Risk-Based Maintenance Planning Model for Oil and Gas Pipelines

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ABSTRACT

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Oil and gas pipelines are the main means of transporting fossil fuels from the wellheads and processing facilities to the distribution centers. The 2013 US infrastructure report card assigned a grade of D^+ to energy pipelines signifying they are in a poor condition. More than 10,000 incidents were reported on oil and gas pipelines during the last two decades, most of which resulted in considerable consequences. Recent failures and ruptures have raised concerns over the risk of failure of such pipes in Canada. The main objective of this research is to develop a risk-based maintenance planning model for oil and gas pipelines. The research develops a probability of failure (POF) and a consequence of failure (COF) prediction model and establishes a risk-based inspection and simulation-based rehabilitation planning models.

The POF model develops a comprehensive index by applying the granular theory of uncertainty and the principles of probability theory to forecast the POF of oil and gas pipes. The neuro-fuzzy technique is employed to develop a model that forecasts the financial consequences of the potential failures of such pipes. An integrated fuzzy risk evaluation model is developed with 25 fuzzy rules to assess a pipeline’s risk index. A fuzzy expert system is developed to select the inspection tools and determine their run-frequency according to the failure risk of a pipeline. Regression analysis is applied to develop a risk growth profile to forecast the maximum failure risk of various inspection scenarios. Scenarios are ranked based on their risk-cost index, which integrates two main indices: 1) maximum risk of failure, and 2) life cycle cost of scenarios, computed by applying the Monte-Carlo simulation. Finally, a comprehensive maintenance model proposes the optimum maintenance plans with the lowest LCC, developing a third-degree risk-based deterioration profile of the pipelines.

The POF model's sensitivity results highlight that cathodic protection effectiveness and soil resistivity are the leading causes of external corrosion failures, while the depth of cover is an important factor of mechanical damages. The COF model attests that diameter, as well as the location properties are important factors for estimating the financial consequences. The developed risk assessment model is validated using a test dataset that proved the models are accurate with about 80% validity. The developed models are applied on a case study of a 24-inch pipe. The POF and COF of the pipe are computed, and the results suggest that the pipe's risk index is above medium with an average index of 3.5. The study proposes the application of an inspection tool, which decreases the risk growth by 50% during the service life of the pipeline. The application of the maintenance planning model proposes a combination of recoat, repair, and replacement with a medium size of rehabilitation. The net present value of the proposed scenario of maintenance is estimated to cost around 1.7 million dollars over the life cycle of the pipeline, compared to the last-ranked alternative that costs over three million dollars. This research offers a framework to develop a comprehensive index to predict the failure risk of pipes using historical data that can be extended to the other infrastructure types. It develops a model to plan for the optimal pipeline maintenance, and provides an overall image of its service life. The developed models will help the operators predict the risk of failure and plan appropriately for the life cycle of their oil and gas pipelines.

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To all of those who provide humanitarian aid

to the people in need.

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CHAPTER 1: INTRODUCTION

1.1 Problem Statement and Research Motivation

While pipelines are considered to be the safest and most efficient way to transport hazardous liquids and natural gas, there is still a probability of failure, with economic, safety and damaging ecological consequences. The Pipeline and Hazardous Materials Safety Administration ($PHMSA_a$ 2014) of the US has gathered and published data on the oil and gas pipeline failures since 1970. Over 10,000 failures were recorded from 1993 to 2013 in the US, which resulted in six billion dollars of property damages and the leakage of around 2.3 million barrels of hazardous liquids into the environment. The records also indicate that 377 fatalities and 1,489 serious injuries occurred during this period. These figures underscore why the assessment of oil and gas pipelines deserves serious attention. In addition, owners or operators of such pipelines must develop and implement an integrity management program as mandated by Canadian Pipeline regulatory. Whereas the Guidelines for Pipeline Integrity Management Programs (Annex N) only provides an overall approach to mitigate risk of failures of the pipelines during the operation phase (CSA 2003).

The failure of oil and gas pipelines has been extensively addressed in the literature, however the studies conducted to-date suffer from several limitations. These research works have either focused on a single type of failure, e.g. corrosion or third-party activities, or they have developed subjective models. Physical models rely on analyzing inline inspection data, which is very expensive to gather and does not even exist in the early stages of a pipeline's operation. In addition, some pipes are not piggable. The existing statistical models do not consider the specific properties of pipes in forecasting the probability and consequences of their failure. Moreover, there is no structured method with which to plan for the inspection and rehabilitation of pipes. Therefore, the current state-of-the-practice is not mature enough to fully support oil and gas operators in the decision-making process.

This study aims to develop an objective quantitative model on the failure assessment of oil and gas pipelines, a model that can also be used to plan maintenance solutions. The result of this research will help oil and gas pipeline operators in their decision-making process for inspection and maintenance plans.

1.2 Research Objectives

The main objective of this research is to develop a risk-based maintenance decision support model for oil and gas pipelines during the operation phase. This objective can be broken down into the following sub-objectives:

1. Identify and study the sources of failure and their effects on oil and gas pipelines;
2. Predict the failure probability of such pipes;
3. Develop a consequence of failure assessment model;
4. Develop an integrated risk evaluation model;
5. Establish a risk-based inspection planning model; and
6. Develop a deterioration-based rehabilitation planning model.

1.3 Research Methodology

A comprehensive description of the methodology developed in this research is presented in chapter 3. A summary of the research methodology is presented in the following steps:

Step 1: Literature Review

The literature is reviewed to find those works that are most relevent to the risk assessment and maintenance of oil and gas pipelines. The literature review also includes an evaluation of the techniques that can be used in the model development.

Step 2: Build a Bow-tie model

A Bow-tie model is applied to develop the graphical representation of the variables that contribute to failure and to show their relationship to the major consequences of the failure. This approach includes two main parts; a fault tree and an event tree. Due to the complexity of oil and gas pipeline behaviour, this is a useful technique with which to elaborate on the causes and after-failure events of pipeline failure. Finally, this step provides a comprehensive view of the pipeline failure scenarios.

Step 3: Probability of Failure Model

The failure probability is assessed based on the bow-tie model, and the contribution of each category of contributing causes is calculated using the historical data from pipeline incidents. The model then computes the failure probability based on the causes of incidents and measures the probability of the occurrence of each major consequence. The model produces all the indices and equations required to compute the absolute probability of failure.

Step 4: Consequences of Failure Model

This model predicts the monetary consequence level of various pipeline failure scenarios. The neuro-fuzzy technique is used to develop this model, utilizing data gathered from the history of pipeline incidents in the US. This technique is a powerful pattern recognition tool,recognising the relationship between the input and output variables. Compared to using regression and artificial neural networks it develops a more accurate and robust model.

Step 5: Integrated Fuzzy Risk Evaluation Model

A fuzzy expert system that integrates the probability of failure with the consequences of failure is developed to evaluate the failure risk level. A fuzzy inference system is developed; its rules defined based on the existig risk matrices and expert opinions.

Step 6: Risk-Based Inspection Planning

The appropriate pipeline inspection techniques are selected and their optimal run frequency of running is proposed. This is performed according to the afore-calculated probabilities of failure and consequences. Various inspection scenarios are developed based on the risk growth prediction profile. The inspection scenarios are ranked based on a newly introduced index, theRisk-Cost, which multiplies the maximum risk of failure by the life cycle cost.

Step 7: Maintenance planning

This step helps oil and gas pipeline operators develop appropriate maintenance scenarios for the pipelines in their network. The rehabilitation scenarios are offered via the prediction of the deterioration profile, and then the required rehabilitation techniques are determined based on the deterioration profile. The Life Cycle Costs (LCCs) of the generated scenarios are calculated using Monte Carlo simulation. Accordingly, the scenarios with the lowest LCCs indicate the associated optimum pipeline maintenance plans.

1.4 Structure of the Thesis

This thesis is comprised of six chapters, summarised as follows:

Chapter 1 highlights the problem statement and the research motivation. The research objectives and the overall model framework are also presented in this chapter.

Chapter 2 reviews the previous works on failure and risk assessment of oil and gas pipelines. The literature review results are organised and the research gaps identified. In addition, the most-suitable techniques for this research are investigated.

Chapter 3 presents the research methodology in detail. It is composed of two distinctive models, a risk assessment model and a maintenance model. The risk assessment model contains three main steps: identification, failure probability assessment, and consequence evaluation. The maintenance model is composed of inspection planning and rehabilitation planning sub-models.

