	4	MAX	40.9	46	42.6	51	55.7	66	61.7	68	77.0	85	83.0	93	84.1	91	79.1	86	78.1	87	-	-	49.4	61	40.2	44	-	-
	4	MAX		33		36		44		50		61		75		75		73		69		-		43		37		-
	4	MIN	36.0	40	37.1	45	50.3	60	55.0	62	68.5	76	75.0	85	76.3	85	72.8	80	71.4	78	-	-	44.8	54	37.7	41	-	-
	4	MIN		32		32		42		41		55		69		70		67		64		-		37		35		-
NORTH CENTRAL 02																												
LAHOMA RESEARCH STN	(IN)																											
BARE GROUND	4	MAX	43.7	54	42.0	54	-	-	-	-	80.7	95	84.3	94	89.4	97	86.7	96	85.0	90	69.4	81	54.2	63	43.8	52	-	-
	4	MAX		32		31		-		-		66		75		75		74		77		61		44		32		-
	4	MIN	36.7	47	36.1	47	-	-	-	-	68.3	79	74.0	79	78.3	84	75.2	82	73.4	79	61.1	70	48.2	58	38.2	47	-	-
	4	MIN		32		32		-		-		54		67		72		68		67		52		39		31		-
MUTUAL	(IN)																											
BARE GROUND	4	MAX	42.4	53	41.8	55	61.5	73	68.7	80	81.8	90	85.4	94	89.6	99	88.0	95	84.7	91	68.3	77	51.9	61	42.5	51	67.2	99
	4	MAX		32		33		45		52		65		73		77		74		75		59		43		33		32
	4	MIN	35.9	44	35.6	44	47.7	63	55.2	65	69.0	78	73.8	81	77.9	85	74.8	84	71.2	79	57.8	67	45.1	56	36.9	44	56.7	85
	4	MIN		30		31		37		43		53		66		69		66		64		43		38		31		30
SOUTHWEST 07																												
ALTUS IRIG RES STN	(IN)																											
BARE GROUND	4	MAX	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	45.4	53	-	-
	4	MAX		-		-		-		-		-		-		-		-		-		-		-		39		-
	4	MIN	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	40.0	44	-	-
	4	MIN		-		-		-		-		-		-		-		-		-		-		-		34		-
SOUTH CENTRAL 08																												
ADA	(IN)																											
BARE GROUND	4	MAX	42.8	54	41.7	54	58.8	70	67.3	76	76.3	84	80.4	88	83.9	92	81.5	90	80.7	86	69.5	78	53.9	64	46.3	60	65.3	92
	4	MAX		32		34		48		52		58		70		70		74		72		56		46		28		28
	4	MIN	36.4	48	35.4	46	49.2	60	54.1	64	63.0	74	67.1	73	72.2	80	70.0	78	65.6	74	59.0	67	47.4	60	36.6	44	54.7	80
	4	MIN		28		30		40		42		52		62		66		64		58		50		39		26		26
SOUTHEAST 09																												
TUSKAHOMA	(IN)																											
BARE GROUND	4	UNKN	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	4	UNKN		-		-		-		-		-		-		-		-		-		-		-		-		-
	4	UNKN	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	4	UNKN		-		-		-		-		-		-		-		-		-		-		-		-		-

Figure 4-3. Sample of the reported soil temperatures in NCDC (NCDC 2017)

4.4.2 Climate regions

In order to confine the collected data according to location, the failure records were also classified according to their climatological locations. Regarding to the location at which the incident occurred, PHMSA database provides both longitudinal and latitudinal coordinates, as well as the city and the state where the incident occurred. However, to develop failure prediction models in the context of the current research, it was referred to the databases with climate classifications in the U.S. to simplify varieties of the location of oil and gas pipelines. As one classification, national climate data center (NCDC) has classified US states in eight different regions according to historical climate trends and climate scenarios of the future. The climate factors that are considered in this analysis include regional floods, thunderstorms, drought, heat waves, water levels and winter storms. On the other hand, the climate trends considered in this classification include temperature, precipitation, extreme heat and cold, extreme precipitation, wind, freeze-free season, snowfall, water levels, ice cover and humidity. These regions include Northeast, Southeast, Midwest, Great Plains, Northwest, Southwest, Alaska, and Hawai'i/Pacific Islands as illustrated in Figure 4-4.

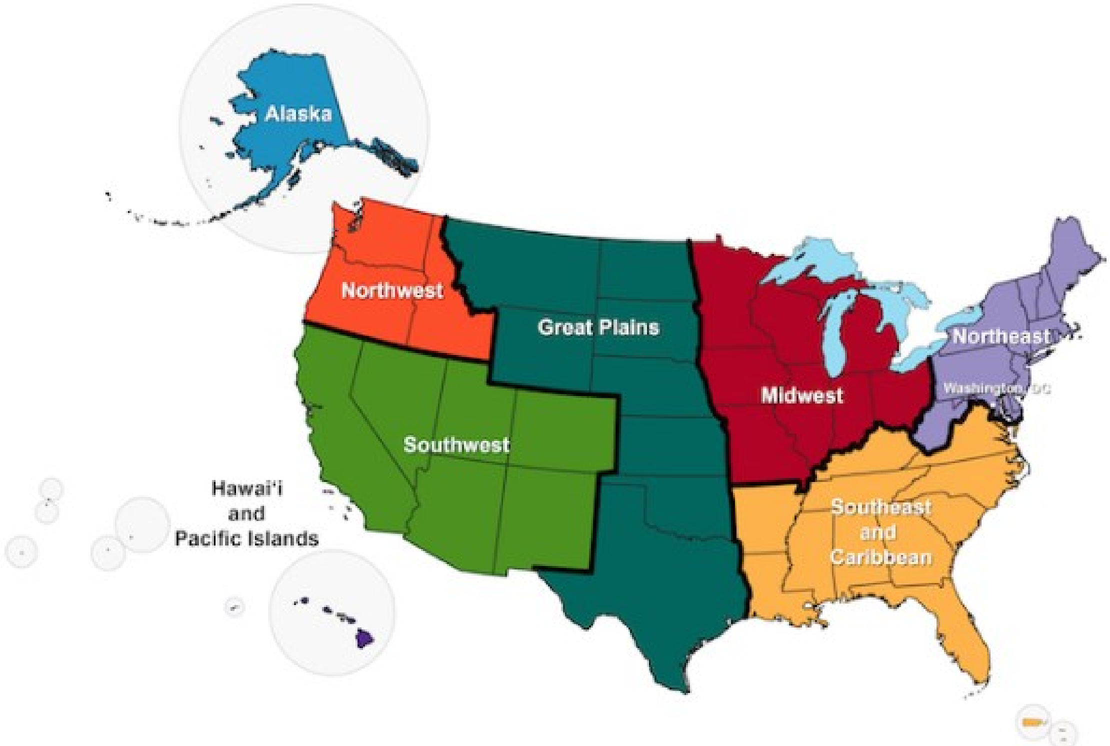


Figure 4-4. Classifications of regions of US (NCDC 2016)

4.5 MAINTENANCE DATA

Development of an availability-based reliability-centered maintenance planning framework requires collecting data for possible maintenance alternatives of oil and gas pipelines. The collected data for each alternative include maintenance costs and the required time to perform a maintenance action.

For pipeline availability assessment, the cost and the required time data for different maintenance actions were collected through reviewing accessible industrial brochures, published articles and reports on maintenance options for gas pipelines. These data were collected for the repair types of the non-leaking defects arising from external corrosion in accordance with ASME (ASME B31.8S 2015), including reinforcement sleeve (type B), composite wrap (type A sleeve) and replacement. In this research, the maintenance action durations are acquired as a measure for mean time to repair (MTTR), while the associated costs are required for calculation of availability per unit cost as the decision criterion.

The data corresponding to pipeline replacement and composite wrap repair were collected from EPA (EPA 2005). This report covers the costs and the required timing for replacement and composite wrap (type A sleeve) repairs. The cost and duration of these repair types are dependent upon the defect length and pipeline diameter. The associated costs for this repair type include labor (operator, pipeline and apprentice), equipment (composite kits butted together, coating, backhoe and sandblast) and material as well as indirect costs such as permit and inspection services. Compared to composite wrap, replacement repair imposes a supplementary cost, i.e. gas loss and purging since this technique requires pipeline shutdown and isolation. In this report, such data are presented for a 24-inch diameter pipeline with defect lengths of 6 and 234 inches.

According to OGJ (OGJ 2001), the timing considered for the installation of a type B sleeve is an hour. On the other hand, the length of both types A and B sleeves shall be long enough to extend at least 2 inches beyond both ends of the defect, and if required, two or more sleeves shall be butted and joined by welding (Jaske et al. 2006). The manufacturing and welding cost for the installation of a 15 cm sleeve is reported as $600. In this research, by considering similar cost elements, the associated costs and required timing for replacement, composite wraps and type B reinforcement sleeves are estimated for a 24-inch diameter pipeline with different defect lengths i.e. 6, 44, 82, 120, 158, 196 and 234 inches (Table 4-5). Then, through a linear regression analysis, the equations for present maintenance costs and the time required for each maintenance action are formulated as a function of defect size. These equations are presented in Figure 4-5 and Figure 4-6. Finally, the associated costs and the required time to perform a maintenance action at each time were formulated as a function of pipeline reliability (Equation 3-33) by assuming as section length of 10 meters for the studied case.

Table 4-5 Time and cost data versus defect size

	composite wrap		replacement		reinforcement sleeve	
Defect size (in)	Cost ($)	Time (hr)	Cost ($)	Time (hr)	Cost ($)	Time (hr)
6	6647	16	48208	40	5834	13
44	12592	19	49810	43	12592	15
82	19051	21	51845	47	13069	17
120	25252	24	53881	50	16725	19
158	33253	27	55917	53	21287	21
196	39455	29	57953	57	24944	23
234	45669	32	59997	60	28991	26

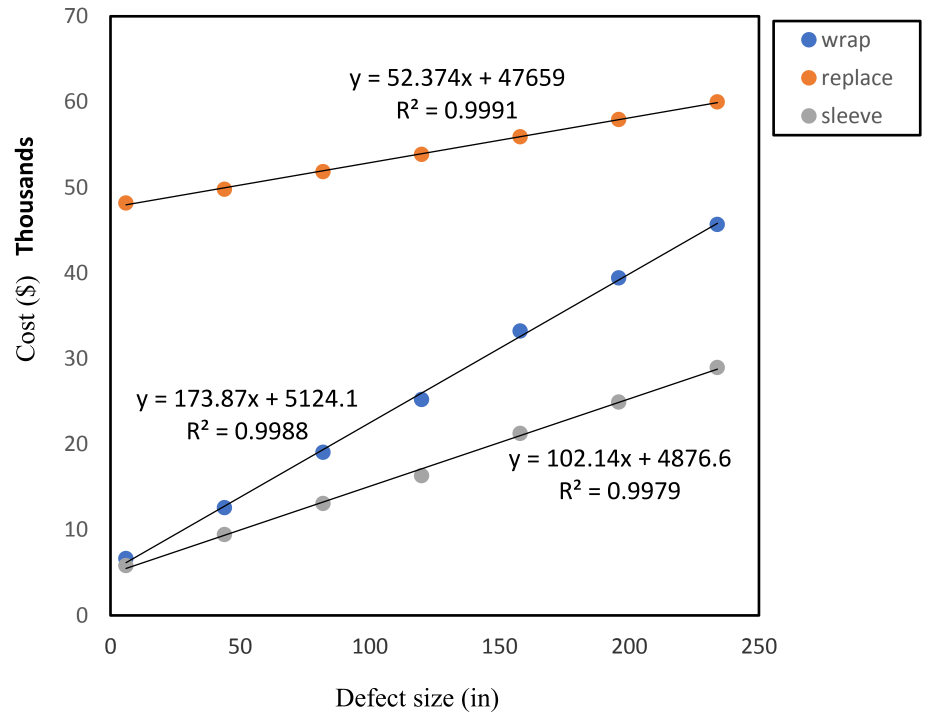


Figure 4-5 Associated costs versus defect size for each maintenance action

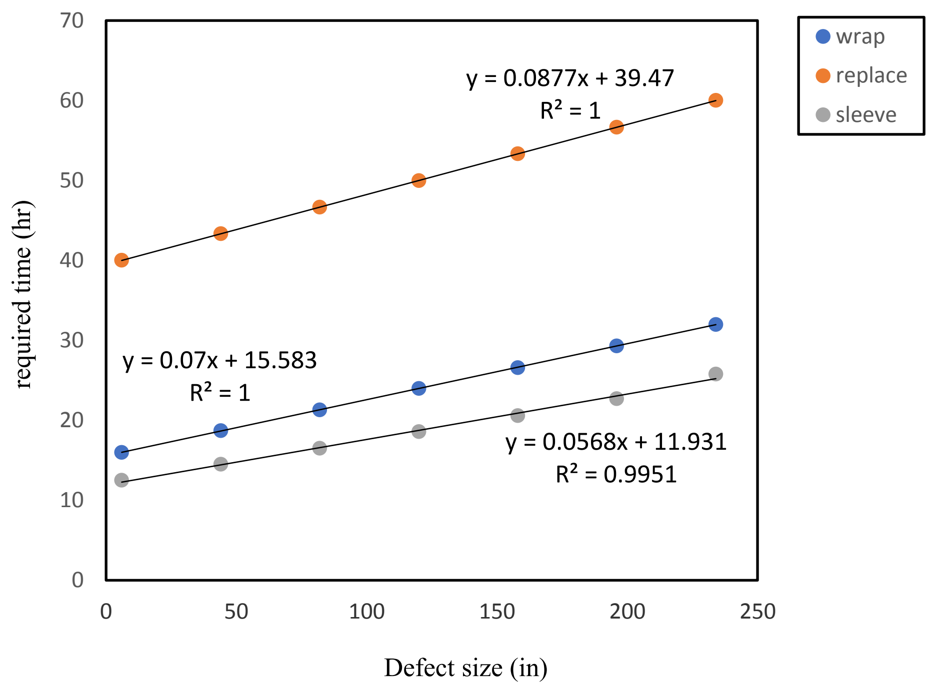


Figure 4-6 Timing required versus defect size for each maintenance action

CHAPTER 5. MODEL IMPLEMENTATION AND ANALYSIS

This chapter presents the details on model development and results analysis for the third step of this research. These developed models include i) time-based failure prediction models and ii) the maintenance planning framework developed for corrosion failure in gas transmission pipelines.

5.1 IMPLEMENTATION OF THE FAILURE PREDICTION MODEL

As previously discussed, in order to ensure pipeline safety, corrosion monitoring of pipelines is performed through different methods of in-line inspection (Baker 2008). This technique requires frequent assessment of pipeline condition through the application of high-tech devices such as magnetic flux and ultrasonic tools to report anomalies including metal loss, dents and gouges. However, due to the required high frequency of in-line inspections and resolution perquisites, this method is considered as excessively expensive and time-consuming. For this reason, in recent years, more focus has been contributed towards the development of models that can estimate corrosion failure to avoid performing unnecessary expensive in-line inspections. These models are usually based on the failure pressure models obtained from theory and experimental tests (Xie and Tian 2018; Chou et al. 2010; Oliveira et al. 2016; Witek 2016). Such tests require information on the design variables of the pipeline and often ignore effective environmental/geographical factors of corrosion failure such as soil temperature.