Chapter 4 explains the historical data gathered to develop the proposed models. It also includes an analysis of the historical data, divided into two main categories: (1) the frequency of failure sources associated with different variables and (2) monetary consequences classification.

Chapter 5 elaborates the development of the models based on the proposed methodology introduced in Chapter 3. It also elaborates on the implementation of the developed model for a 24-inch pipe. This chapter continues with an explanation of the semi-automated system.

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

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

This chapter aims at providing a retrospective and comprehensive literature review of the risk assessment, maintenance solutions, and decision support models of oil and gas pipelines in the operation phase. It starts with an introduction to oil and gas pipelines and their types (Section 2.2). Then, a comprehensive review of the risk assessment researches including the general risk management methods and those related to the oil and gas pipelines is presented (Section 2.3). After that, the existing guidelines on various types of operations for the maintenance of such pipelines are introduced (Section 2.4). Finally, selected techniques that have the potential to be used in this research are reviewed, and the advantages and disadvantages of each are demonstrated (Section 2.5). At last, the limitations of the previous studies and overall finding of this review are presented (Section 2.6).

2.2 Oil and Gas Pipelines

Statistics proves that 24% of US energy consumption is provided by natural gas and another 39% from petroleum products. The pipelines network in the US transport almost all of the natural gas and around 65% of the hazardous liquid products. Pipelines are considered as the most practical and safest way of transporting these products. The pipeline network in the US consists of 2.5 million miles and includes three primary types according to their function as follows ($PHMSA_a$ 2014):

- Gas transmission and gathering pipelines: There are approximately 320,000 miles of onshore and offshore transmission pipelines in the US. Gathering pipelines gather natural gas from wellheads and transmission pipelines carry products in large volumes from the processing facilities to the communities, power plants, and factories over long distances. These pipelines may range from 2 to 42 inches in diameter ($PHMSA_a$ 2014).
- Gas distribution pipelines: There were around 2.1 million miles of distribution pipelines in 2001. They carried products from the processing facilities to the residential, commercial, and industrial customers. Gas distribution pipelines are also divided into two groups of main and service lines. Main lines are larger in diameter; while the service lines are from ½ to 2 inches in diameter ($PHMSA_a$ 2014).
- Hazardous liquid pipelines: These pipelines cover 185,000 miles of the network. They carry hazardous liquids from the wellheads to the customers. These pipelines are ranged from 2 to 42 inches in diameter. ($PHMSA_a$ 2014)

Figure 2.1 presents a schematic view of the network of oil and gas pipelines. The life cycle of these pipeline projects includes three main phases including design, construction, and operation. The main steps of pipeline construction are as followed ($PHMSA_a$ 2014):

1- Site Preparation
2- Pipe Stringing
3- Trenching
4- Bending
5- Welding

6- Coating

7- Lowering and Backfilling

8- Testing

9- Site Restoration

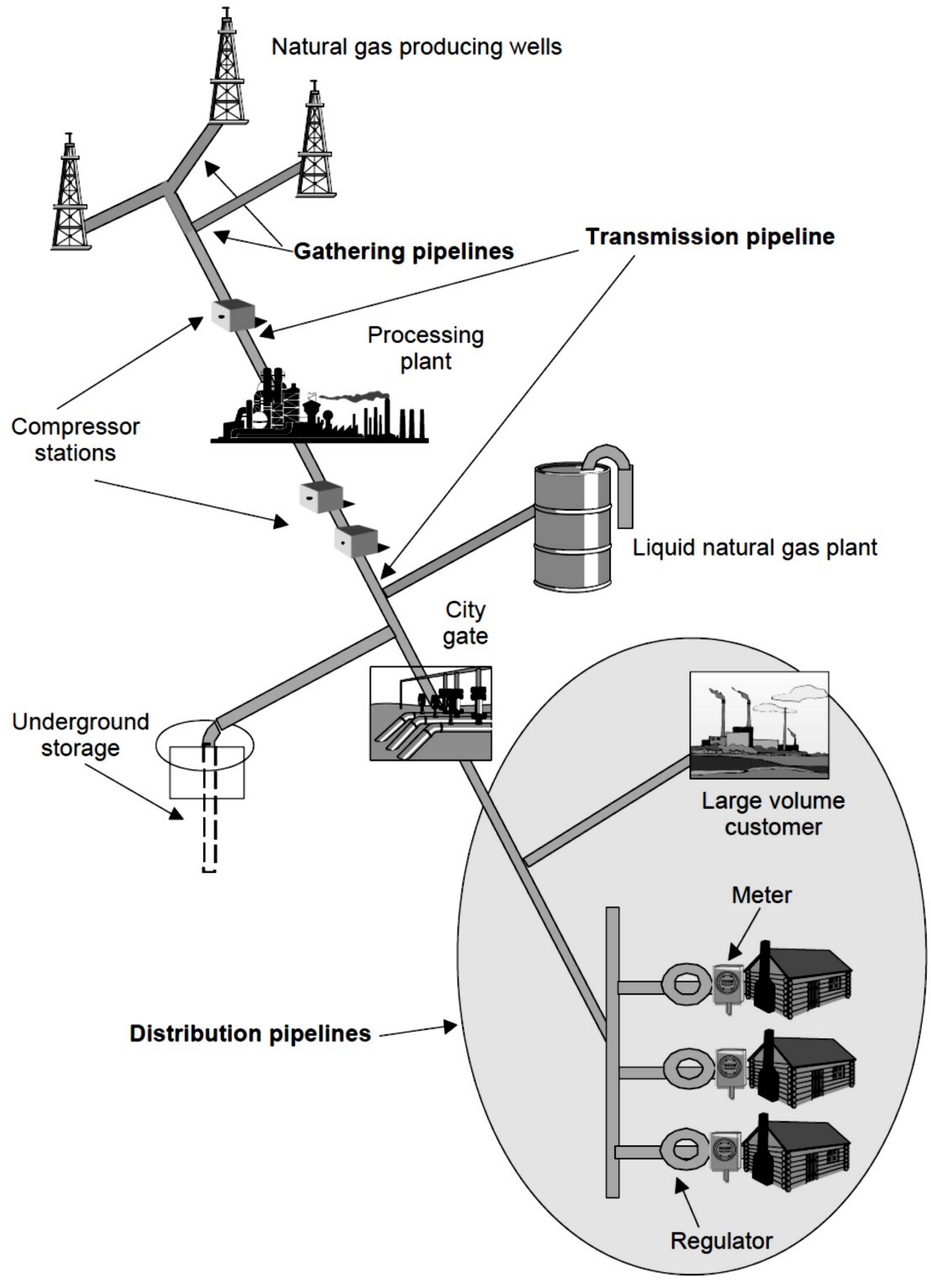


Figure 2- 1: Components of Natural Gas Pipelines Network (GAO 2000)

2.3 Risk Assessment

2.3.1 Definition of Risk Assessment

Failures have happened over the life of oil and gas pipelines; although, they are assumed the safest and more economic than the other methods of transporting the petroleum products. Risk assessment is a tool that can facilitate maintenance decision-making by forecasting the failures of oil and gas pipelines. Risk assessment guidelines have provided a definition of risk from various perspectives (Infraguide 2006, Dey 2009, and Dey 2010). Infraguide (2006) defined risk as a combination of the probability and the consequences of the scenarios that have adverse effects on the operation of different infrastructure types. Consequently, risk management aims to decrease the risk of failure and details this process in three main phases: Identification, Evaluation, and Mitigation planning of the risks.

DNV (2010) published a report about the recommended practice on risk assessment of third party sources of failures. The report defined sources of failure of pipelines as accidental events that can lead to the failure of the pipes, which was titled: the end-event. Then, it defined risk assessment as the evaluation of the frequency and consequences of the end-event. DNV (2009) developed recommendations on the integrity management of sub-sea pipelines. This study suggested selecting the activities in the operation phase of pipelines based on the risk assessment. Then, it specified the steps of the risk assessment process as are followed:

- Identify risks and types of failures
- Evaluate failure probabilities (PoF)
- Evaluate failure consequences (CoF)

- Estimate risk of failure level ($\mathrm{CoF} \times \mathrm{PoF}$)

2.3.2 Risk-Based Decision Support Models for Oil and Gas Pipelines

There has been an extensive effort in the previous studies to analyze and assess the risks of oil and gas pipelines and develop risk-based decision support systems for oil and gas pipes (Han & Weng 2010, Han & Weng 2011, Dey 2003, Dey 2004, Dey et al. 2004). A quantitative method was proposed by Han & Weng (2010) to evaluate the individual risks of natural gas pipeline networks. This method combined the probability of failures and their internal and external consequences. External effects included those of individual and societal while internal effects evaluated the monetary consequences. The model applied an overall rate of failure to calculate the probability of failure and multiplied it by a function of variables. Then, pipelines were classified into external and internal ones. For the former group, the individual and social consequences were computed. This part of the model focused on the safety related consequences and considered harms of a failure on gas pipelines. The coefficient of the pressure of the pipeline with the expected economic loss was multiplied by the pressure of the node that was vulnerable to fail to calculate the economic consequences. The failure rate was an average rate of incidents that was computed based on the historical data that was recorded through the historical data of failures on European gas pipeline network (EGIG 1999). The failure rate of all pipelines was considered equal unless the correction factor was applied; however, no function was developed to calculate this factor.

Han and Weng (2011) developed a model to compare the risk of failure of urban gas pipelines in a network. This model considered the causes of failures of such pipelines and calculated their weights based on the historical data. Frequency of the failures was obtained to calculate the weight of importance of the causes of failure applying reliability engineering theory. Then, the probability of happening of each cause of failure was computed and multiplied by its related weight. The method was implemented on two pipelines and was compared with the results of a quantitative method proposed by Han and Weng (2010) to prove the validity of the developed model.

Dey (2003) evaluated the risk of failure of different segments of a cross-country pipeline and developed strategies for the selection of the inspection techniques for such pipelines. Risk-based decision-making support system was developed by Dey (2004) using Analytic Hierarchy Process (AHP) technique. This model applied expert opinion to obtain the weight of variables that were identified to contribute to the failure of pipelines. Variables were categorized as risk factors that included external and internal corrosion, construction and material defects, as well as acts of God.

Later, Dey et al. (2004) developed a risk-based maintenance model for offshore pipelines. After introducing likelihood and consequence loops of risks, expert opinion was obtained to calculate the relative weights of each factor of the loops applying AHP. Ranges of effect values from 1 to 10 were considered for assessing each factor. The model calculated the risk score of each pipeline by summing up the effect values multiplied by associated weights of the factors. Finally, one of the results was prioritizing assets of a network of pipelines. Most of the factors such as corrosion were evaluated subjectively; although, the research tried to minimize the subjectivity of the decision-making process in this problem. The model did not recognize the severity of different risks of failures. Consequently, inspection tools were proposed through an experience-based process, which was built upon a set of primary factors. Consequently, the research did not develop a comprehensive model and needed the expertise to analyze and propose the best technique.

2.3.3 Sources of Failure

The first step in the risk assessment of infrastructures is to identify the risks associated with their failure (Infraguide 2006; DNV 2009 & 2010). There are different classifications of infrastructure risks. Sources of failures and defects that result in the failures of oil and gas pipelines have been the subject of grouping risks of failures (Shahriar et al. 2012, Dawotola et al. 2009, Yuhua & Datao 2005, and Muhlbauer 2004). This section details how previous works categorized the failures of oil and gas pipelines.

Muhlbauer (2004) defined the risk of oil and gas pipelines as the loss of integrity and product. He also extended the risk definition to the failure of executing the intended functions by blockage, contamination or equipment failure. It was mentioned that leakage in most urban pipelines such as water, sewer, and urban gas distribution can tolerate some amount of leakage and would not be considered failed. However, the case was different for the transmission pipelines, and any amount of leakage was defined as failure. Failures cause interruptions in the function of transmission pipelines. This research classified failures from the viewpoint of the sources in four categories: third party, corrosion, design, and incorrect operations. Parvizsedghy and Zayed (2013) classified risks of oil and gas pipelines based on their sources of failure. Failures were recognized as happening because of physical, external or operational sources. Although, there may seem different categorization of the failures of oil and gas pipelines, most of the identified risk factors or failure types are similar. Table 2-1 presents the types of failures each study has identified.

The identification was based on the frequency of the failures of oil and gas pipelines with respect to their sources.

Table 2- 1: Failure types in six various sources

Failure Types	Sources					
	Shahriar et al. 2012	**Dawotola et al. 2009**	**Yuhua & Datao 2005**	**Muhlbauer 2004**	**$PHMSA_a$ 2014**	**EGIG 2004**
External Corrosion	*	*	*	*	*	*
Internal Corrosion	*	*	*	*	*	*
Construction and Material Defects	*	*	*	*	*	*
Incorrect Operation	*	*	*	*	*	*
Bad Design	*	*	*	*	NA	NA
Third Party	*	NA	*	*	*	*
Natural Hazards	*	NA	*	*	*	*

2.3.4 Probability of Failure

Failure probability is one of the required parameters to assess the risk of failure in infrastructures. Different guidelines tried to provide a definition of the probability of failure and a scale of evaluation for infrastructures (Infraguide 2006, and DNV 2010). Infraguide (2006) defined probability as the frequency of happening of a hazard. The study proposed Table 2-2 to assess the probability of failure of infrastructures. The probability of failure assessment for oil and gas pipelines has been the subject of several researches. The probability of failure scale should be adapted to the nature of the infrastructure type. Some types of infrastructures are more dangerous to the human and environment. DNV (2009) developed failure probability scale for offshore gas pipelines. Table 2-3 presents categories of probability assessment and their description.

Table 2- 2: Probability Assessment Scale (Infraguide 2006)

Probability level		Likelihood
10	Will occur more than 4 times over next 2 to 5 years	Frequent
8	Will occur 2 to 4 times over next 2 to 5 years	Likely
6	Will occur once over next 2 to 5 years	Occasional
3	May occur once over next 2 to 5 years	Seldom
1	Unlikely to occur over next 2 to 5 years	Unlikely

Table 2- 3: Failure Probability Scale of Assessment (DNV 2010)

Category	Annual Frequency	Description
1	$<10^{-5}$	So low frequency that event considered negligible.
2	10^{-5} to 10^{-4}	Event rarely expected to occur.
3	10^{-4} to 10^{-3}	Event individually not expected to happen, but when summarized over a large number of pipelines have the credibility to happen once a year.
4	10^{-3} to 10^{-2}	Event individually may be expected to occur during the lifetime of the pipeline. (Typically 100-year)
5	$>10^{-2}$	Event individually may be expected to occur more than once during the lifetime.

Inline inspection data was widely used by previous researchers to develop a model to estimate the POF (Caleyo et al. 2009, Sinha 2002, and Ahammed 1998, and Sinha and Pandey 2002). Caleyo et al. (2009) developed probability distribution functions of corrosion depth and rate of growth applying Monte Carlo simulation. Different curves were proposed for underground pipelines considering the properties of various soil types. Sinha (2002) and Ahammed (1998) developed probabilistic models due to the uncertainties of pipeline parameters. Both obtained data from Inline inspection tools to predict the failure probability of oil and gas pipelines under corrosion. These tools were used to gather data on the condition of oil and gas pipelines. The models required data on defects' depth and length from inline inspection tools. Sinha and Pandey (2002) applied ANN to develop a model to predict the probability of failure of oil and gas pipelines. This model used the metal loss to forecast the burst pressure of such pipelines based on the model developed by Kiefner et al. (1973). The estimated pressure was used to forecast the remaining strength of the pipelines. Noor et al. (2011) proposed a probabilistic method to forecast the remaining strength of offshore pipelines obtaining data from inline inspection tools. This method was developed based on the assessment rules of DNV's Recommended Practice for Corroded Pipelines (Veritas 2010) considering the standard deviation of inspection tools in determining the size of defects.

Qualitative researches on POF evaluation model applied expert opinion to develop a POF assessment model (Al-Khalil et al. 2005, Zeng and Ma 2009, Dawotola et al. 2009, Dey 2003, and Dey 2004). Al-Khalil et al. (2005), ranked a group of cross-country pipelines applying AHP. They classified risks of failure in seven groups: corrosion, mid wall defects, external interference, structural defects, operation problems, and loss of ground support. Then, experts scored the probability and cost of failure for each pipeline against the identified risk factors to calculate the overall expected cost of failure for each pipeline. These scores were later used to prioritize pipelines with respect to the budget. This Research tried to offer a "systematic risk-based approach" to prioritize a group of pipelines; although, it lacked the objectivity and did not develop a comprehensive model. Zeng and Ma (2009) developed a risk model for underground pipelines. The model applied two sets of variables, general, and inspection and correlated them with six major types of failure titled: shape, seam, and structural failures, pipe alignment, and blockage. Then, it considered the consequences of failure, cost, performance, interruption, and safety, and finally offered a max-average method to maximize the effect of severe consequences in assessing the risk level. As the author described, this model did not develop any rating index to calculate the probability of failure. It only proposes an ordinal table of scales for different consequences; the absence of objectivity was apparent in this model.