The objective of this section is to present the failure prediction models that estimate the time of corrosion failure in gas transmission pipelines by considering environmental/geographical attributes in addition to the conventional variables. To attain this objective, the effective design parameters on pipeline corrosion failure were first identified from a review of the state of arts as discussed in chapter 2. Then, the corresponding data were collected concerning both historical data on pipeline failure as well as climatological databases as previously discussed in chapter 4. After collecting the corresponding data on external corrosion failure of gas transmission pipelines, the procedures to develop time of failure prediction models are pursued. For this objective, a multiple regression analysis is employed to exploit the collected data and generate prediction models for two selected climatological regions in the U.S. Then the selected effective design parameters on external corrosion of petroleum pipelines obtained from the literature review and the databases (PHMSA and NCDC) are fed into the models. Since the objective of the prediction model is to estimate the time of failure, the subtraction between pipeline installation and incident date is considered as the output (time of failure). As model inputs from experimental assessment methods discussed earlier (Equation 3-1 to Equation 3-5), corrosion failure is a function of pipe wall thickness, diameter, pressure at the time of the incident, maximum allowable pressure and tensile strength (a function of specified minimum yield strength). These parameters were collected from the PHMSA database (PHMSAa 2014). On the other hand, soil temperature and depth of cover are considered as other input variables as soil property parameters obtained from the literature which are extracted from the national climatic and PHMSA data center according to chapter 4. To investigate whether corrosion failure time prediction can be attributed to climatological measures, the climate regions obtained from the national climatic data center for each data record are considered as another explanatory variable. These variables are presented in Table 5-1.

It should be also noted that such model development was not a straightforward procedure and required numerous trials and errors. In the next section, the details regarding to results analysis of such models are presented.

Table 5-1 Model variables and their descriptions

Variable	Depth of cover	Soil temp.	Incident pressure	Max operating pressure	diameter	Thickness	Min yield strength	Climate region	Failure time
Type	quan.	quan.	quan.	quan.	quan.	quan.	quan.	qual.	quan.
Abbrev.	COV	TEMP	INCP	MAOP	DIAM	THK	SMYS	REG	TIME
Prediction role	exp.	exp.	exp.	exp.	exp.	exp.	exp.	exp.	resp.

5.1.1 Results analysis of failure prediction model

After selection of explanatory and response variables, multiple linear regression and best-subset analyses are deployed to generate the prediction model. These models are developed for steel, underground offshore pipelines with cathodic protection and coating. It should be noted that the process of model development is not straightforward and requires numerous trials and error. For the sake of clarification, three different scenarios are highlighted to present model development procedure.

Prior to model development for each scenario, data preparation was performed through detecting the outliers, standardization of input and output values and processing data through mutual imputation as previously discussed in chapter 4. For each scenario, data were randomly divided into training and validation datasets consisting of 80% and 20% of the total data set respectively. To develop a regression-based model for each scenario, the regression model is first developed for the training dataset through an automated best-subset procedure using Minitab software. This method was selected since this it facilitates modeling and exploring datasets in which many potential predictors are available. In this method, according to Mallow’s Cp, the model that presents the testing database more efficiently is selected and its corresponding diagnostic measures are extracted. In best-subset analysis, the best subset is selected according to its Mallow’s Cp value which shall be close to the number of variables plus one. If the diagnostic measures of the selected subset are not satisfactory, the subsequent scenario is implemented until satisfactory diagnostic measures are obtained. As diagnostic measures for the training phase, R-Sq, R-Sq adjusted, mean square error and residual analysis are examined. Upon satisfactory diagnostic measures, the model is also tested for the validation dataset. Finally, the model that best describes the relationship between input and output variables is selected as acceptable.

5.1.1.1 Scenario 1. Best subset on all failure records

As the first attempt to predict time of failure for gas transmission pipelines, the data was entered into the model as are, without any prior filtering and classification and the analysis was performed through considering linear and nonlinear terms (with second-order and interactions) in the model. The explanatory variables are either quantitative or qualitative. The qualitative data is transformed into quantitative values to facilitate their input in the model. Between different subsets presented, the one with four variables is selected since it has a Mallow’s Cp value of 4.9 which is close to 5. However, the proficiency of this scenario in the prediction of the time of failure is rejected due to weak diagnostic measures of the training dataset for both linear and nonlinear analysis R-sq and R-sq (adj) of 16.7% and 15.6% respectively as presented in Table 5-2. Therefore, the analysis was prolonged to scenario 2 as follows.

Table 5-2 Model development based on all records

Vars	R^2	R^2 (adj)	Mallows Cp	S	TEMP	INCP	MAOP	DIAM	THK	SMYS	REG
1	12.6	12.4	14.5	0.16			X				
1	5.4	5.1	42.4	0.17		X					
2	14.8	14.3	8.2	0.16			X				X
2	14.0	13.5	11.3	0.16			X		X		
3	15.6	14.8	6.9	0.16			X		X		X
3	15.6	14.8	7.1	0.16		X	X				X
4	16.7	15.6	4.9	0.16		X	X		X		X
4	16.0	15.0	7.5	0.16		X	X	X	X		
5	17.4	16.1	4.1	0.16		X	X	X	X		X
5	16.8	15.5	6.3	0.16		X	X		X	X	X
6	17.4	15.9	6.0	0.16	X	X	X	X	X		X
6	17.4	15.9	6.1	0.16		X	X	X	X	X	X
7	17.4	15.6	8.0	0.16	X	X	X	X	X	X	X

5.1.1.2 Scenario 2. Geographical classification of data

For scenario 2, data were classified according to the geographical variable and best-subset regression was performed for each regional dataset. According to the diagnostic measures obtained from these analyses, it is concluded that such classification improves prediction model efficiency. Due to the limited number of records for some regions, two test data groups were generated for model implementation including,

• Underground pipelines located at Great Plains region with external corrosion failures,

• Underground pipelines located South-East region with external corrosion failures.

Best subset linear multiple regression analyses were performed on these data classifications as presented in Table 5-3 and Table 5-4. The results show that the diagnostic measure of R-sq for training data set has improved compared to the first scenario (41% and 60% for Great plains and South East respectively, versus 15%). However, the results are not yet satisfactory. Therefore, another scenario is considered to verify the results.

Table 5-3 Best subset model development based for Great Plains region (Scen. 2)

Vars	R^2	R^2 (adj)	Mallows Cp	S	TEMP	INCP	MAOP	DIAM	THK	SMYS	COV
1	32.2	31.1	10.9	0.17			X				
1	19.5	18.3	25.1	0.19							X
2	43.1	41.3	0.7	0.16			X				X
2	34.3	32.3	10.6	0.17		X	X				
3	44.9	42.4	0.6	0.16			X		X		X
3	44.2	41.6	1.5	0.16		X	X				X
4	45.4	42	2.1	0.16			X	X	X		X
4	45.4	42	2.2	0.16		X	X		X		X
5	45.5	41.2	4	0.16		X	X	X	X		X
5	45.4	41.1	4.1	0.16	X		X	X	X		X
6	45.5	40.2	6	0.16	X	X	X	X	X		X
6	45.5	40.2	6	0.16		X	X	X	X	X	X
7	45.5	39.3	8	0.16	X	X	X	X	X	X	X

Table 5-4 Best subset model development for South East region (Scen. 2)

Vars	R^2	R^2 (adj)	Mallows Cp	S	TEMP	INCP	MAOP	DIAM	THK	SMYS	COV
1	24.9	23.3	48.4	0.19			X				
1	19.9	18.2	54.7	0.19							X
2	49.3	47.2	19.4	0.15			X				X
2	41.4	38.9	29.4	0.17		X					X
3	54.1	51.2	15.2	0.15			X		X		X
3	53.9	50.9	15.6	0.15			X			X	X
4	61.8	58.5	7.5	0.14			X		X	X	X
4	60.6	57.2	9	0.14			X	X		X	X
5	64.5	60.5	6.1	0.13			X	X	X	X	X
5	63.8	59.7	7	0.138		X	X		X	X	X
6	66	61.4	6.1	0.13		X	X	X	X	X	X
6	64.8	60	7.7	0.13	X		X	X	X	X	X
7	66.1	60.6	8	0.13	X	X	X	X	X	X	X

5.1.1.3 Scenario 3. Parametric ratios from empirical equations

Though the diagnostic measures obtained from scenario 2 were improved compared to scenario number 1, further effort was dedicated to improving diagnostic measures of the training dataset model. The results obtained from multiple linear regression using nonlinear terms proved that in general, adding nonlinear terms improves model efficiency by improving the diagnostic measures. In this step, other terms were also added into the model by going through the experimental equations (Equation 3-1 to Equation 3-5). For this objective, linear variables, their corresponding second-order terms and, nonlinear terms and their corresponding second-order terms were fed into the model. These terms are presented in Table 5-5 which are based on the first term of Equation 3-1 and by assuming the ratio of incident pressure and specified minimum yield strength with maximum operating pressure as new variables.

Table 5-5 Nonlinear terms fed into the model

Nonlinear variables entered in the model				
DIAM/THK	MAOP/SMYS	INCP/MAOP	SMYS*THK/DIAM	MAOP*THK/DIAM

After the selection of the variables to be fed into the model, an automated best subset regression was performed and according to Mallow's Cp and adjusted R^2, the subset which can best describe the output was selected. Table 5-6 and Table 5-7 present the results corresponding to performing the automated best subset regression for Great Plains and South East regional classifications, respectively. In the next step, the variables of the selected subset were fed into a multiple linear regression analysis to present a mathematical model. Equation 5-1 corresponds to the model developed for Great Plains region with diagnostic measures of S=0.12, R^2= 73% and R^2 (adj)=65%. In addition, Equation 5-2 corresponds to the models developed for South East region, respectively, with diagnostic measures of S=0.08, R^2=89% and R^2(adj)=84%. Compared to the previous scenarios, these measures have improved considerably. However, these cannot be claimed as final models since the null hypothesis tests and normality shall also be investigated.

$$
\begin{aligned}
&\mathrm{TIME} \\
&= 0.985 + 1.389 \times \mathrm{TEMP} - 1.669 \times \mathrm{THK} - 0.1746 \times \mathrm{COV} - 4.308 \times \frac{MAOP}{SMYS} \\
&+ 1.194 \times \frac{INCP}{MAOP} - 1.629 \times \frac{SYMS \times THK}{DIAM} + 1.304 \times \frac{MAOP \times THK}{DIAM} + 3.817 \times \left(\frac{MAOP}{SMYS}\right)^2 \\
&- 0.847 \times \left(\frac{INCP}{MAOP}\right)^2 - 1.488 \times TEMP^2 - 0.5963 \times MAOP^2 + 1.856 \times THK^2
\end{aligned}
$$

Equation 5-1

$$
\begin{aligned}
&TIME \\
&= 1.785 - 0.0750 \times TEMP + 1.980 \times INCP + 0.834 \times THK - 2.417 \times \frac{MAOP}{SMYS} \\
&- 3.530 \times SMYS \times \frac{THK}{D} + 6.36 \times MAOP \times \frac{THK}{D} - 0.925 \times (\frac{INCP}{MAOP})^2 \\
&- 3.25 \times (\frac{MAOP \times THK}{D})^2 - 0.919 \times MAOP^2 - 0.668 \times THK^2 - 0.882 \times SMYS^2 \\
&- 0.3599 \times COV^2
\end{aligned}
$$

Equation 5-2

Table 5-6 Best subset model development based for Great Plains region (Scen. 3)

Vars	R^2	R^2 (adj)	Mallows Cp	S	TEMP	INCP	MAOP	DIAM	THK	SMYS	COV	DIAM/THK	MAOP/SMYS	INCP/MAOP	SMYS*THK/DIAM	MAOP*THK/DIAM	$(DIAM/THK)^2$	$(MAOP/SMYS)^2$	$(INCP/MAOP)^2$	$(SMYS*THK/DIAM)2)^2$	$(MAOP*THK/DIAM)^2$	$TEMP^2$	$INCP^2$	$MAOP^2$	$DIAM^2$	THK^2	$SMYS^2$	COV^2
1	26.6	25.2	71.1	0.173																				X				
1	24.1	22.7	75.2	0.176			X																					
2	34.8	32.3	59.5	0.165							X													X				
2	33.5	30.9	61.7	0.167																				X				X
3	40.1	36.5	52.8	0.160							X		X														X	
3	39.5	35.8	53.9	0.161									X														X	X
4	51.6	47.7	35.8	0.145									X							X	X			X				
4	49.2	45.1	39.8	0.149									X			X				X				X				
5	60.4	56.3	23.4	0.133									X		X	X		X						X				
5	57.5	53.1	28.1	0.137									X		X			X			X			X				
6	63.6	58.9	20.1	0.128		X							X		X	X		X						X				
6	63.5	58.9	20.2	0.129							X		X		X	X		X						X				
7	65.9	60.7	18.3	0.126							X		X	X	X	X		X						X				
7	65.8	60.5	18.5	0.126		X					X		X		X	X		X						X				
8	67.3	61.5	18.0	0.124							X		X	X	X	X		X				X		X				
8	67.1	61.2	18.3	0.125	X						X		X	X	X	X		X						X				
9	68.5	62.0	18.0	0.123		X			X		X		X		X	X		X						X		X		
9	68.3	61.9	18.2	0.124		X			X				X		X	X		X						X		X		X
10	70.2	63.3	17.2	0.121		X			X		X		X		X	X		X				X		X		X		
10	70.0	63.0	17.5	0.122		X			X				X		X	X		X				X		X		X		X
11	71.8	64.5	16.5	0.119	X	X			X		X		X		X	X		X				X		X		X		
11	71.6	64.2	16.9	0.120					X		X		X	X	X	X		X	X			X		X		X		
12	**73.1**	**65.3**	**16.3**	**0.118**	**X**				**X**		**X**		**X**	**X**	**X**	**X**		**X**	**X**			**X**		**X**		**X**		
12	72.8	64.8	16.9	0.119	X				X				X	X	X	X		X	X			X		X		X		X
13	74.1	65.7	16.7	0.117	X	X			X		X	X	X		X			X			X	X	X	X		X		
13	73.9	65.4	17.1	0.118	X	X			X		X		X		X		X	X			X	X	X	X		X		
14	74.8	65.8	17.5	0.117	X		X		X		X	X	X	X	X			X	X		X	X		X		X		
14	74.5	65.3	18.1	0.118	X		X		X			X	X	X	X			X	X		X	X		X		X		X
15	75.6	65.9	18.3	0.117	X	X		X	X		X	X	X		X			X			X	X	X	X	X	X		
15	75.4	65.8	18.5	0.117		X		X	X		X	X	X		X		X	X			X	X	X	X	X	X		
16	76.4	66.2	18.9	0.116	X	X		X	X		X	X	X		X		X	X			X	X	X	X	X	X		
16	76.3	66.1	19.1	0.117			X	X	X		X	X	X	X	X		X	X	X		X	X		X	X	X		
17	77.1	66.3	19.8	0.116	X	X		X	X	X	X	X	X		X			X			X	X	X	X	X	X	X	
17	77.1	66.2	19.8	0.116	X		X	X	X		X	X	X	X	X		X	X	X		X	X		X	X	X		
18	78.0	66.7	20.3	0.116			X	X	X	X	X	X	X	X	X		X	X	X		X	X		X	X	X	X	
18	77.9	66.6	20.4	0.116	X		X	X	X		X	X	X	X	X	X	X	X	X		X	X		X	X	X		
19	78.8	66.9	21.0	0.115	X		X	X	X	X	X	X	X	X	X		X	X	X		X	X		X	X	X	X	