Dey (2003) evaluated the risk of failure of various segments of a cross-country pipeline. The probability of failure of segments of a pipeline was assessed based on the judgment of experts comparing various sources of failure in each segment against the other sources. The calculated weights for each source of failure were considered as the likelihood of failure for each segment. These weights were then used to prioritize different segment to be inspected. Also, the inspection tool was selected based on the relative likelihood of failure of segments versus each other. Dey (2004) applied a similar method to calculate the probability of failure on oil and gas pipelines. Several experts judged the importance of different sources of pipeline failures applying AHP. The relative importance of the identified sources of failure was evaluated based on the calculated weights. Finally, the expert opinion was applied to rate the probability of failure of pipelines against each type of failure. This score multiplied by the calculated weights resulted in the calculation of failure probability.

Dawotola et al. (2009) proposed a model to calculate the failure probability of different causes of pipeline incidents. The model was designed with the combination of AHP and

Fault Tree Analysis (FTA). In fact, the model aimed to rank the causes responsible for pipeline failures based on the expert opinion. The model did not consider properties of the pipelines and only evaluated the relative importance of each failure cause.

Some of the previous studies used the artificial neural networks to develop a model on the probability of failure of pipes due to corrosion or third party activities. Bersani et al. (2010) proposed a model to predict the probability of failures with respect to different causes, applying Artificial Neural Networks. For each cause of failure, a set of factors was proposed as independent variables. Preliminary results were presented to predict the third party failures; however, results did not prove the importance of the proposed factors and neither the soundness of the model. Ren et al. (2012) applied back propagation neural networks in a model to predict the maximum corrosion rate of natural gas pipelines. Input variables included pipeline length, the difference of elevation between different sections, pipe inclination, and pressure. The model also considered the Reynolds number as an important factor in predicting the corrosion rate of various sections of gas pipelines. Menon (2005) defined the Reynolds number as an important factor in classifying the flow of natural gas pipelines. The study developed a function of average gas velocity, inside diameter of pipe, gas density and velocity as input parameters to compute the Reynolds number.

An extensive effort has been performed over the past years to model the reliability of the pipes subject to corrosion. Feng et al. (2011) developed a physical model for oil and gas pipelines. This research studied the effect of several factors on pipelines' reliability. Data was obtained through "field measurement and physical and mechanical tests." Sensitivity analysis proved the importance of the effect of Yield Strength, internal pressure and wall thickness of the pipelines. Teixeira et al. (2008) developed a model to assess the reliability of pipelines with corrosion defects. The model computed the probability of pipelines' failure based on the calculation of their burst pressure. It applied the numerical computations of reliability of the pipes. Sensitivity analysis proved the importance of corrosion depth and internal operational pressure on the burst failure of pipelines. The model was developed based on limited data from some field tests.

Forecasting the cause of failure for oil and gas pipes has been the subject of study for many researchers. Bertolini et al. (2006) developed a decision support system (DSS) to forecast the spillage class in the cross-country oil and gas pipelines. Classification and Regression technique was applied to develop a decision tree that was aimed at forecasting the cause of leakage in such pipelines. The objective of the research was to select the most appropriate inspection tool of oil and gas pipelines. Regression technique was applied to develop this model. Developed model was aimed to recognize pipelines with potential third party failures from those prone to the natural hazards failures. The model used variables such as pipe diameter, service type, location type, the age of failure, the environment, and the equipment used for detecting the leakage. Data was collected from Concawe (Davis et al. 2010) to forecast the cause of failure.

Senouci et al. (2013_a) predicted possible failure sources for oil and gas pipelines applying regression and ANN models. The models considered forecasting failure types besides corrosion, such as mechanical, third party, natural hazard, and operational failures. The models obtained historical data on the failures of pipelines in Europe that was prepared by Concawe (Davis et al. 2010). The accuracy of the model was acceptable; however, it applied only five variables for all failure types. These variables included the type of product, pipe location, pipe age, land use, and pipe diameter. Except the age, variables remained constant over the life of a pipeline and consequently did not represent the changes that may happen in the environment and pipe itself. Also, as the author mentioned, the model applied a limited number of factors that can be developed to forecast the failure rate of other types. These limitations were mostly due to the model's reliance on the Concawe database.

Most of the developed models were either subjective and were dependent on the expert judgment (Dey et al. 2004 and Dey 2003) or only addressed one source of failure of pipelines such as corrosion (Liao et al. 2012; Ren et al. 2012; Sinha and Pandey 2002; and Ahammed 1998). Consequently, they were not comprehensive. They also lacked the objectivity in estimating various sources of failures in oil and gas pipelines.

Several researchers tried to develop models to cover these limitations. They attempted to develop models that could predict other sources of failures besides corrosion. Senouci et al. (2013_b) applied fuzzy logic technique to develop a model in order to predict the failure type of oil and gas pipelines and compared the results with those of Senouci et al. (2013_a). The comparison results proved that the developed fuzzy-based model outperformed the regression and ANN models with respect to the model validity. Despite the attempts made to predict the failure type of oil pipelines considering causes other than corrosion developed pipeline condition assessment models did not apply other factors besides corrosion. In other words, they mainly addressed factors that cause failures due to corrosion or third party damages only. In addition to that, the important issues of "interdependency" between different factors' relations and "uncertainty" of factors' severity weights were not addressed simultaneously. Consequently, El-Abbasy et al.

(2014_a) developed a model to evaluate the condition of oil and gas pipelines applying a number of factors comprising corrosion. The model applied Analytic Network Process (ANP) and Monte Carlo simulation. Interdependency of factors was considered through ANP, and the suggested decisions took the uncertainty into consideration (using simulation). The implementation of the model on an existing offshore gas pipeline in Qatar was successful. The results of the model were compared with the actual pipeline condition.

The simulation model built by El-Abbasy et al. (2014_a) was considered as a first phase to evaluate or assess the condition of offshore oil and gas pipelines. El-Abbasy et al. (2014_b) developed the second phase of the model the objective of which was to predict the current and future condition of offshore oil and gas pipelines. The model was developed based on the historical inspection data that was collected in Qatar. The developed model used the regression analysis technique to predict the pipeline condition and when compared with the actual condition yielded an average validity percentage above 96%. El-Abbasy et al. (2014_c) applied ANN technique to develop another model with the same objective. The ANN model outperformed the regression model with respect to the validity results. These models applied several factors in predicting the condition of pipelines with considerably high accuracy. However, they could not develop a model to predict the sources of failures or their consequences. Also, the models designed in these studies were dependent on inline inspection data, which is expensive to gather frequently. They did not consider the specification of the location of pipes in developing the models.

Shahriar et al. (2012) developed a comprehensive model to assess the risk of failure on oil and gas pipelines applying Bow-tie analysis. Bow-tie analysis is a new approach that takes advantage of graphical techniques to analyze different scenarios of pipeline failures. This technique combines Fault Tree Analysis (FTA) with Event Tree Analysis (ETA). The model used the fault tree developed by Dawotola et al. (2009) and Yuhua and Datao (2005) with some modifications. Figures 2-2, 2-3 and 2-4 present the FT that was applied in this model. The Bow-tie diagram for the natural gas pipeline was centered over the gas release of the pipeline that was the top event for the fault tree. Sources of failure such as third party activities, corrosion, incorrect operation, unreasonable design, and geological hazards were the first level of expanding the causes of failure. In the lower levels, the variables that were in charge of different failure types were identified and considered as the basic events. Expert opinion was used to assess the fuzzy likelihood of basic risk events.

An 11-grade fuzzy scale was used to assess the probability of failure, which was developed by Sadiq et al. (2004). Triangular fuzzy membership functions were applied to develop the granular scale to evaluate the likelihood of failure. The scale translated the linguistic terms into fuzzy numbers evaluating the probability of failure from absolutely low to absolutely high level. The probability of the occurrence of final event was calculated by multiplying the probabilities attributed to the basic events. Finally, sensitivity analysis proved the importance of bad installation and construction defects. As mentioned before, the expert opinion was used to analyze the failure probability of gas pipelines. However, it was very hard for the experts to analyze the effect of 40 basic events on the failure probability of the final event (Shahriar et al. 2012). The limitations of the model can be minimized by applying the historical data in developing the model.