Table 5-7 Best subset model development based for South East region (Scen. 3)

Vars	R-Sq	R^2 (adj)	Mallows Cp	S	TEMP	INPRS	MAOP	DIAM	THK	SMYS	COV	DIAM/THK	MAOP/SMYS	M	SMYS*THK/DIAM	MAOP*THK/DIAM	$(DIAM/THK)^2$	$(MAOP/SMYS)^2$	$(INCP/MAOP)^2$	(SMYS*THK/DIAM)2)^2	$(MAOP*THK/DIAM)^2$	$TEMP^2$	$INCP^2$	$MAOP^2$	$DIAM^2$	THK^2	$SMYS^2$	COV^2
1	27.5	25.4	90.1	0.182																								X
1	26.5	24.5	91.8	0.183							X																	
2	50.4	47.6	52.9	0.152			X																					X
2	49.9	47.0	53.7	0.153																				X				X
3	66.3	63.3	27.7	0.127				X																			X	X
3	65.8	62.8	28.5	0.128				X			X																X	
4	71.5	68.1	20.7	0.119				X										X									X	X
4	70.9	67.4	21.8	0.120				X					X														X	X
5	76.0	72.2	15.1	0.111							X				X	X		X									X	
5	75.7	71.9	15.6	0.111											X	X		X									X	X
6	79.5	75.5	11.1	0.104								X				X	X	X									X	X
6	79.0	74.9	12.0	0.105				X			X				X	X		X									X	
7	81.4	77.1	9.8	0.100					X									X		X	X					X	X	X
7	81.2	76.9	10.1	0.101				X			X				X	X		X					X				X	
8	83.4	78.9	8.4	0.097		X							X		X	X			X					X			X	X
8	83.0	78.3	9.1	0.098		X		X					X			X			X	X							X	X
9	85.7	81.2	6.4	0.091		X			X				X			X			X	X				X			X	X
9	85.7	81.1	6.5	0.091		X			X				X		X	X			X					X			X	X
10	88.0	83.5	4.6	0.085		X			X				X			X			X	X				X		X	X	X
10	87.6	83.0	5.3	0.087		X			X				X		X	X			X					X		X	X	X
11	88.7	83.9	5.4	0.084		X			X				X		X	X			X		X			X		X	X	X
11	88.5	83.6	5.7	0.085	X	X			X				X			X			X	X				X		X	X	X
12	**89.3**	**84.1**	**6.3**	**0.084**	**X**	**X**			**X**				**X**		**X**	**X**			**X**		**X**			**X**		**X**	**X**	**X**
12	89.2	84.0	6.5	0.084		X			X				X		X	X			X		X	X		X		X	X	X
13	89.7	84.2	7.6	0.083	X	X			X				X	X	X	X			X	X	X			X			X	X
13	89.7	84.1	7.6	0.084	X	X			X				X		X	X			X		X	X		X		X	X	X
14	90.2	84.2	8.8	0.083	X	X			X				X	X	X	X		X	X	X	X			X			X	X
14	90.1	84.1	8.9	0.084		X			X				X	X	X	X		X	X	X	X	X		X			X	X
15	90.7	84.4	9.8	0.083	X	X			X			X	X	X	X	X		X	X	X	X			X			X	X
15	90.7	84.4	9.9	0.083		X			X			X	X	X	X	X		X	X	X	X	X		X			X	X
16	91.2	84.5	11.0	0.082	X	X	X		X	X		X	X	X	X	X		X	X	X	X			X				X
16	91.2	84.4	11.1	0.083		X	X		X	X		X	X	X	X	X		X	X	X	X	X		X				X
17	91.6	84.5	12.3	0.083	X	X	X		X			X	X	X	X	X	X	X	X	X	X			X			X	X
17	91.6	84.5	12.3	0.083	X	X	X		X	X		X	X	X	X	X	X	X	X	X	X			X				X
18	91.9	84.1	13.9	0.084	X	X	X		X		X	X	X	X	X	X	X	X	X	X	X			X			X	X
18	91.8	84.1	14.0	0.084	X	X	X		X	X	X	X	X	X	X	X	X	X	X	X	X			X				X

5.1.1.4 Null hypothesis test

According to Table 5-8 and Table 5-9, ANOVA results illustrate that for a significance level of 5% the developed models are valid and the null hypothesis is rejected. This is an indication of robust results.

Table 5-8 ANOVA results for Great Plains region model

Term	Coef	SE Coef	T-Value	P-Value
Constant	0.985	0.181	5.43	0.000
TIME	1.389	0.905	2.23	0.03
THK	-1.669	0.686	-2.43	0.019
COV	-0.1746	0.0651	-2.68	0.010
MAOP/SMYS	-4.308	0.721	-5.98	0.000
INCP/MAOP	1.194	0.583	2.05	0.047
SMYS*THK/DIAM	-1.629	0.259	-6.29	0.000
MAOP*THK/DIAM	1.304	0.206	6.32	0.000
$(MAOP/SYMS)^2$	3.817	0.714	5.34	0.000
$(INCP/MAOP)^2$	-0.847	0.541	-2.57	0.013
$TEMP^2$	-1.488	0.866	-3.43	0.001
$MAOP^2$	-0.5963	0.0731	-8.16	0.000
THK^2	1.856	0.722	2.57	0.014

Table 5-9 ANOVA results for South East region model

Term	Coef	SE Coef	T-Value	P-Value
Constant	1.785	0.223	8.01	0.000
TIME	-0.0750	0.0629	-2.12	0.040
INCP	1.980	0.459	4.31	0.000
THK	0.834	0.412	2.08	0.044
MAOP/SMYS	-2.417	0.480	-5.03	0.000
SMYS*THK/DIAM	-3.530	0.735	-4.80	0.000
MAOP*THK/DIAM	6.36	1.78	3.56	0.002
$(INCP/MAOP)^2$	-0.925	0.238	-3.90	0.001
$(MAOP*THK/DIAM)^2$	-3.25	1.91	-2.09	0.043
$MAOP^2$	-0.919	0.307	-3.00	0.006
THK^2	-0.668	0.409	-2.36	0.023
$SMYS^2$	-0.882	0.144	-6.11	0.000
COV^2	-0.3599	0.0736	-4.89	0.000

5.1.1.5 Residual analysis

As discussed earlier, regarding residual analysis, a satisfactory model shall have a normal probability plot, implying the normal distribution of the residuals that is an assumption in regression analysis. Both developed models are in accordance with these criteria resulting from a visual residual analysis (Figure 5-1).

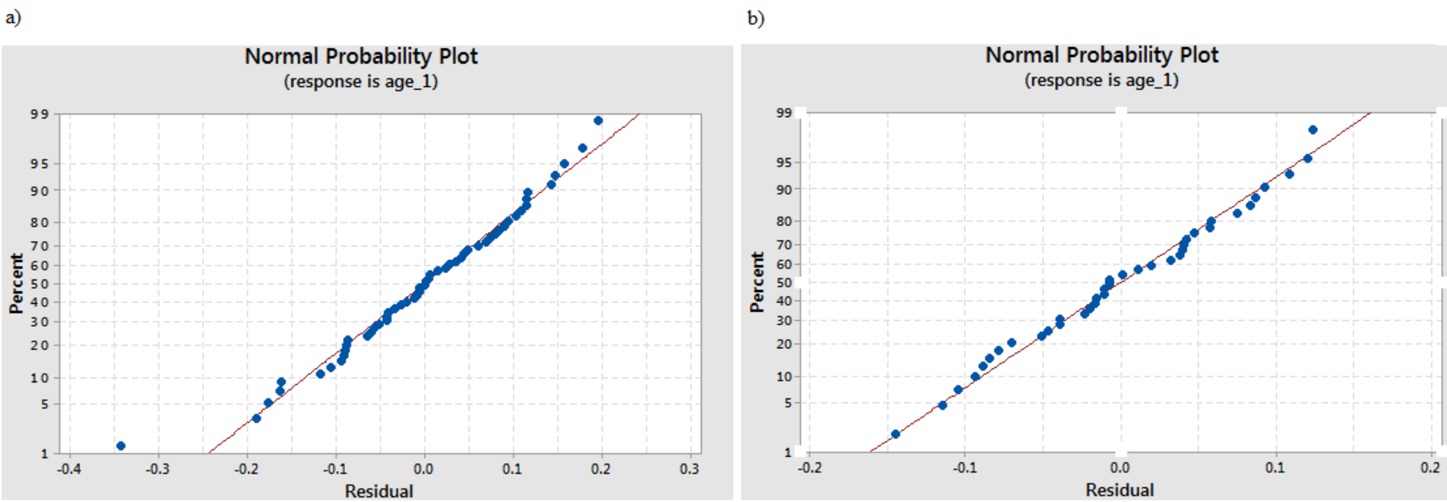


Figure 5-1 Normal probability plot of a) Great Plains and b) South East models regions

5.1.1.6 Validations and sensitivity analysis

After examination of the diagnostic measures, null hypothesis and residual analysis, scenario 3 was selected as the final model for the time of failure prediction in gas transmission pipelines of both regions. To verify the application of such models, they were tested by feeding the remaining 20% data (validation data set) into the developed models and some mathematical validation procedures were conducted on the estimated values obtained from the validation dataset. These mathematical validation procedures include average validity percentage (AVP), root mean square error (RMSE) and mean absolute error (MAE)

Table 5-10 summarizes the results obtained from testing the validation dataset for each regional classification. According to this table, the validation measures are not optimum yet satisfactory. This can be due to the fact that according to the state of the arts, numerous criteria are effective on corrosion failure of a pipeline while in the framework of this research, only several parameters are considered due to limited access to all effective failure parameters.

Table 5-10 Validation outputs for developed failure prediction models

Validation measure	Underground Great Plains	Underground South East
AVP	0.73	0.70
RMSE	0.04	0.07
MAE	0.12	0.11

A sensitivity analysis of the contributing variables was also implemented to highlight the most sensitive variables in the model and their corresponding influence on the model output. For this objective, regarding the threshold of each variable in the prediction model, for one record each variable is adjusted between is the corresponding minimum and maximum values in uniform discernments while others are kept as constant and is then fed into the model. In this process, other input variables and the output results shall also satisfy the minimum and maximum thresholds of the prediction model, otherwise the corresponding sensitivity point is removed from the analysis. Figure 5-2 presents the results corresponding to the sensitivity analysis of the developed prediction models. Accordingly, both models are sensitive to all input variables. However, for South East regional classification, the output results are the most sensitive to diameter, incident pressure and depth of cover. On the other hand, for Great Plains regional classification, the most sensitive variables include, incident pressure, specified minimum yield strength and maximum operating pressure. Regarding to the effect of diameter on time of failure, it can be concluded as diameter increases, sensitivity of models to this parameter becomes less. It should be also noted that for some sensitivity results, fewer records exist since the minimum and maximum thresholds for either input or output variables were not respected. In addition, the augmentation or diminishment trend of sensitivity results for each input variable is similar for both models. However, as dimeter increases, the Great Plains regional model outputs get less sensitive compared to the South East regional model. In addition, South East model outputs get more sensitive as incident pressure increases compared to the other model. On the other hand, for maximum operating pressure, the sensitivity level of Great Plains model is more than that of South East model.

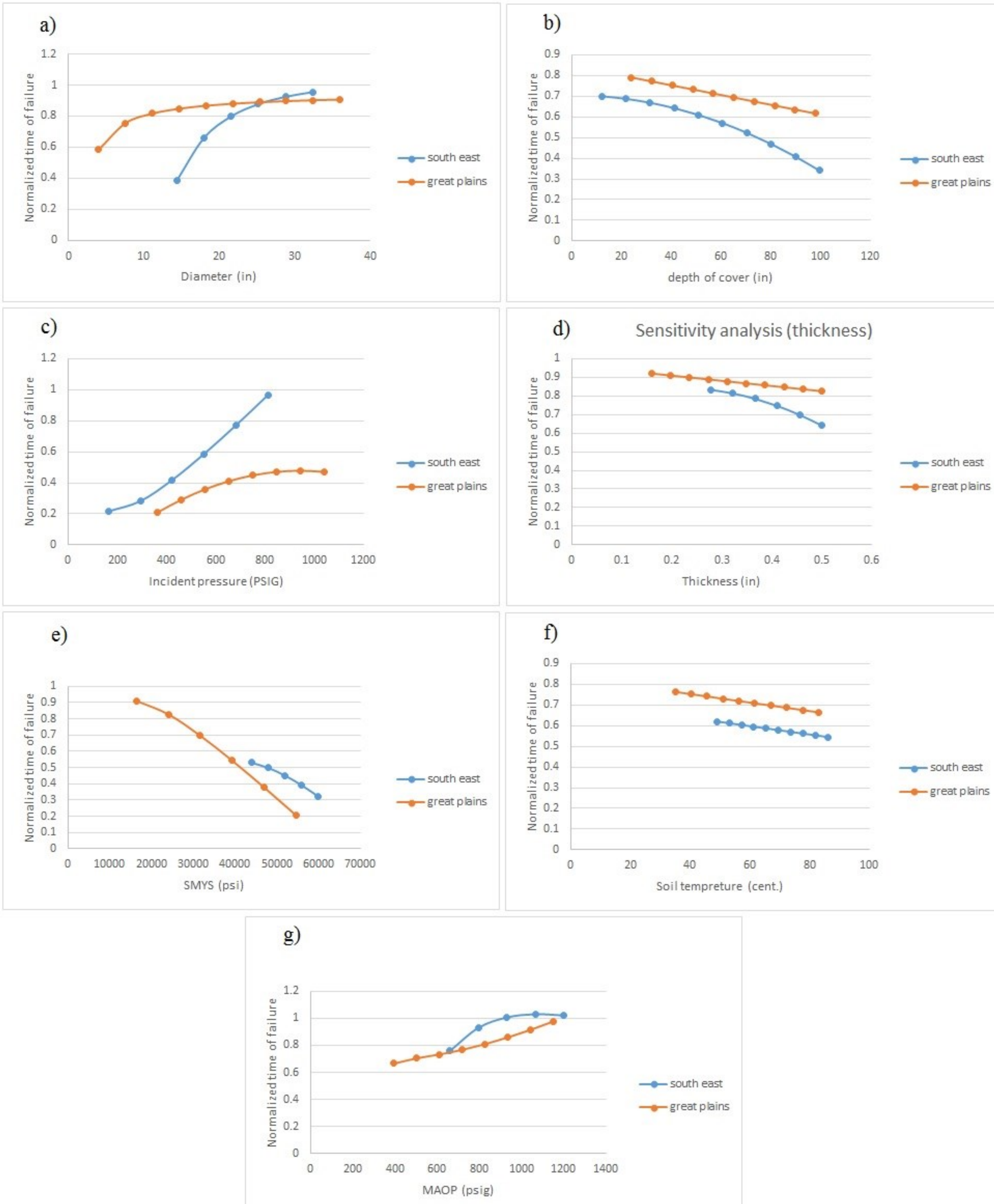


Figure 5-2 Sensitivity analysis of developed regression models

5.2 IMPLEMENTATION OF AVAILABILITY-BASED RELIABILITY-CENTERED MAINTENANCE MODEL

Most of the maintenance decisions for oil and gas pipelines are usually based upon the field data collected from in-line inspections. In addition, some standards propose maintenance intervals without addressing pipeline condition (Li et al. 2017). In the recent years, thanks to the advancements in data collection methods and data analysis techniques, new maintenance planning models have been developed to avoid unnecessary, time and cost consuming inspections. However, the majority of these studies are based upon condition-based or reliability-based methods in which maintenance planning is scheduled by considering pipeline deterioration profile. These methods often ignore the effect of required time for repair and maintenance arrangements and actions that could aggravate pipeline unavailability and lead to further loss of profit. In other words, due to the importance of continued operation of a gas or petroleum pipeline on a nation's economy, it is important to take account of pipeline availability as a decision criterion in the selection procedure of maintenance actions (Zakikhani et al. 2019). Such consideration shall be taken in addition to the associated costs, pipeline's condition or reliability level.

In that sense, the objective of this section is to develop an availability-based maintenance planning framework for gas transmission pipelines by considering system's availability jointly with reliability levels and the associated costs. This framework is based on a failure prediction model previously developed for external corrosion of gas transmission pipelines buried in the Great Plains region of the U.S. in section 5.1.1. To consider the uncertainties associated with the time of external corrosion failure, a Monte Carlo simulation is performed on the failure prediction model and accordingly, the reliability profile of gas transmission pipelines is derived.

Such simulation compensates limitation in historical data by considering a wide range of design parameters. In the next step, for a case study of a 24-inch pipeline, three maintenance scenarios comprising of several actions are considered through a discrete event simulation (DES). These scenarios are defined as scenario no. 1, “sleeving and replacement”, scenario no. 2, “composite wrap and replacement”, and scenario no. 3 “replacement only”. The decision criteria for the proper time of each maintenance action are based upon both considering pipeline availability due to a maintenance action and the associated costs through the proposed availability-cost indicator.

The research on availability-based maintenance planning reveals that for scenario 2, performing the corresponding maintenance actions at the service life of 30.1 and 40.5 years, respectively, could lead to the highest availability improvement per spending. In addition, the corresponding results are associated with the service life of 33.3 and 42.2 years for scenario no. 1 and 24.2 years for scenario no. 3 respectively. These results present the simulation points at which availability per spending reaches its highest level due to the initiated balance between cost and availability values. In case of maintaining a pipeline prior to the reported schedules, too frequent maintenance interventions are carried. This leads to an over maintenance due to marginal improvement in availability compared to the high maintenance costs. On the other hand, performing a maintenance action after this schedule, will lead to under maintenance due to compromising pipeline availability, though cost saving may be achieved.

In this section, first a review on the recent efforts on maintenance planning of oil and gas pipeline is presented. Then, according to the proposed research methodology and collected data for maintenance planning of gas transmission pipelines (chapters 3 and 4), the maintenance framework is developed. Finally, model implementation and analysis obtained from the developed framework are presented.

5.2.1 Result analysis of the maintenance framework

To obtain the reliability profile of a gas transmission pipeline, first the probability of corrosion failure and reliability profiles were obtained from a Monte Carlo simulation using *Companion by Minitab* software. Such simulation considers the associated uncertainties with external corrosion failure and considers a wider range of scenarios for the design parameters. The reliability profile and cumulative failure distributions obtained from the Monte Carlo simulation are presented in Figure 5-3.

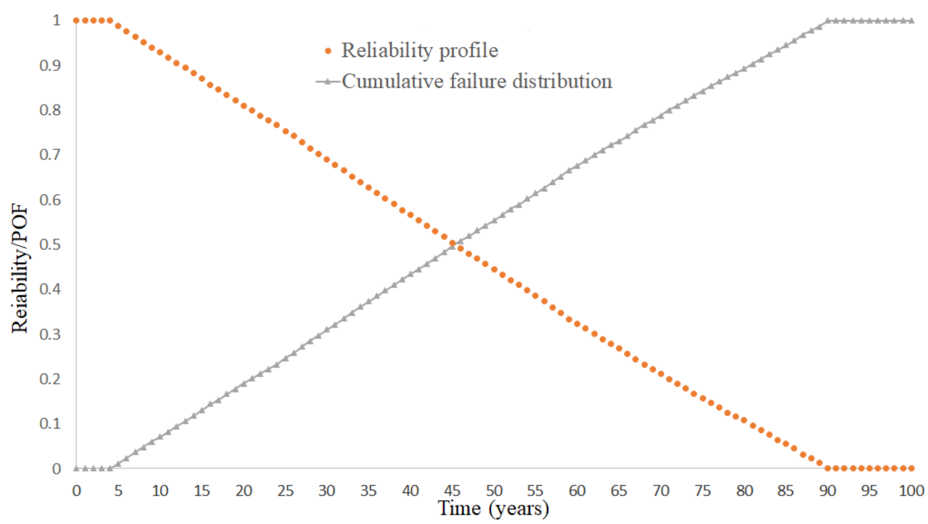


Figure 5-3 Reliability/POF profiles

In the next step, based on the principles of reliability analysis, the best fitting distribution for the reliability profile was obtained as Weibull from Equation 3-27 to Equation 3-29 using MATLAB software *dfit* tool with R-square of 0.99 and root mean square (RMSE) of 0.032. In annex 2, the fitting results of different reliability distributions are presented among which Weibull was selected as the best fitting option. Compared to reliability distributions with a constant failure rate (such as exponential), Weibull distribution is applied to systems in which failure rate is time dependent. Therefore, use of such distribution in reliability analysis of gas transmission pipelines is consistent with the nature of corrosion failure in which rate of growth is nonstationary (Zhang, S. et al. 2014; Alfon et al. 2012). Figure 5-4 presents the Weibull reliability distribution for gras transmission pipelines.

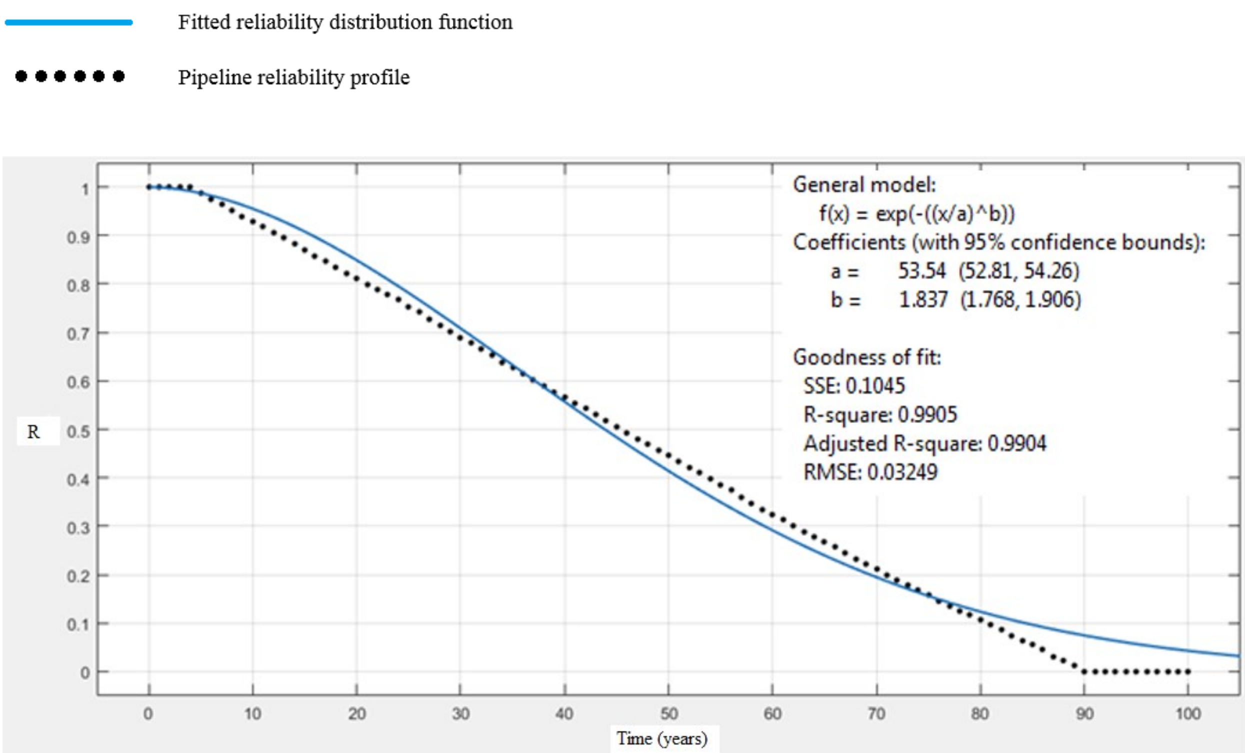


Figure 5-4 Weibull reliability profile

After formulating the associated costs and the required time for maintenance actions as a function of defect sizes (Figure 4-5 and Figure 4-6), a discrete event simulation technique is developed to determine the intervening time for different maintenance options through MATLAB Programming at different time steps. Figure 5-5 presents phases of such simulation. In this method, for each maintenance scenario, by assuming to perform the maintenance action at different discrete time steps, the reliability profile is updated for each step according to the discussed assumptions (Equation 3-31 and Equation 3-32). Then, at each discrete step, the changes of availability values per unit cost before and after performing the maintenance action are calculated from Equation 3-30 and Equation 3-34. Finally, based on the fitting distribution and the maximum values of changes of availability per unit cost ($\frac{\Delta\alpha}{C}$), the time at which the maintenance action shall be performed is selected. Therefore, in this method, the decision criteria for the optimum maintenance scheduling is based on the maximum values for availability-cost indicator. For the maintenance scenarios with more than one action, after updating the reliability profile for the second action, a similar procedure is followed to determine the schedule of the second action. In availability analysis, by considering the mean time to repair next to mean time to failure, failure is penalized due to accounting the time loss due to pipeline repair. On the other hand, by incorporating the associated costs as a decision factor, those maintenance options with marginal improvement in availability but excessive expenditures are penalized and avoided. Due to such considerations, the availability-cost indicator was selected as the decision factor, representing changes (improvements) in availability per unit cost spent ($\frac{\Delta\alpha}{C}$) performing a maintenance action. Annex 1 presents the MATLAB Programming scripts for maintenance scenario 1 as an example.

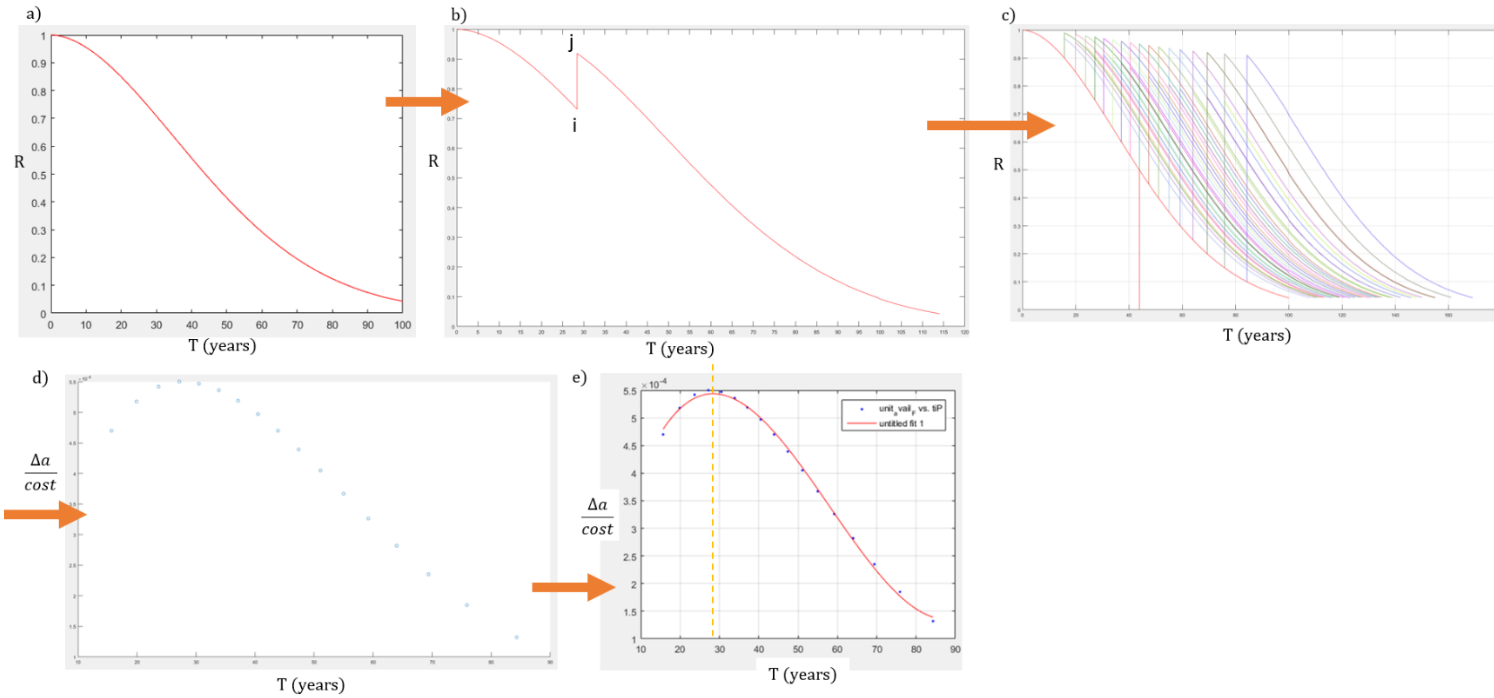


Figure 5-5 Different phases of discrete event simulation

Figure 5-6 and Table 5-11 represent the time of first maintenance action for each maintenance scenario according to the maximum values of availability-cost indicator ($\frac{\Delta\alpha}{C}$). In case of taking a maintenance action prior to this point, an over maintenance will occur due to a marginal improvement in availability compared to the high associated maintenance costs. On the other hand, if a maintenance intervention is carried after this point, an under maintenance takes place due to compromising pipeline availability, though some cost-saving may be achieved.