Some researchers tried to develop models to forecast the probability of failure as mentioned before (Shahriar et al. 2012; Dawotola et al. 2009; Yuhua & Datao 2005; Muhlbauer 2004; Kiefner 1997). In Tables 2-5, 2-6 and 2-7, the variables that were considered when developing the aforementioned models to estimate the probability of failure are summarized for each type of failure.

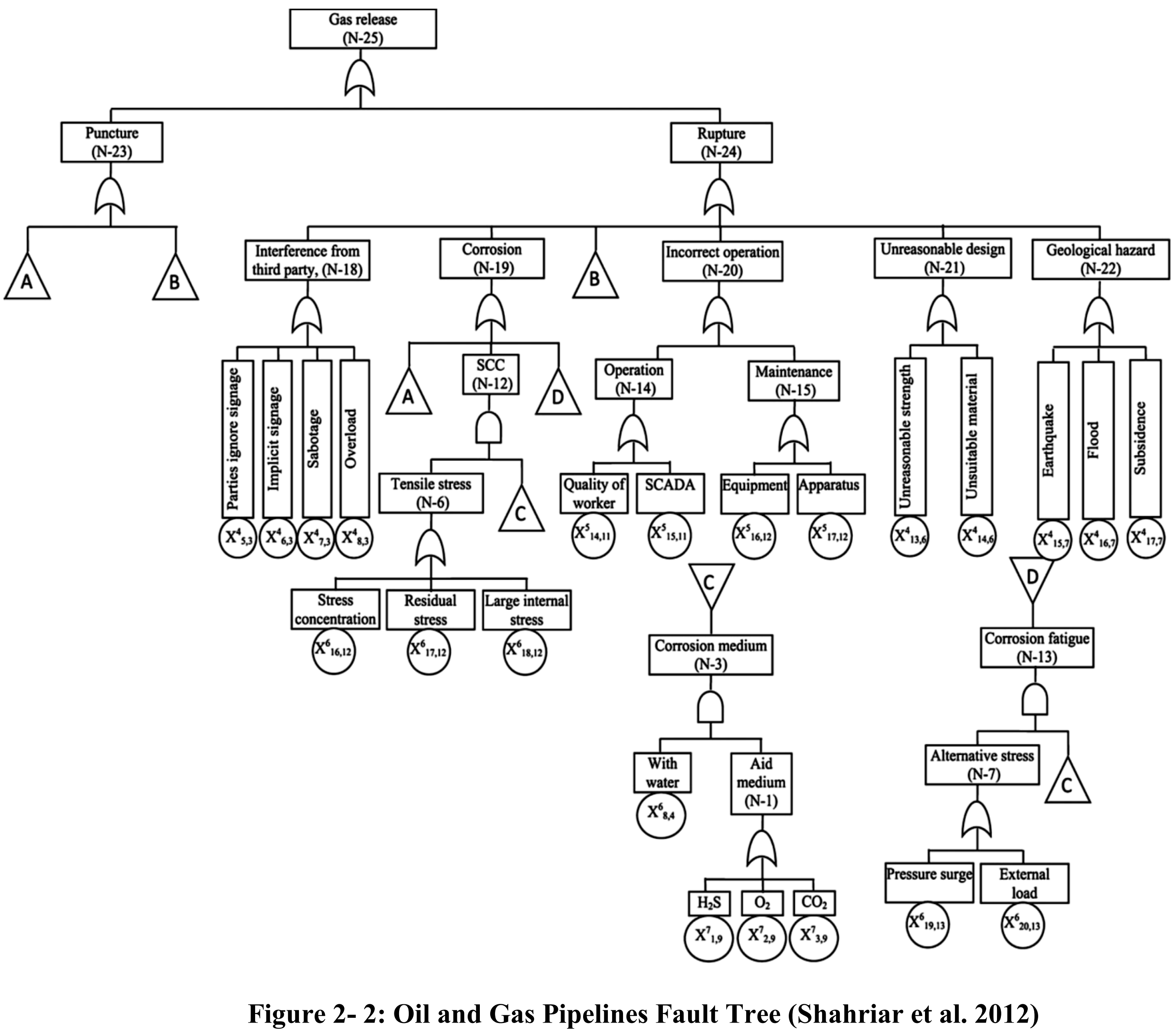


Figure 2- 2: Oil and Gas Pipelines Fault Tree (Shahriar et al. 2012)

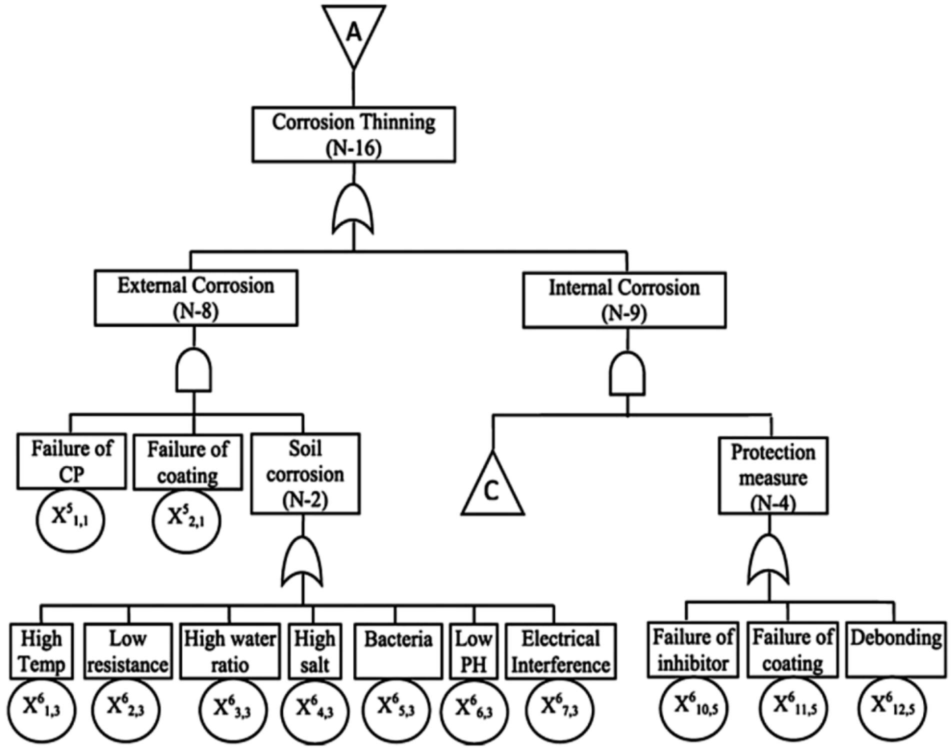


Figure 2- 3: Oil and Gas Pipelines Fault Tree; part A (Shahriar et al. 2012)

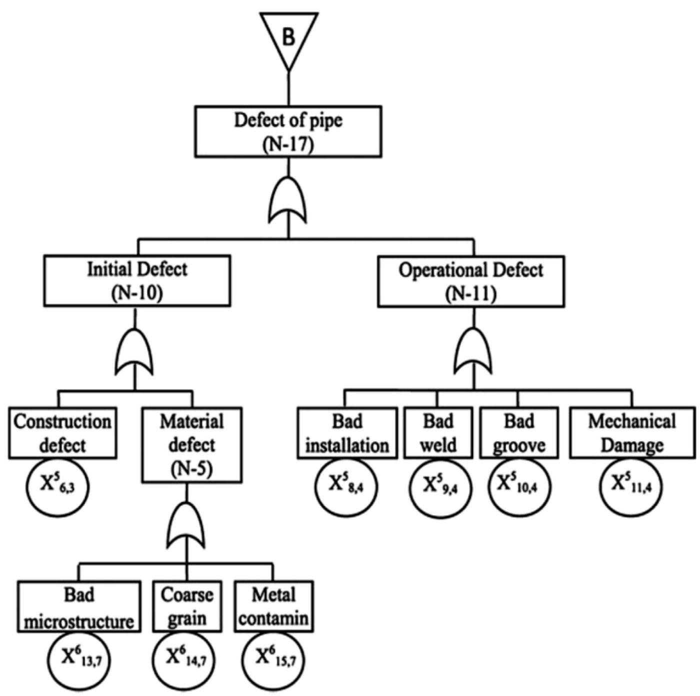


Figure 2- 4: Oil and Gas Pipelines Fault Tree; part B (Shahriar et al. 2012)

Table 2- 4: Summary of the variables affecting the probability of corrosion failures