For scenario no. 1, the first maintenance action (sleeves) can be postponed to up to the service life of 33.3, compared to 30.1 and 24.2 years for maintenance scenarios no. 2 and 3. As presented in Figure 5-6, improvement of pipeline availability per unit cost for the first maintenance action of scenarios no. 1 and 2 is considerably higher than that of scenario no. 3. This points that performing merely a replacement action is not a favorable strategy in terms of improvement of availability per unit cost. Similarly, upon completion of the first maintenance action and updating the reliability profile, the optimum coupled availability-cost based schedule for the second maintenance action is determined as 42.2 years compared to 40.5 for scenario no. 1 and 2 respectively. As presented in Figure 5-7, pursuing maintenance scenario no. 2 (application of composite wrap) will lead to higher improvement of availability per unit cost compared to scenario no. 1.

Table 5-11 Maintenance action schedule obtained from discrete event simulation

	maintenance schedule (year)	
Maintenance scenario	Action 1	Action 2
1	33.3	42.2
2	30.1	40.5
3	24.2	-

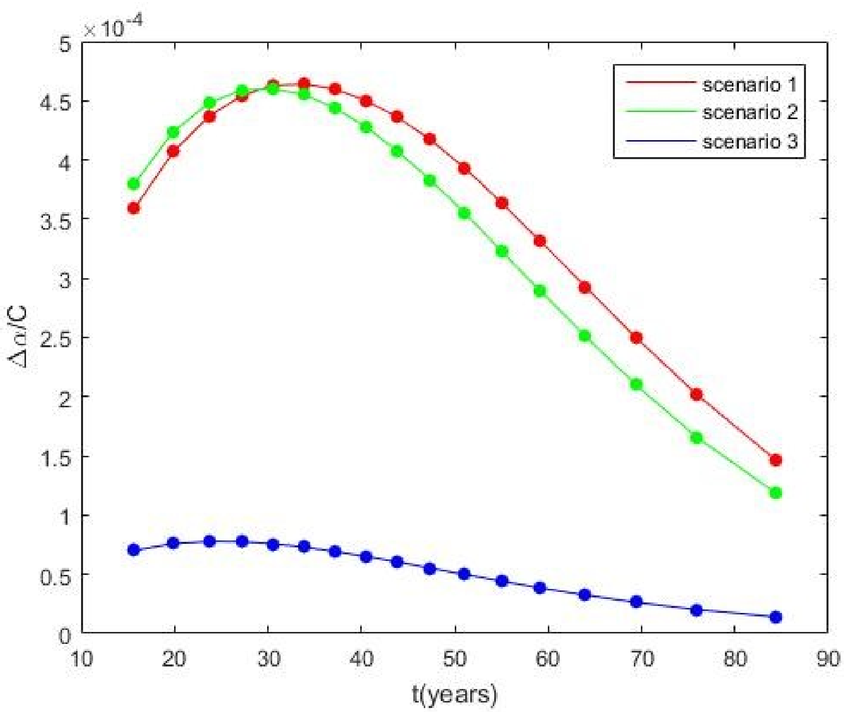


Figure 5-6 Improvement of availability per unit cost versus time for first action

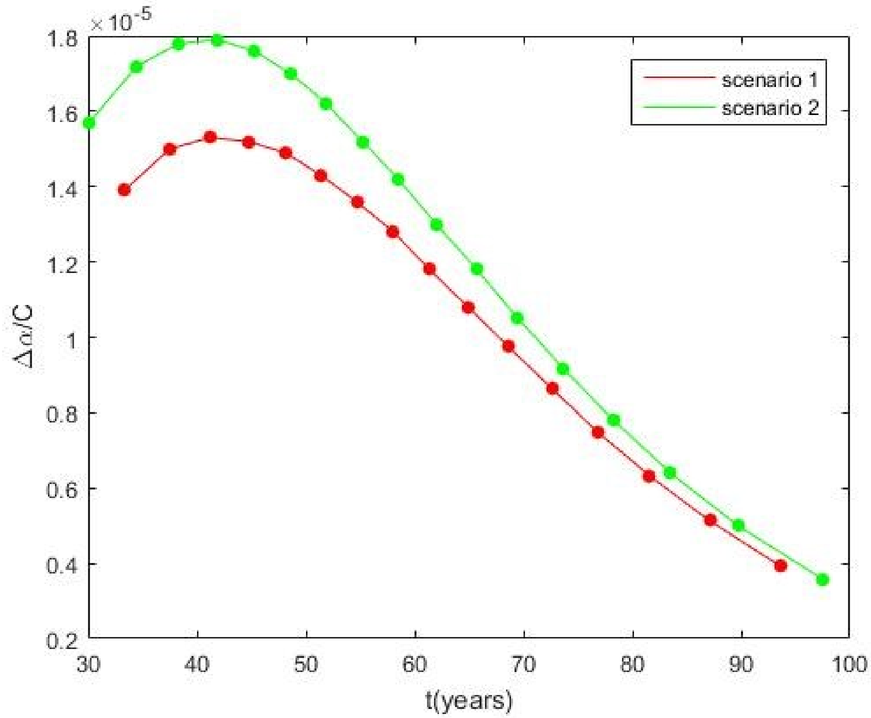
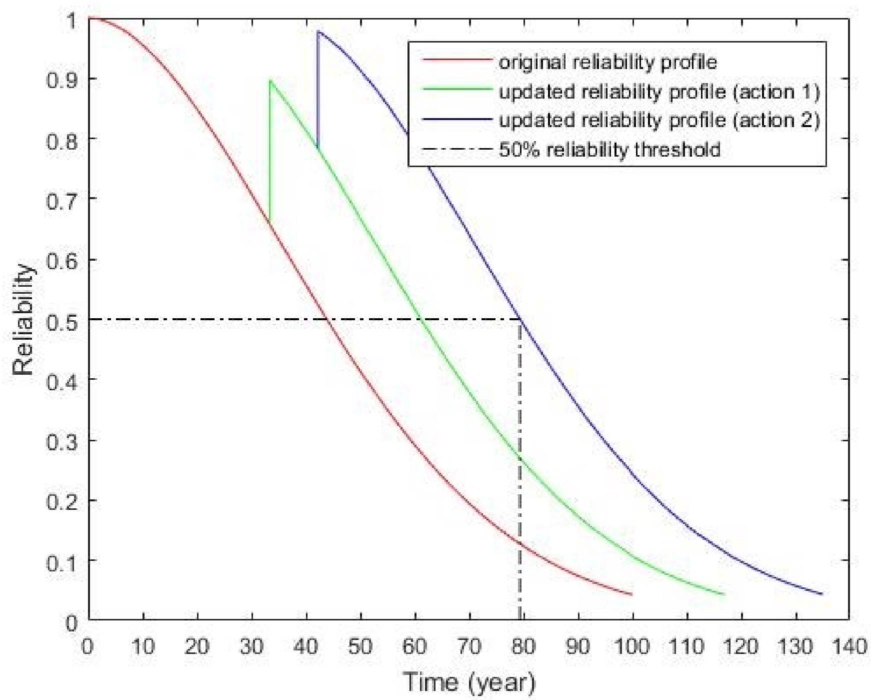


Figure 5-7 Improvement of availability per unit cost versus time for the second action

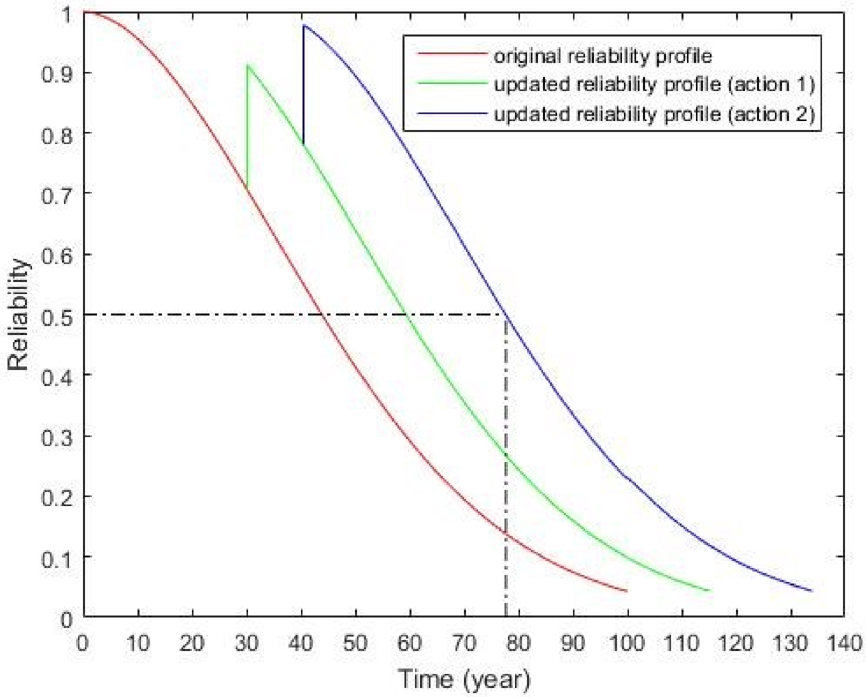
In reliability-based maintenance planning, for a conservative scenario, pipeline condition shall not undergo 50% (Parvizsedghy et al. 2015). Considering this threshold, for maintenance scenario no. 1 and 2, pipeline service life will be closely extended to 79.4 and 77.7 years respectively. However, for maintenance scenario no. 3, this threshold is attained at 56 years compared to 43.9 years in case of no maintenance intervention (Figure 5-8). On the other hand, the results obtained from two separate discrete event simulations on the associated maintenance costs and availability improvement (C and $\Delta\alpha$), prove that for each maintenance scenario, these values increase at each time step (Figure 5-9 and Figure 5-10). Such observation indicates that for maximum availability, the maintenance action shall be performed later. On the other hand, for minimum costs, the action shall be performed sooner. Therefore, it is interpreted that consideration of a coupled-availability-cost indicator in the decision-making process, will provide a benchmark for the tradeoffs between availability and cost. Such an indicator will lead to attaining the maximum availability per unit cost spent for the maintenance action, justifying the expenditures that create availability improvements.

It shall be noted that the developed reliability profile of gas transmission pipelines was validated through MATLAB *dfit* tool with R-square and root mean square error (RMSE) of 0.99 and 0.032, respectively. On the other hand, the presented life cycle cost corresponds to the specific case study. Therefore, subject to the availability of data, the proposed methodology can be extended to other case studies.

a)



b)



c)

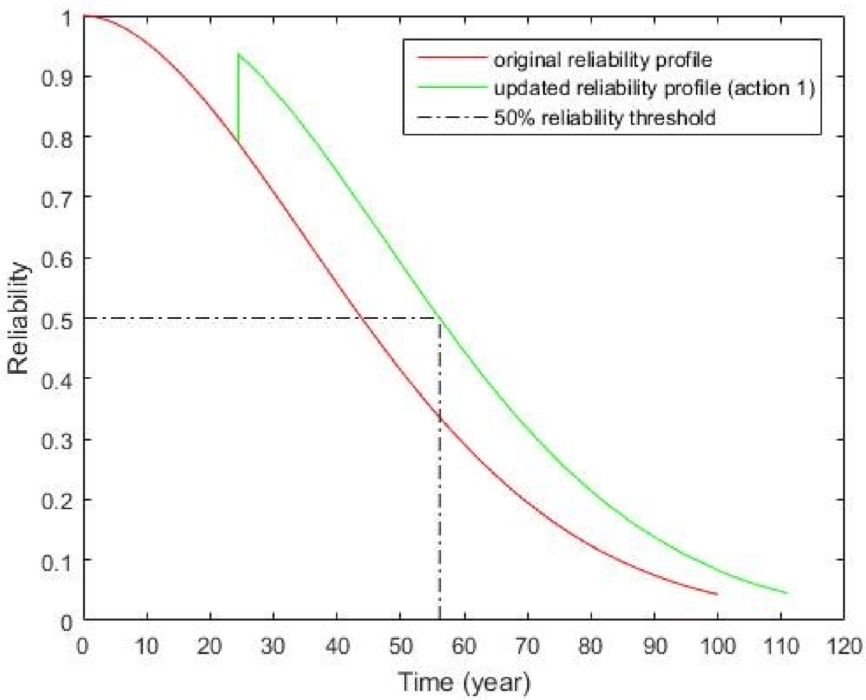


Figure 5-8 Reliability profile of a) maintenance scenario no. 1, b) maintenance scenario no. 2 and c) maintenance scenario no. 3

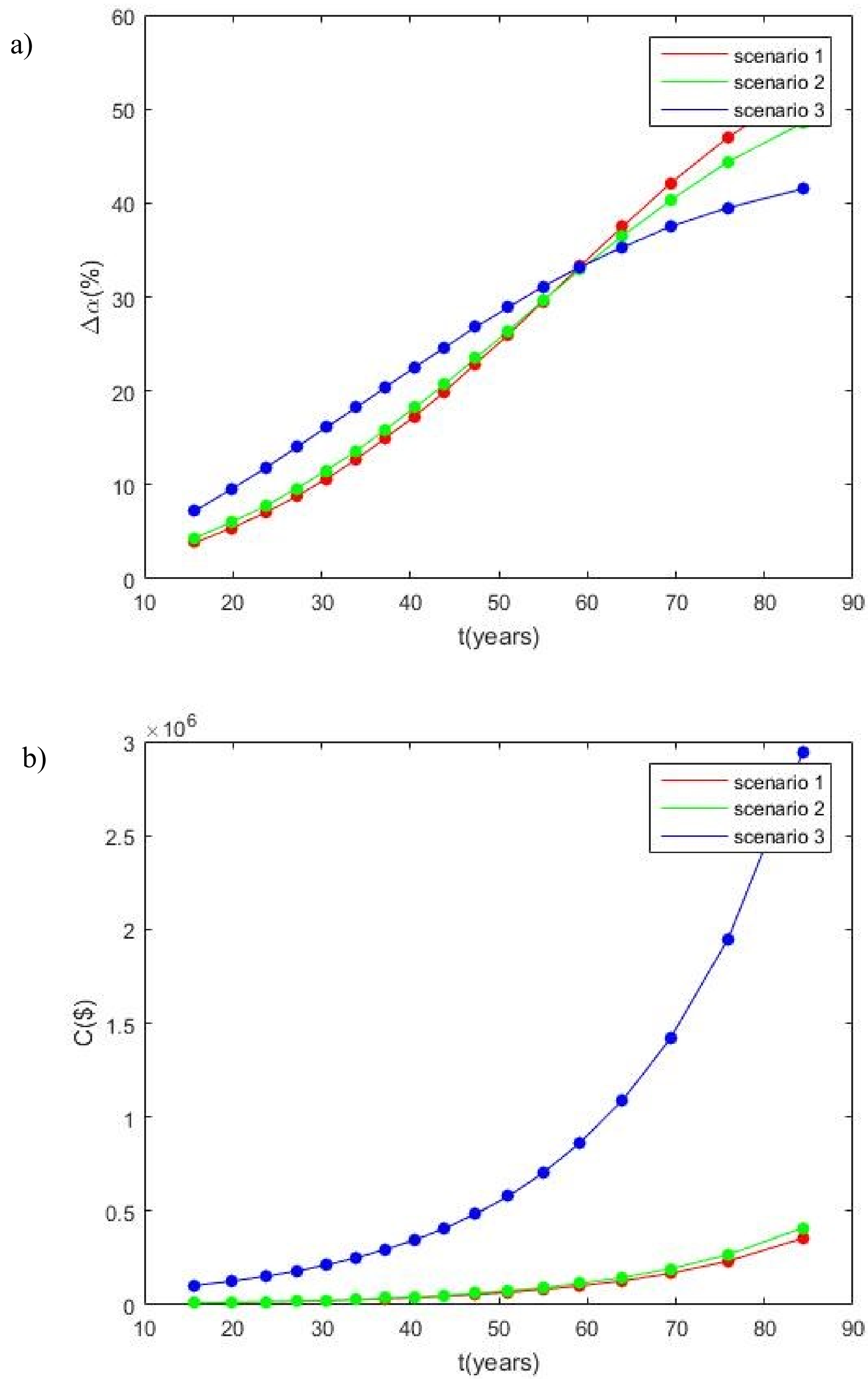
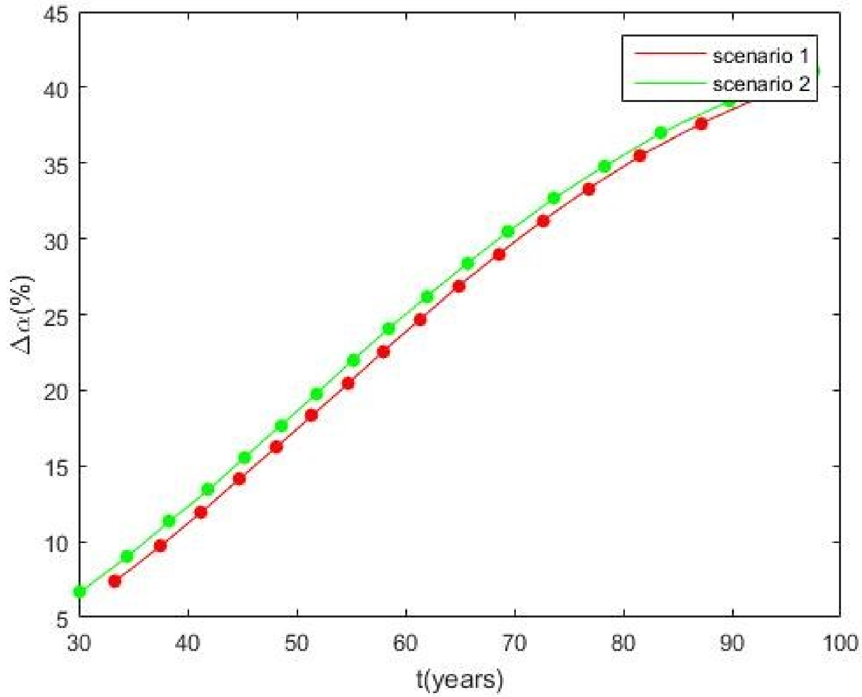


Figure 5-9 Simulation results on a) improvement in availability and b) the associated costs for the first maintenance action

a)



b)

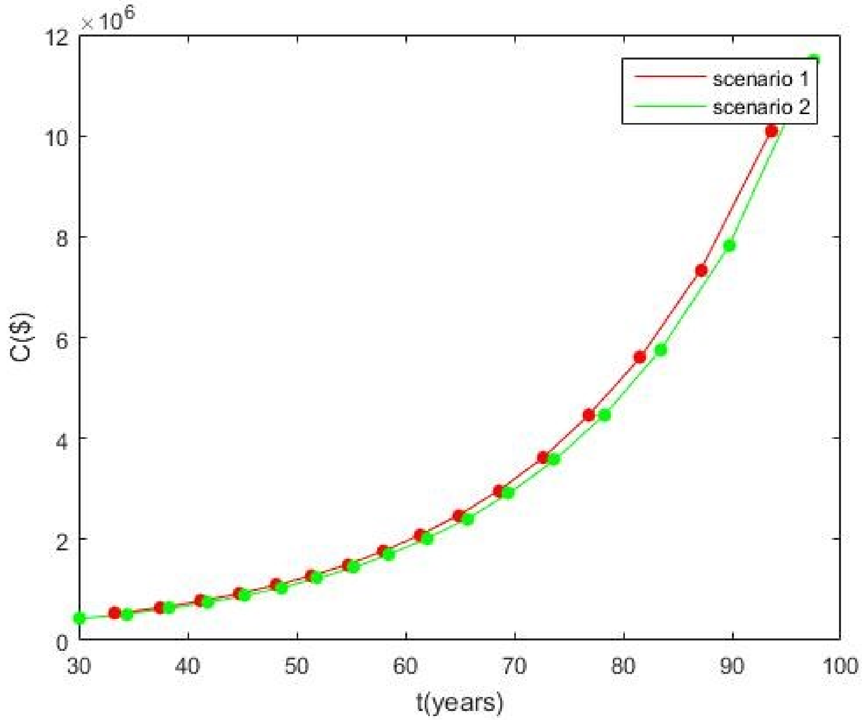


Figure 5-10 Simulation results on a) improvement in availability and b) the associated costs for the second maintenance action

5.3 DISCUSSION

In this chapter two main model were developed for corrosion failure prediction and maintenance of gas transmission pipelines. The developed failure prediction models provided a first attempt to consider geo-environmental parameters in corrosion failure prediction of gas transmission pipelines. For development of such failure prediction models, both experimental equations reported in the literature were considered with the incorporation of geo-environmental parameters. For this objective, based on the results obtained from the literature review and collected data on failure records, the explanatory and response variables of the prediction models were determined. Following a step by step procedure, time of failure prediction models were established and evolved using automated best subset and multiple regression analysis supported by diagnostic measures and statistical tests. In addition, a validation/sensitivity analysis procedure was adopted leading to MAE and RSME of 0.12 and 0.04, for Great Plains, and 0.11 and 0.07, for South East regional classifications, respectively. The results point to that both models were mostly sensitive to incident pressure and specified minimum yield strength for South East and Great Plains regional specifications, respectively.

In the next step, an availability-based reliability-centered maintenance planning framework was proposed for gas transmission pipelines. Such a framework was based upon considering these pipelines as critical assets where continuity of pipeline operation (availability) is of high importance in maintenance planning, in addition to safety levels and the associated costs. The proposed framework was applied to a case study of a 24-inch (diameter) buried gas transmission pipeline. The case study was chosen in line with the developed failure prediction model for gas transmission pipelines buried in the Great Plains region of the United States. Though in this research the presented results correspond to the case studied, this framework can be similarly extended to any other critical asset such as distribution or transmission oil pipelines in case of having access to the corresponding maintenance and failure prediction data. This general applicability is tied to the framework basis upon principles of life cycle cost and availability analysis that is a function of asset's mean time to failure, mean time to repair and future maintenance costs.

In the proposed framework, the cumulative distribution function of the gas transmission pipeline was first developed through a Monte Carlo simulation (to consider a wide range for design parameters) where the model was fed by two inputs, i.e. failure prediction model and the corresponding explanatory variables. Through the principles of reliability analysis and based on the cumulative failure distribution, a Weibull reliability profile of gas transmission pipelines was developed. Three maintenance scenarios composed of different maintenance actions were defined and the corresponding data for the required timing and associated costs were collected. Then, through a discrete event simulation and by obtaining associated maintenance costs and changes in availability at each time step, improvement of availability per unit cost was derived. Finally, for each maintenance action, the maintenance time decision was made according to an availability-cost indicator.

The results of the developed maintenance planning framework reveal that in terms of coupled availability-cost-based maintenance planning, the second maintenance scenario (composite wrap and replacement) is more effective. This order is followed by the first (sleeve and replacement) and the third (replacement only) maintenance scenarios respectively. Through the proposed framework, consideration of changes in availability per unit cost will provide compensation between the improvement of availability and the associated costs. Such compensation is obtained due to the ascending order of both variables over the pipeline service life. The determined maintenance schedules correspond to the points with the maximum improvement of availability per unit cost to avoid over/under maintenance.

CHAPTER 6. CONCLUSIONS AND RECOMMENDATIONS

6.1 CONCLUSIONS

Gas transmission pipelines include a major part of the gas network, transporting millions of dollars of wealth natural gas across countries and provinces. As reported by pipeline and hazardous safety administration (PHMSA), only in the U.S., more than 3,569 failures occurred in these facilities since 1984 leading to more than 1 billion dollar of property damage. Among these failures, corrosion, as a time-dependent failure source, is ranked as the most frequent one corresponding to approximately one-quarter of total failures and leading to 30% of total property damage in these assets.

To minimize such failures, currently, pipeline integrity programs are widely practiced. As the most widely used integrity program, defect detection through extensive in-line inspection (ILI) and monitoring of pipeline conditions is applied. However, this technique is considered as time-consuming and expensive due to the necessity of performing frequent inspections with high-resolution tools to obtain accurate results and minimize the associated uncertainties. As the second step of integrity programs, defect prediction is carried out through the implementation of failure prediction models based on historical data, experimental tests, or inspection results obtained from the first step.

Within this research, first, a detailed review of the developed prediction models was carried out to investigate the current limitations of the currently applied prediction models. Such review revealed that despite large contributions in this domain, several important limitations are remaining that need to be addressed. As the main shortcomings in the literature, these limitations include, subjectivity due to reliance of models on expert judgment, need to expensive inspection/experiments, limited historical data, and inclusion of a limited number of failure types or consequences. For prediction of corrosion failures, as the number one failure source, most of current failure prediction models are usually based on the failure pressure models obtained from theory and experimental tests. Such tests require information on the design variables of the pipeline and often ignore effective environmental/geographical factors in corrosion failure such as soil temperature.

As the second objective of this research, several failure prediction models were developed to estimate the time of corrosion failure of gas transmission pipelines by considering environmental/geographical attributes, in addition to the conventional variables. To attain this objective, first the effective design parameters on pipeline corrosion failure were identified. Then, the corresponding data were collected concerning both historical data on pipeline failure as well as climatological databases. Finally, best subset and multiple regression analyses were employed to exploit the collected data and generate prediction models for two selected climatological regions in the US including Great Plains and South East. The developed models were validated with MAE and RSME of 0.12 and 0.04, for Great Plains, and 0.11 and 0.07, for South East regional classifications, respectively.

For corrosion failure prediction and maintenance planning of oil and gas pipelines, the available design codes tend to provide considerably conservative results. Such results lead to economic loss and under maintenance of the pipes, mainly due to ignoring the probabilistic nature of corrosion failure. Also, in recent years, new maintenance planning models have been developed to avoid unnecessary, time and cost consuming inspections through data collection and analysis. However, most of these studies are based upon condition-based or reliability-based methods in which maintenance planning is scheduled by considering pipeline deterioration profile. Such methodologies often ignore the effect of required time for repair and maintenance arrangements and actions that could aggravate pipeline unavailability and lead to further loss of profit. In other words, due to the importance of continued operation of a gas or petroleum pipeline on a nation's economy, it is important to take account of pipeline availability as a decision criterion in the selection procedure of maintenance actions.

In the third step of this research, an availability-based maintenance planning framework for gas transmission pipelines was developed by considering the system's availability jointly with reliability levels and the associated costs. This framework was based on the failure prediction model previously developed for external corrosion of gas transmission pipelines buried in the Great Plains region of the US. The uncertainties associated with the time of external corrosion failure were considered through a Monte Carlo simulation on the developed failure prediction model, and accordingly, the reliability profile of gas transmission pipelines was derived. In the next step, for a case study of a 24-inch pipeline, three maintenance scenarios comprising of several actions were considered through a discrete event simulation (DES). These scenarios were defined as scenario no. 1, "sleeving and replacement", scenario no. 2, "composite wrap and replacement", and scenario no. 3 "replacement only". The decision criteria for the proper time of each maintenance action were based upon both considering pipeline availability due to a maintenance action and the associated costs through the proposed availability-cost indicator.

This step of the research revealed that for scenario 2, performing the corresponding maintenance actions at the service life of 30.1 and 40.5 years, respectively, could lead to the highest availability improvement per spending. In addition, the corresponding results were associated with the service life of 33.3 and 42.2 years for scenario no. 1 and 24.2 years for scenario no. 3, respectively. These results present the simulation points at which availability per spending reaches its highest level due to the initiated balance between cost and availability values. In case of maintaining a pipeline prior to the reported schedules, too frequent maintenance interventions are carried. This leads to an over maintenance due to marginal improvement in availability compared to the high maintenance costs. On the other hand, performing a maintenance action after this schedule will lead to under maintenance due to compromising pipeline availability, though cost saving may be achieved.

6.2 RESEARCH CONTRIBUTIONS

This research provided a reference for pipeline operators, researchers and standards associations on the state-of-the-art literature on oil and gas pipeline safety. It distinguished the different models proposed for predicting failure parameters of pipelines as reported in the literature and as practiced in the industry through code-based methods. In addition, this research proposed new methodologies on failure prediction and maintenance planning of gas transmission pipelines. The proposed prediction models will be capable of predicting time of failure for the records that fall within input and output variable thresholds in the training phase of the model prediction. These models are not subjective as they are based on historical failure data rather than inspection or experimental data on a few pipelines. In addition, such models considered both conventional design variables in addition to the environmental/geographical conditions of the pipelines.

In the maintenance planning domain, this research provided the primary steps towards development of a novel methodology for maintaining gas transmission pipelines. Such methodology considered criticality of gas pipeline operation, randomness of pipeline design parameters and availability in contrary to the existing cost-based practices. The findings of this study could be beneficial for researchers and practitioners in pipeline operations and maintenance management by providing them with several benchmark models to predict the time of corrosion failure and maintain these assets. Such benchmark could prevent the necessity of performing excessive and expensive in-line inspections.