Failure Types	Sources	Variables
External Corrosion	Shahriar et al. 2012	Failure of CP Failure of Coating Soil corrosion (High temperature, low resistance, high water ratio, high salt, bacteria, low pH, electrical interference)
	Dawotola et al. 2009	Failed CP Soil corrosion Failure of coating
	Yuhua & Datao 2005	Failure of CP Failure of Coating Soil Corrosion Anti-corrosion
	Muhlbauer 2004	Subsurface environment soil corrosivity (resistivity, pH, moisture, carbonates) Mechanical corrosion (stress level, stress cycling, temperature, coating, CP, pH) CP effectiveness Interference potential (DC & AC related, shielding potential) Coating (type, age, visual inspection age, other inspection age)
	Kiefner 1997	Pipe wall thickness CP efficiency Soil factor Experience factor
Internal Corrosion	Shahriar et al. 2012	Failure of inhibitor Failure of coating Debonding
	Dawotola et al. 2009	Failure of inhibitor Failure of coating Interfacial debonding Corrosive medium
	Yuhua & Datao 2005	Anti-corrosion Failure of inhibitor Failure of coating Bad clear pipe Medium (with water or acid)
	Muhlbauer 2004	Flow characteristics Product corrosivity Flow stream characteristics (solid and water related) Preventions

Table 2- 5: Summary of the variables affecting the probability of operational failures

Failure Types	Sources	Variables
Construction and Material Defects	Shahriar et al. 2012	The same as Yuhua & Datao 2005
	Yuhua & Datao 2005	Construction defect Material defect Operation defect (bad installation, weld, groove Mechanical damage)
	Muhlbauer 2004	Inspection Materials Joining Backfill Handling Coating
	Kiefner 1997	MAOP Hydrostatic test pressure Age factor Seam factor Girth weld factor
Incorrect Operation	Shahriar et al. 2012	The same as Yuhua & Datao 2005
	Yuhua & Datao 2005	Quality of worker, SCADA, Equipment maintenance, Apparatus maintenance
	Muhlbauer 2004	Procedures SCADA Drug-testing Safety program Survey Training Mechanical error preventers
Bad Design	Shahriar et al. 2012	The same as Yuhua & Datao 2005
	Yuhua & Datao 2005	Unreasonable strength Unsuitable material
	Muhlbauer 2004	Safety factor (MOP, OP, material strength, th., external Loading, OD., strength of fitting, valves, components) Fatigue Integrity verifications

Table 2- 6: Summary of the variables affecting the probability of external failures

Failure Types	Sources	Variables
Third Party	Shahriar et al. 2012	Parties ignore signage Implicit signage Sabotage Overload
	Yuhua & Datao 2005	Parties ignore signage Implicit signage Sabotage Overload
	Muhlbauer 2004	Minimum depth of cover (soil cover, type of soil, pavement type, warning tape or mesh, water depth) Activity level (population density, stability of the area, one-call, other buried utilities, anchoring) Aboveground facilities (vulnerability, threats such as traffic) One-call system (mandated, response by owner, well-known and user) Public evacuation (methods such as door to door, mail, advertisement, frequency) Right of way condition (signs, markers, overgrowth, undergrowth) Patrol (Ground and air patrol frequency, Ground and air patrol effectiveness)
Natural Hazards	Shahriar et al. 2012	Earthquake Flood Subsidence [The same as Yuhua & Datao (2005)]
	Yuhua & Datao 2005	Earthquake Flood Subsidence
	Muhlbauer 2004	Land movements (seismic shaking, fault movement subsidence, landslide, water bank erosion)

CP: Cathodic Protection; **MAOP: M**aximum allowable pressure; **HTTP: H**ydrostatic test pressure; **OD.** Pipe outside diameter, OP: Operating Pressure

2.3.5 Consequences of Failure

There has been an extensive effort during the past decades to model the consequences of the failure of oil and gas pipelines. Some of the guidelines provided a qualitative scale of assessment for this parameter of risk assessment from various points of view. DNV (2010) considered the consequences of failures of oil and gas pipeline with respect to safety (personal), environmental and economic hazards. Economic consequences accounted for the possible pipelines' production delay, whereas the safety consequences were proposed to be measured with respect to the personnel. The cost of repairing damages to the pipeline was ignored in evaluating the economic consequences as it was deemed negligible. The proposed method was based on the experts' judgment and hence was subjective. Table 2-8 presents the scores that were defined in different levels of safety consequences.

Table 2- 7: Safety consequences scale (Adapted from: DNV 2010)

Category	Description
1(low)	No person(s) are injured.
2	(not used)
3(medium)	Serious injury, one fatality (working accident)
4	(not used)
5(high)	More than one fatality (gas cloud ignition)

DNV (2010) defined the environmental consequences as the effects of the product release with respect to the eco-system. As a result, the amount of the product spillage was used to rank the environmental consequences of a pipeline failure as shown in Table 2-9. Different levels of economic consequences and their attributed delay of production are shown in Table 2-10. The method developed in this guideline is a subjective method and needs experts' opinion. However, the experts are not known of the risks of oil and gas pipelines that are mostly underground or are laid offshore.

Table 2- 8: Environmental consequences scale (Adapted from: DNV 2010$_a$)

Category	**Description**	***Amount of release***
1(low)	None, small or insignificant on the environment. Either due to no release of internal medium or only insignificant release.	~ 0
2	Minor release of polluting media. The released media will decompose or be neutralized rapidly.	<1,000 tones
3(medium)	Moderate release of the polluting medium. The released media will use some time to decompose or neutralize, or can easily be removed.	<10,000 tones
4	Large release of the polluting medium which can be removed, or will after some time decompose or be neutralized.	<100,000 tones
5(high)	Large release of high polluting medium which cannot be removed and will use long time to decompose or be neutralized.	> 100,000 tones

Table 2- 9: Economic consequences scale (Adapted from: DNV 2010$_a$)

Category	**Description**	**Production delay/ Downtime**
1(low)	Insignificant effect on operation, small or insignificant cost of repair	0 days
2	Repair can be deferred until scheduled shutdown, some repair costs will occur.	<1 month
3 (medium)	Failure causes extended unscheduled loss of facility or system and significant repair costs. Rectification requires unscheduled underwater operation with prequalified repair system before further production.	1-3 months
4	Failure causes indefinite shutdown and significant facility or system failure costs. Rectification requires unscheduled underwater operation without pre-qualified repair system before further production. Or Failures resulting in shorter periods of shutdown of major parts of (or all of) the hydrocarbon production for the field.	3-12 months
5(high)	Total loss of pipeline and possible also loss of other structural parts of the platform. Large cost of repair including long time of shut down of production. Or Failures resulting in shutdown of the total hydrocarbon production for a longer period.	1-3 years

Some researchers tried to develop numerical models to estimate the consequences of the pipelines' failure. Resterpo et al. (2009) developed logistic regression models to predict the monetary consequences of pipeline failures. The models obtained data from the office of pipeline safety (OPS) a section of the US Department of Transportation (DOT). Data on the incidents of the hazardous liquid pipelines from 2002-2005 was obtained to develop this model. First, the probability of occurrence of non-zero consequences was assessed through logistic regression models. The models were trained embedding data on several parameters from the database. The parameters included the system part involved in the accident, location of the pipeline (offshore versus onshore), occurrence in a high consequence area (HCA versus non-HCA), as well as the binary factors representing the occurrence of ignition, explosion and/or product loss. For non-zero consequence incidents, other models were developed. The inputs of these models included characteristics of the incidents such as the occurrence of ignition and/or explosion, the amount of the product loss, the location specifications (i.e., offshore versus onshore, and HCA versus non-HCA), the system part involved, and the cause of the accident. These models could be used to analyze different scenarios of accidents on such pipelines. However, there were some limitations in their application to predict the consequence of failures. First, the amount of the product loss and the part of the system involved in the incident is very hard to predict and is not known before the happening of an accident. Besides, the models were not validated, and their accuracy in the prediction of monetary consequences was not tested.

Simonoff et al. (2010) developed models to evaluate different scenarios of pipeline failures. This study obtained historical data recorded from 2002-2009 and 2004-2009 on the failures of transmission and distribution pipelines respectively. Similar to Resterpo et al. (2009) this study developed a two-step model. In the first step, the probability of the occurrence of a non-zero cost consequence was evaluated through logistic regression models. These models included binary variables on the incident characteristics of pipelines failure. In the second step, the magnitude of a cost consequence was measured applying least square regression models. These models used variables presenting the causes of incidents and incident types. Results of the models were the scenarios of pipelines' failure. One of the scenarios was the failure of an onshore transmission pipeline as a result of internal corrosion in a non-HCA with rupture. This scenario was assumed not to be involved with an ignition or explosion. The computed cost of failure was predicted to be in the interval of 17,093 to 281,815 the average of which was calculated as 71,093 US$. The analyzed scenarios did not consider the characteristics of the pipeline such as diameter, wall thickness or age. As a result, the models developed in this study cannot be applied to assess the consequences of failure risk of a specific pipeline.

Event Tree (ET) was used by some of the researchers to model the consequence of failures of oil and gas pipes. Brito et al. (2009) developed an event tree to analyze the accidental failures of natural gas pipelines. The main factors that were considered in developing this event tree were failure mode (rupture versus puncture), delay in the possible ignition, as well as the "degree of space confinement" of released gas. Consequences of the product release were identified as: detonation, Jet fire, Confined Vapor Cloud Explosion (CVCE), Flash Fire and gas dispersion. An additive function of human, environmental, and financial consequences was considered to calculate the consequence probabilities. Each pipeline was divided into sections covering tens of meters. The probability of consequences for each section was computed obtaining the experts' opinion through probabilistic judgments. However, it had been very hard for the experts to estimate the probability distribution function of the consequences' happening. As a result, the average pipeline failure rate was used as the failure probability that was calculated based on the EGIG reports (2009). This average value was used as the basic failure probability in gas pipelines that was equal to 0.00041/km. per year. Some adjusting factors including land use and soil, third party activities, distance from residential areas were used. The experts estimated the value of the adjusting factors in different sections of the pipeline. Consequently, the sections were ranked according to their risk of failure. Although, the model benefited from the historical data, it was subjective and depended on the experts' opinion. Besides, the experts needed to be highly experienced as the model needed detailed data on the estimation of the adjusting factors.

As mentioned before, Shahriar et al. (2012) developed a "Bow-tie" analysis model that considered the post-failure events of gas pipelines to estimate the consequences of failure. Figure 2-5 depicts the event tree developed by this model. This model adapted the ET developed by Sklavounos and Rigas (2006). The main factors that were considered in developing the ET were mentioned as the delay in the ignition of the released gas due to the pipe failure and the degree of space confinement. The events after a gas release were identified as Detonation, Fireball, Confined Vapor Cloud (CVC) explosion, Flash Fire, and material loss. The probability of the occurrence of each post-failure event was assessed by multiplying the probability of gas release by the probability of happening of the two primary factors (i.e. ignition delay and space confinement). The calculation resulted in analyzing the probability of happening of each scenario of failure. Then the triple bottom line sustainability criteria were used to evaluate the social, environmental, and economic consequences of failures. Social consequences included the assessment of casualty, society response and evacuation requirement. Environmental consequences required the evaluation of consequences with respect to the air, endangered habitats, vegetation, soil, and water. Finally, economic evaluation of the consequences included the effects of failure on supply interruption, repair, material loss, and property and third party damages. The granular fuzzy scale was applied to assess the consequences of each failure scenario by experts' opinion (Shahriar et al. 2012). Applying expert elicitation decreased the objectivity of the model and made it difficult for the experts to judge the probability of occurrence of each scenario and estimating several factors to estimate the consequences of a pipeline failure.

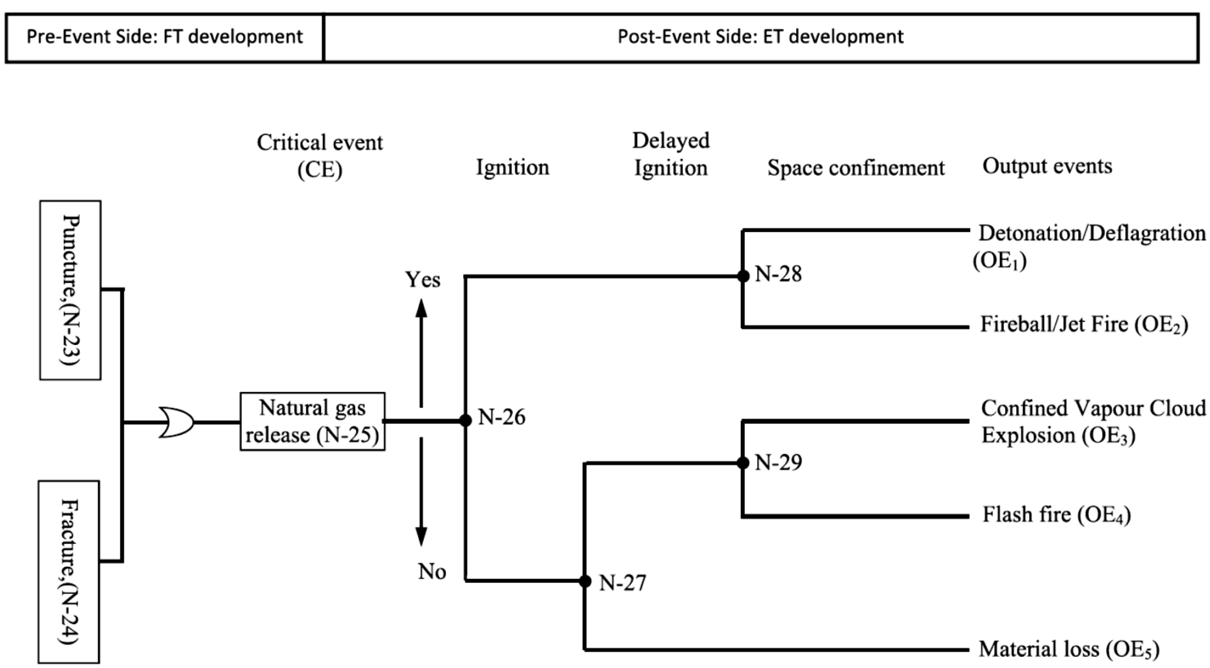


Figure 2- 5: Event Tree Diagram of Natural Gas Pipelines (Shahriar et al. 2012)

2.4 Oil and Gas Pipelines' Operation Phase

Operation phase of oil and gas pipelines is comprised of different activities including inspection and maintenance. Parvizsedghy et al. (2014) classified the activities of the operation phase of such pipelines in five categories as shown in Table 2-11. The research classified activities in regular maintenance, inspection, remedial actions, repair, and replacement, as the major categories of the operation. According to this research, these activities were defined as follows:

1) Regular maintenance: This operation type includes the activities that should regularly be repeated, which contains the office setup, monitoring systems, annual corrosion inspection and cathodic protection survey as well as the Right of Way Extension.
2) Due to the fact that various failure types are threatening oil and gas pipelines, they should regularly be inspected. There is not any specific recommendation for the selection of inspection technique. The research by Parvizsedghy et al. (2014) has considered an Inline inspection with a regular frequency of seven years.
3) Remedial action is envisaged to repair the coating of the pipes.
4) Repair types have been extensively studied in the study by Parvizsedghy et al. (2014) to find the most suitable and generic types of repair as it is not possible to forecast various defect types. Table 2-12 presents different repair types that are recommended for different defect types.
5) Replacement: Replacing the pipe is usually possible; although, it may not be the most economical solution.

Table 2- 10: Different operation elements (Parvizsedghy et al. 2014)

No.	Operation Type	Details
1	Regular Maintenance	Including office costs and regular annual operations
2	Inspection	Inline Inspection (ILI), Hydrostatic Testing
3	Remedial Actions	Recoat
4	Repair	Sleeve Type B, Bolt-on Clamps
5	Replace	Hot Tapping (Small sizes), Replace Pipe

2.4.1 Inspection Methods

Different types of Inspections are developed to monitor the condition of the pipelines and assess their risks of failure. Each inspection is suitable for detecting a type of failure and would not be efficient to be used for the other purposes. Moreover, running the Inline inspections frequently could be too expensive, and the risks of failure should be considered while selecting the inline inspection and its frequency to run. Hopkins et al. (2013) recommended assessing the risk of failure and selecting the inspection method that suits the purpose. Table 2-13 summarizes various inspection types that are suitable for different sources of failures. For example, aerial/ ground patrols are recommended for the failures the sources of which are the third party activities.