In summary, the main contributions of this research include:

- Detailed review on the current failure prediction models and their corresponding shortcomings;
- Development of historical data-based time of corrosion failure prediction models for gas transmission pipelines through consideration of experimental equations incorporated with geo-environmental parameters. Such models are based on design parameters;
- Obtaining reliability profile of the pipeline through Monte Carlo simulation to consider the associated uncertainties with design parameters in failure prediction model in a wider range of scenarios.
- Due to the significant role of oil and gas industry on national economy, in this research, maximizing pipeline availability was taken into account in maintenance decision making. This research is the first attempt in considering criticality of pipeline continued operation in maintenance planning next to reliability levels and the associated costs to avoid over/under maintenance.
- Development of a novel methodology in maintenance planning of gas transmission pipelines by considering criticality of pipeline continued operation and availability;
- Development of a coupled cost and availability-based maintenance planning procedure through assessing availability-cost indicator;
- Consideration of pipeline uncertainties in maintenance planning framework in addition to pipeline availability and reliability parameters.

6.3 RESEARCH LIMITATIONS

The research has some limitations, which can be summarized as follows:

- The developed failure prediction models apply to the pipelines that fall within the specified thresholds for input and output variables. Therefore, these models may be having limitations in application.
- The developed failure prediction models are based on predicting the first failure. For subsequent failures a dynamic time-based failure prediction model needs to be developed that that considers changes of metal loss over time in the predicting failure time in addition to the geo-environmental parameters.
- The failure prediction models do not consider the effect of preventive measures such as cathodic protection or coatings.
- This research is contributed to gas transmission pipelines. Application of a similar methodology for other assets requires access and analysis of the corresponding historical data.
- The proposed maintenance planning framework is based on some pre-assumptions, including improvement of reliability in case of a maintenance intervention and the relationship between reliability level and the defect size.
- Due to limited access to maintenance data, in this research the mostly practiced maintenance alternatives are considered. For a more comprehensive maintenance planning schedule, additional data on maintenance costs and repair time shall be collected.

6.4 FUTURE WORK

The developed model was able to achieve the proposed objectives of the research, but certain areas are recommended for enhancement in the future.

6.4.1 Enhancement areas

- Develop a more comprehensive failure prediction model that also considers the effect of preventive measures such as cathodic protection in time of corrosion failure.
- Collect more data to develop additional models for other geographical regions and study model prediction through classification.
- In order to examine the impact of the accepted assumptions from the literature on improvement of reliability in case of intervention in the maintenance framework, perform a sensitivity analysis on such assumptions made and assess relation between reliability and the defect size by collecting historical data or expert opinion survey.
- Expand the developed framework to a network of pipelines au lieu of a pipeline section and compare maintenance plan results with conventional reliability/conditioned-based methods. For this objective, the reliability profile of the whole system should be obtained by considering the configuration of different sections.
- Expand the propose framework to other maintenance actions and scenarios upon access to additional data to come up with a more comprehensive plan.

6.4.2 Extension areas

- Though this research prevents the necessity of performing excessive in-line inspections, yet such measures shall be conducted to assure pipeline safety. The developed reliability profile cab be adjusted and updated upon access to new in-line inspection data. The maintenance framework can then be updated according to the new reliability profile.

- The proposed methodology for availability-based maintenance planning can be further extended to other critical pipelines and assets, including gas distribution, hazardous liquid and liquified natural gas pipelines.

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ANNEX 1 RESULTS OF FITTING RELIABILITY DISTRIBUTIONS

Exponential:

General model Exp1:

f(x) = a*exp(b*x)

Coefficients (with 95% confidence bounds):

a = 1.183 (1.131, 1.235)

b = -0.02238 (-0.02391, -0.02084)

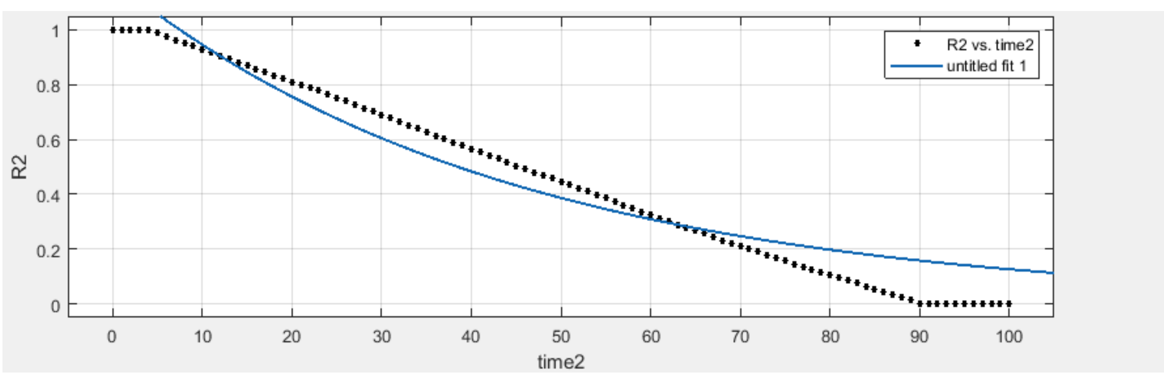
Goodness of fit:

SSE: 0.7238

R-square: 0.9341

Adjusted R-square: 0.9334

RMSE: 0.08551



Exponential reliability distribution

Weibull:

General model:

f(x) = exp(-((x/a)^b))

Coefficients (with 95% confidence bounds):

a = 53.54 (52.81, 54.26)

b =   1.837 (1.768, 1.906)

Goodness of fit:

SSE: 0.1045

R-square: 0.9905

Adjusted R-square: 0.9904

RMSE: 0.03249

Distribution: Weibull

Log likelihood: -48198.9

Domain: 0 < y < Inf

Mean: 45.8551

Variance: 613.313

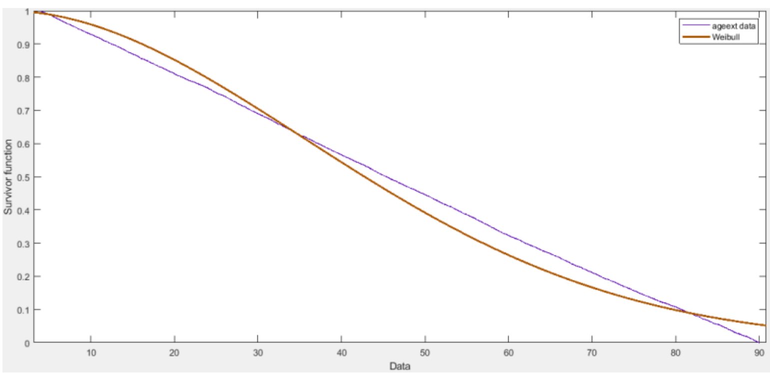
Parameter Estimate Std. Err.

A   51.6989   0.274136

B   1.9288   0.0156341

Estimated covariance of parameter estimates:

	A	B
A	0.0751505	0.00128608
B	0.00128608	0.000244425



Weibull reliability distribution

Gamma:

Distribution: Gamma

Log likelihood: -48628.8

Domain: $0 < y < Inf$

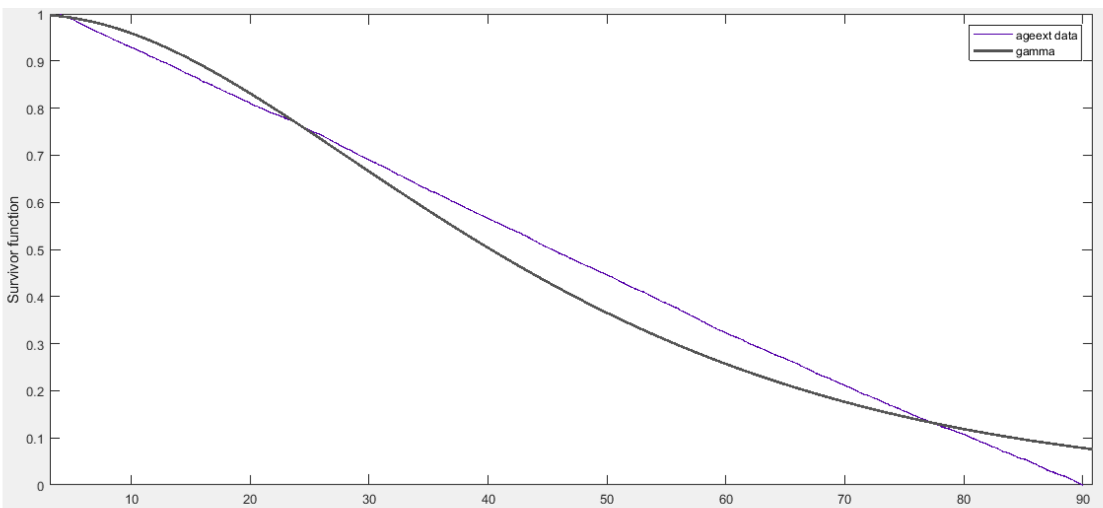
Mean: 45.9712

Variance: 813.831

Parameter	Estimate	Std. Err.
a	2.5968	0.0337815
b	17.703	0.254016

Estimated covariance of parameter estimates:

	a	b
a	0.00114119	-0.00777977
b	-0.00777977	0.0645241



Gamma reliability distribution

Rayleigh:

Distribution: Rayleigh

Log likelihood: -48209.1

Domain: $0 < y < Inf$

Mean: 46.1452

Variance: 581.832

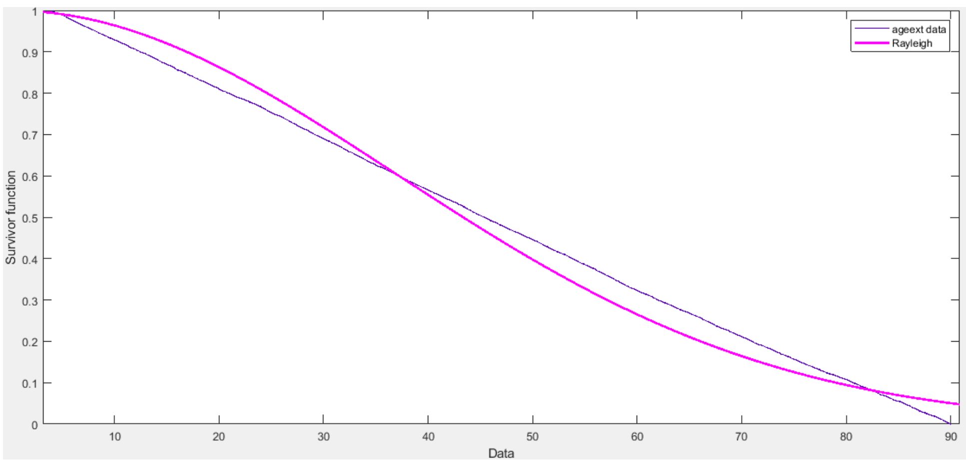
Parameter Estimate Std. Err.

B 36.8186 0.179605

Estimated covariance of parameter estimates:

B

B 0.0322579



Rayleigh reliability distribution

Distribution: Lognormal

Log likelihood: -49564.4

Domain: -Inf < y < Inf

Mean: 48.6473

Variance: 1624.5

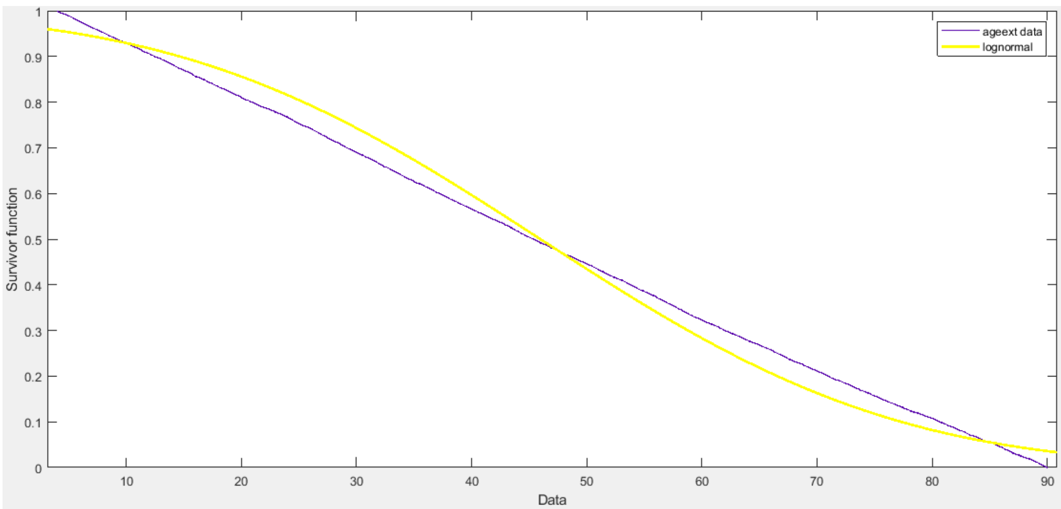
Parameter Estimate Std. Err.

mu 3.62329 0.00705301

sigma 0.722925 0.00498759

Estimated covariance of parameter estimates:

	mu	sigma
mu	4.97449e-05	-2.83366e-19
sigma	-2.83366e-19	2.4876e-05



Lognormal reliability distribution

ANNEX 2 MATLAB PROGRAMMING SCRIPT- SCENARIO 1

```
%% sleevement
syms x
%assuming reliability threshold for sleevement is 0.5 (regular)
eqn=exp(-(x/53.54)^1.837)==0.5
digitsOld = digits(3);
solx = solve(eqn,x)
t1=vpa(solx)
t0=t1
% to verify reliability level in the threshold
R0=myfunction1(t0)
count = 0
no=1
firstCol = 'A';
lastCol = 'O';
P=130000
i=0.05
t2=0:1:100
RR1=myfunction2(t2)
figure(1)
plot(t2,RR1,'r')
hold on
p3 = [t0 0]
p4 = [t0 R0]
%plot([p3(1) p4(1)], [p3(2) p4(2)],'r');
grid

for RRi=0.9:-0.05:0.1
eqn2=exp(-(x/53.54)^1.837)==RRi
digitsOld = digits(3);
solxRRi = solve(eqn2,x)
tti=vpa(solxRRi)
ti=tti.';
Ri=exp(-((ti)/53.54).^1.837)*1;
syms k
RR1=myfunction2(k);
mttfi=vpa(int(RR1,tti,inf));
Rii= Ri+0.7*(1-Ri);
tii=53.54*(-log(Rii))^(1/1.837);
mttfii=vpa(int(RR1,tii,inf));
mttr_sleevei=myfunction6s(Ri);
mttr_sleeveii=myfunction6s(Rii);
avail_i=(mttfi)/(mttfi+mttr_sleevei);
avail_i=vpa(avail_i,7);
avail_ii=(mttfii)/(mttfii+mttr_sleeveii);
avail_ii=vpa(avail_ii,7);
d.avail_i=abs(avail_i-avail_ii)*100;
count=count+no
firstRow = no+count;
```

```
lastRow = no+count;
k=double(1+count)
ti
%F is obtained by converting present cost(from trendline) to future
F=myfunction41s(RRi,ti,i);
EAC=myfunction5(F,ti,i);
unit_avail_EAC=d.avail_i/EAC;
unit_avail_F=d.avail_i/F;
filename=['test-sleeve-1-mod','.xlsx'];
cellRange = [firstCol,num2str(k),':',lastCol,num2str(k)]
%cellRange =
[firstCol,num2str(double(firstRow)),':',lastCol,num2str(double(lastRow
))
xlswrite(filename,[double(ti),double(RRi),double(mttfi),double(mttr_sl
eevei),double(Rii),double(tii),double(mttfii),double(mttr_sleeveii),do
uble(avail_i),double(avail_ii),double(d.avail_i),double(F),double(EAC)
,double(unit_avail_EAC),double(unit_avail_F)],cellRange)
p1 = [ti myfunction2(ti)];
p2 = [ti Rii];
t3=tii:1:100;
t4=ti:1:100+ti-tii;
%for verification
n = numel(t3)
n = numel(t4)
R2=myfunction2(t3);
for p=1:numel(x)
a=rand(1,3);
figure(1)
plot([p1(1) p2(1)], [p1(2) p2(2)],'color',a);
hold on;
plot (t4,R2,'color',a);
end
savefig('1.fig');
end
xlswrite(filename,[{'ti'},{'RRi'},{'mttfi'},{'mttr_sleevei'},{'Rii'},{
'tii'},{'mttfii'},{'mttr_sleeveii'},{'avail_i'},{'avail_ii'},{'d.avail
_i'},{'F'},{'EAC'},{'unit_avail_EAC'},{'unit_avail_F'}])
tiP = xlsread(filename,'A:A')
unit_avail_EAC = xlsread(filename,'N:N')
unit_avail_F = xlsread(filename,'O:O')
figure(2)
scatter(tiP,unit_avail_EAC)
savefig('2.fig')
figure(3)
scatter(tiP,unit_avail_F)
savefig('3.fig')
%%
%function [fitresult, gof] = createFit(tiP, unit_avail_F)
%CREATEFIT(TIP,UNIT_AVAIL_F)
%  Create a fit.
%
%  Data for 'untitled fit 1' fit:
```

```
%       X Input : tiP
%       Y Output: unit_avail_F
%   Output:
%       fitresult : a fit object representing the fit.
%       gof : structure with goodness-of fit info.
%
%   See also FIT, CFIT, SFIT.
%   Auto-generated by MATLAB on 17-Apr-2019 11:45:59
%% Fit: 'untitled fit 1'.
[xData, yData] = prepareCurveData( tiP, unit_avail_F );
% Set up fittype and options.
ft = fittype( 'poly3' );
% Fit model to data.
[fitresult, gof] = fit( xData, yData, ft );
% Plot fit with data.
figure( 'Name', 'untitled fit 1' );
h = plot( fitresult, xData, yData );
legend( h, 'unit_avail_F vs. tiP', 'untitled fit 1', 'Location',
'NorthEast' );
% Label axes
xlabel tiP;
ylabel unit_avail_F;
grid on
fitresult
gof
coef=coeffvalues(fitresult)
%%%%
%y = coef(1,1)*t5^3+coef(1,2)*t5^2+coef(1,3)*t5+coef(1,4)
%DER1=diff(y,t5)
%%%%
t5=linspace(0,90,900);
f=@(t5)(coef(1,1)*t5.^3+coef(1,2)*t5.^2+coef(1,3)*t5+coef(1,4))
y=f(t5);
[fMax,iMax]=max(y)
t5Max=t5(iMax)
savefig('4.fig')
Results_Names={'fMax','t5Max'};
Results_Values=[fMax,t5Max];
sheet=2;
xlRange='A2';
xlswrite(filename,Results_Values,sheet,xlRange);
R3=myfunction1(t5Max)
R4=R3+0.7*(1-R3)
%%%%%
t2=0:0.1:t5Max;
RR1=myfunction2(t2);
figure(5)
plot(t2,RR1,'r')
hold on
p11 = [t5Max myfunction2(t5Max)]
p21= [t5Max (myfunction2(t5Max)+0.7*(1-myfunction2(t5Max)))]
plot([p11(1) p21(1)], [p11(2) p21(2)],'r');
```

```
hold on
eqn3=exp(-(x/53.54)^1.837)==R4
digitsOld = digits(3);
solx3 = solve(eqn3,x)
t6=vpa(solx3)
t7=t5Max:1:100+t5Max-t6
t8=t6:1:100
R5=myfunction1(t8)
plot(t7,R5,'r')
%savefig('5.fig')
hold on
%%%%%%%%%%%%%%
%replacement part
count = 0
no=1
firstCol = 'A';
lastCol = 'O';
i=0.05;
for RRi_2=R4:-0.05:0.1;
eqn4=exp(-(x/53.54)^1.837)==RRi_2;
digitsOld = digits(3);
solRRi_2= solve(eqn4,x);
tti_2=vpa(solRRi_2);
ti_2=tti_2.'
Ri_2=exp(-((ti_2)/53.54).^1.837)*1;
syms k
RR1_2=myfunction2(k);
mttfi_2=vpa(int(RR1_2,tti_2,inf));
Rii_2= Ri_2+0.9*(1-Ri_2);
tii_2=53.54*(-log(Rii_2))^(1/1.837);
mttfii_2=vpa(int(RR1_2,tii_2,inf));
mttr_replacei_2=myfunction6r(Ri_2);
mttr_replaceii_2=myfunction6r(Rii_2);
%mttr_replaceii=mttr_replace;
%mttr_replacei=mttr_replace*(1-myfunction1(ti));
%mttr_replaceii=mttr_replace*(1-myfunction1(tii));
avail_i_2=(mttfi_2)/(mttfi_2+mttr_replacei_2);
avail_i_2=vpa(avail_i_2,7);
avail_ii_2=(mttfii_2)/(mttfii_2+mttr_replaceii_2);
avail_ii_2=vpa(avail_ii_2,7);
d.avail_i_2=abs(avail_i_2-avail_ii_2)*100;
count=count+no;
firstRow = no+count;
lastRow = no+count;
k=double(1+count)
ti_2;
%F is obtained by converting present cost(from trendline) to future
F_2=myfunction41r(RRi_2,ti_2+t5Max,i);
EAC_2=myfunction5(F_2,ti_2+t5Max,i);
unit_avail_EAC_2=d.avail_i_2/EAC_2;
unit_avail_F_2=d.avail_i_2/F_2;
filename_2=['test-replace-2-mod','.xlsx'];
```

```
filename_3=['test-replace-3-mod','.xlsx'];
cellRange = [firstCol,num2str(k),':',lastCol,num2str(k)]
cellRange2 = [firstCol,num2str(k),':',firstCol,num2str(k)]
%cellRange =
[firstCol,num2str(double(firstRow)),':',lastCol,num2str(double(lastRow
))
xlswrite(filename_2,[double(ti_2),double(RRi_2),double(mttfi_2),double
(mttr_replacei_2),double(Rii_2),double(tii_2),double(mttfii_2),double(
mttr_replaceii_2),double(avail_i_2),double(avail_ii_2),double(d.avail_
i_2),double(F_2),double(EAC_2),double(unit_avail_EAC_2),double(unit_av
ail_F_2)],cellRange)
xlswrite(filename_3,[double(tii_2+(t5Max-t6)+(ti_2-
tii_2))],cellRange2)
p1_2 = [tii_2+(t5Max-t6)+(ti_2-tii_2) myfunction2(ti_2)];
p2_2 = [tii_2+(t5Max-t6)+(ti_2-tii_2) Rii_2];
t3_2=tii_2:1:100;
t4_2=tii_2+(t5Max-t6)+(ti_2-tii_2):1:100+(t5Max-t6)+(ti_2-tii_2);
%for verification
n = numel(t3_2);
n = numel(t4_2);
R2_2=myfunction2(t3_2);
for p=1:numel(x);
a=rand(1,3);
%figure(5)
plot([p1_2(1) p2_2(1)], [p1_2(2) p2_2(2)],'color',a);
hold on;
plot (t4_2,R2_2,'color',a)
end
savefig('5.fig')
end
xlswrite(filename_2,[{'ti_2'},{'RRi_2'},{'mttfi_2'},{'mttr_replacei_2'
},{'Rii_2'},{'tii_2'},{'mttfii_2'},{'mttr_sleeveii_2'},{'avail_i_2'},{
'avail_ii_2'},{'d.avail_i_2'},{'F_2'},{'EAC_2'},{'unit_avail_EAC_2'},{
'unit_avail_F_2'}])
tiP_2 = xlsread(filename_2,'A:A');
unit_avail_EAC_2 = xlsread(filename_2,'N:N');
unit_avail_F_2 = xlsread(filename_2,'O:O');
figure(6)
scatter(tiP_2,unit_avail_EAC_2)
savefig('6.fig')
figure(7)
scatter(tiP_2,unit_avail_F_2)
savefig('7.fig')
%%
%function [fitresult, gof] = createFit(tiP, unit_avail_F)
%CREATEFIT(TIP,UNIT_AVAIL_F)
%  Create a fit.
%
%  Data for 'untitled fit 1' fit:
%      X Input : tiP
%      Y Output: unit_avail_F
%  Output:
```

```
%      fitresult : a fit object representing the fit.
%      gof : structure with goodness-of fit info.
%
%  See also FIT, CFIT, SFIT.
%  Auto-generated by MATLAB on 17-Apr-2019 11:45:59
%% Fit: 'untitled fit 1'.
[xData_2, yData_2] = prepareCurveData( tiP_2, unit_avail_F_2);
% Set up fittype and options.
ft_2 = fittype( 'poly3' );
% Fit model to data.
[fitresult_2, gof_2] = fit( xData_2, yData_2, ft_2 );
% Plot fit with data.
figure( 'Name', 'untitled fit 1' );
h = plot( fitresult_2, xData_2, yData_2 );
legend( h, 'unit_avail_F vs. tiP', 'untitled fit 1', 'Location',
'NorthEast' );
% Label axes
xlabel tiP
ylabel unit_avail_F
grid on
fitresult
gof
coef_2=coeffvalues(fitresult_2)

%%%%
%y_2=
coef_2(1,1)*t5_2^3+coef_2(1,2)*t5_2^2+coef_2(1,3)*t5_2+coef_2(1,4)
%DER1=diff(y_2,t5_2)
%%%%
t5_2=linspace(0,90,900);
f_2=@(t5_2)(coef_2(1,1)*t5_2.^3+coef_2(1,2)*t5_2.^2+coef_2(1,3)*t5_2+c
oef_2(1,4))
y_2=f_2(t5_2);
[fMax_2,iMax_2]=max(y_2)
t5Max_2=t5_2(iMax_2)


savefig('8.fig')
Results_Names_2={'fMax_2','t5Max_2'};
Results_Values_2=[fMax_2,t5Max_2];
sheet=2;
xlRange='A2';
xlswrite(filename_2,Results_Values_2,sheet,xlRange);

%%%%%
R3_2=myfunction1(t5Max_2)
R4_2=R3_2+0.9*(1-R3_2)
eqn3=exp(-(x/53.54)^1.837)==R4
digitsOld = digits(3);
solx3 = solve(eqn3,x)
t6=vpa(solx3)
eqn3_2=exp(-(x/53.54)^1.837)==R4_2
```

```
digitsOld = digits(3);
solx3_2 = solve(eqn3_2,x)
t6_2=vpa(solx3_2)
%removes extension of profile after jump
%t2=0:0.1:t5Max;
t2=0:0.1:100;
RR1=myfunction2(t2);
figure(9)
a1=plot(t2,RR1,'r')
XTick = [0:10:150];
set(gca,'xtick',XTick)

hold on
p11 = [t5Max myfunction2(t5Max)]
p21= [t5Max (myfunction2(t5Max)+0.7*(1-myfunction2(t5Max)))]
b=plot([p11(1) p21(1)], [p11(2) p21(2)],'g');
set(gca,'xtick',XTick)
hold on
eqn3=exp(-(x/53.54)^1.837)==R4
digitsOld = digits(3);
solx3 = solve(eqn3,x)
t6=vpa(solx3)
R3_2=myfunction1(t5Max_2)
R4_2=R3_2+0.9*(1-R3_2)
eqn3=exp(-(x/53.54)^1.837)==R4
digitsOld = digits(3);
solx3 = solve(eqn3,x)
t6=vpa(solx3)
eqn3_2=exp(-(x/53.54)^1.837)==R4_2
digitsOld = digits(3);
solx3_2 = solve(eqn3_2,x)
t6_2=vpa(solx3_2)

%removes extension of profile after jump
t7=t5Max:1:100+t5Max-t6
%t7=t5Max:1:t6_2+(t5Max-t6)+(t5Max_2-t6_2)
t8=t6:1:100
%t8=t6:1:t6_2+(t5Max-t6)+(t5Max_2-t6_2)-t6

R5=myfunction1(t8)
plot(t7,R5,'g')
hold on
%%%
p1_2 = [t6_2+(t5Max-t6)+(t5Max_2-t6_2) myfunction2(t5Max_2)]
p2_2 = [t6_2+(t5Max-t6)+(t5Max_2-t6_2) R4_2]
t3_2=t6_2:1:100
t4_2=t6_2+(t5Max-t6)+(t5Max_2-t6_2):1:100+(t5Max-t6)+(t5Max_2-t6_2)
%for verification
n = numel(t3_2)
n = numel(t4_2)
R2_2=myfunction2(t3_2)
for p=1:numel(x)
```

```
a=rand(1,3);
c=plot([p1_2(1) p2_2(1)], [p1_2(2) p2_2(2)],'color','b');
hold on;
plot (t4_2,R2_2,'b')
set(gca,'xtick',XTick)
end
legend ([a1 b c],'original reliability profile','updated reliability
profile (action 1)','updated reliability profile (action 2)')
xlabel ('Time (year)');
ylabel ('Reliability');

hold on
digitsOld = digits(3);
eqntk=exp(-(x/53.54)^1.837)==0.5
solxtk = solve(eqntk,x)
tk=vpa(solxtk)
tk=tk+(t5Max-t6)+(t5Max_2-t6_2)
p1_3 = [tk 0]
p2_3 = [tk 0.5]
d=plot([p1_3(1) p2_3(1)], [p1_3(2) p2_3(2)],'-.k');
hold on

p1_4 = [0 0.5]
p2_4 = [tk 0.5]
e=plot([p1_4(1) p2_4(1)], [p1_4(2) p2_4(2)],'-.k');
legend ([a1 b c e],'original reliability profile','updated reliability
profile (action 1)','updated reliability profile (action 2)','50%
reliability threshold')
savefig('9.fig')


filename=['test-replace-2-mod','.xlsx'];
Results_Values=[t5Max,double(t6_2+(t5Max-t6)+(t5Max_2-t6_2))];
sheet=2;
xlRange='A3';
xlswrite(filename,Results_Values,sheet,xlRange);

filename=['test-replace-2-mod','.xlsx'];
Results_Values1=[double(tk)];
sheet=2;
xlRange='A4';
xlswrite(filename,Results_Values1,sheet,xlRange);
```