Table 2- 11: Recommended Types of Rehabilitation for Different Types of Defects (Parvizsedghy et al. 2014)

Type of Rehab. / Type of Defect	Grinding	Type A sleeve	Compression Sleeve	Type B Sleeve	Composite Sleeve	Weld Deposition	Bolt-on Clamp with Seals	Hot Tapping (1)	Epoxy-filled Sleeve
1. Leaks	NA	NA	NA	BP PRM API	BP(temp) API (<0.8t)	NA	BP PRM	PRM	NA
2. External Corrosion	BP	BP PRM(<0.8t) API (<0.8t)	PRM(<0.8t)	BP PRM API	BP PRM (<0.8t)	PRM(<0.8t) API (min. wall>0.8t)	BP PRM	PRM API	BP
3. Internal Corrosion (2)	NA	BP(Temporary) PRM	PRM	BP PRM API	BP(temp) PRM	NA	BP PRM	API	BP (temporary)
4. Dents	PRM(No smooth dents)	PRM API	PRM	BP PRM API	BP(<12.5%t) PRM	NA	PRM	PRM (Only on smooth dents) API (If dent can be removed completely.)	BP
5. Crack	BP PRM(<0.4t)	BP PRM (<0.8t)	PRM(<0.8t)	BP PRM(<0.8t) API	BP(after grinding) PRM (<0.8t)	PRM (<0.8t)	PRM (<0.8t)	PRM (<0.8t)	BP
6. Seam Weld Defect	BP PRM (3)	PRM (3)	PRM	PRM	PRM (3)	NA	BP PRM	PRM (3)	BP
7. Girth Weld Defect	BP PRM	NA	NA	PRM API (After grinding)	NA	PRM (After grinding)	PRM	NA	NA

(1) Hot tapping can be applied only to defects that are small enough to be removed by the hot tap.
(2) For internal defect or corrosion make sure that it does not continue to grow beyond acceptable limits.
(3) Not proper for defects in or near ERW seam.
BP = British Petroleum Guideline (BP, 2006),
PRM = Pipelines Repair Manual prepared by USA Pipeline Research Council (Jaske et al. 2006)
API = American Petroleum Institute the recommendations of which on the rehabilitation techniques are summarized by Palmer-Jones et al. (2005).

Table 2- 12: Major categories of inspection to monitor various failure types (Hopkins et al. 2000)

Defects / Damages	Monitoring/ Inspection Method (P=Proactive Methods, R= Reactive Methods)						
	Aerial/ Ground Patrols	Intelligent Pigs	Product Quality	Leak Survey	Geotech Surveys & Gauges	CP & Coating Survey	Hydrostatic
3rd Party Damage	P	R					R
Ext. Corrosion		R				P	R
Int. Corrosion		R	P				R
Fatigue/ Cracks		R					R
Coating						P	
Materials/ Construction Defects		R					R
Ground Movement					R		
Leakage	R	P		R			R
Sabotage/ Pilferage	P						

Thompson (2000) divided major inspection methods other than patrolling into three main items. Table 2-14 presents the classification that includes inline inspection, hydrostatic testing, and direct assessment. Each inspection method has flaws that should be taken into consideration while choosing the inspection method. Also, the piggability of the pipeline should be evaluated as some of the pipelines in the US and other countries especially the older ones cannot accommodate the intelligent pigs.

Table 2- 13: Major Assessment Methods (Adapted from: Thompson 2000)

Method	Strength	Weakness
Inline Inspection	Measures and maps the remaining wall thickness.	Single run does not identify active corrosion and the accuracy of multiple run predictions is uncertain. Resolution of tools varies.
Hydrostatic Testing	Causes a controlled hydrostatic rupture of near-critical flaws.	Does not identify the presence or severity of flaws other than critical axial flaws that fail at the pressure tested.
Direct Assessment	Identifies areas of high probability of active corrosion.	Verifies accuracy through digging does not provide 100% direct assessment of the pipeline.

There are different techniques for the inline inspections (ILI) the characteristics of each should be studied for an efficient selection. Thompson (2000) stated that there are two main types of ILI tools: magnetic flux leakage (MFL) tools and ultrasonic tools (UT). The resolution level of various types of these two main ILI types makes them different in their capability to detect defects especially to distinguish between external and internal corrosion. Hopkins et al. (2013) mentioned MFL as the most commonly used method of ILI. MFL is not able to detect the axial defects and cracks; however, they are suitable for the circumferential defects.

The cost of operation of different ILI tools varies according to their capabilities. The preparation cost of the pipelines for an inline inspection should be estimated for the pipelines that cannot receive the Inline inspection tools. Cost elements of pipe preparation are presented in Table 2-15. Cost data is gathered from Thompson (2000). The costs are discounted with historical inflation rates of the US to be converted into 2013 US dollars.

Table 2- 14: Cost elements of Pipeline Preparation for ILI (Adapted from: Thompson 2000)

Cost elements	Function	Min. Cost	Max. Cost	Unit
Launchers and receivers	Modify capability to receive and launch pigs	150,000	190,000	US$ (One time)
Caliper tools	Identify the restrictions and bend the radius of pipe and ensure pipe is free from defects to stuck the pigs	1,200	1,500	US$ per Km.
Clearing bend & other restrictions	Digging and exchanging the valves or sections of pipe that reduce opeaning of the pipe	94,000	470,000	US$ per pipe section or valve.
Cleaning the pipeline	Required before running MFL and UT while Ut requires a cleaner pipe	Gas	585	US$ per km.
		Oil	2,923	US$ per km.

The overall cost of converting a pipeline to be able to accommodate ILI tools is estimated to be 8,000 to 17,000 US$ per kilometer (2013 dollars). The cost of preparation for gas pipelines with multiple defects and bends can be over 35,000 US$ per kilometer (Thompson 2000). Different inspection tools can be applied for detection of various failure sources. Table 2-16 summarizes the application of various inspection tools and the sources from which this data is gathered.

2.4.2 Life Cycle Cost Assessment

Life cycle cost (LCC) assessment models are applied to analyze the equivalent economic value of the service life of infrastructures. LCC is used to compare different alternatives from an economic point of view. The method considers the cost of maintenance for various alternatives of operations during the whole life of the projects. Life cycle cost analysis models have been developed to analyze different scenarios of repair and replacement of various infrastructure types. Frangopol et al. (2001) estimated the net present worth of the life cycle operations of bridges based on the reliability assessment. Hegazy et al. (2004) developed a condition-based life cycle cost model for the maintenance optimization of bridge decks. A genetic algorithm was applied to develop the model and optimize the required budget of this infrastructure type in the project and network level. The research applied Markovian approach to predict the condition of bridge decks. A scale assessment was developed to help in the selection of appropriate repair type. Ammar et al. (2013) proposed a fuzzy-based model to estimate the life cycle cost of different scenarios. A fixed interval between different operation types was considered to develop the scenarios.

Table 2- 15: Summary of application of inspection tools (INGAA 2007; NACE 2002)

Inspection tool	Threat to be assessed	Source
MFL Standard Resolution	Internal & External Corrosion (No internal or external diameter discrimination)	**1, 2**
MFL High Resolution	Internal & External Corrosion, Circumferential Cracking	**1, 2**
UT (Compression wave)	Internal & External Corrosion, Narrow Axial External Corrosion, Cracks, Lamination	**1, 2**
UT (Shear wave)	Internal & External Corrosion, Narrow Axial External Corrosion, Cracks, Circumferential Cracking, Dents, Sharp Dents, Wrinkle Bends, Buckle, Lamination	**1,2**
Transverse Flux	Internal & External Corrosion, Narrow Axial External Corrosion, Cracks, Dents, Sharp Dents, Wrinkle Bends, Buckle	**1,2**
Caliper Tools	Dents, Sharp Dents, Wrinkle Bends, Buckle, Bends, Ovalities	**2**
Mapping Tools	Dents, Sharp Dents, Wrinkle Bends, Buckle, Bends, Ovalities (Sizing is not reliable through this tool)	**2**
Deformation or Geometry	Excavation Damage, Outside Force damage, Construction	**1**
Pressure Testing	Internal & External Corrosion, Manufacturing, Construction, SCC, Excavation Damage	**1**
ECDA	External Corrosion	**1**
ICDA	Internal Corrosion	**1**
SCCDA	SCC	**1**

1: INGAA (2007), **2:** NACE (2002)

Several models were suggested to analyze the LCC of water pipelines. Shahata and Zayed (2012) developed a simulation-based model to evaluate the LCC of various scenarios. The scenarios were developed based on the prediction of the time of the five first breaks of pipelines according to the historical data of the pipe failures. The maintenance actions were estimated according to the breaks' estimated time and their order. The model optimized the maintenance LCC based on the annual worth of the developed scenarios. Condition-based LCC assessment model was developed by Parvizsedghy et al. (2014) to analyze various scenarios of repair/replacement considering the uncertainty of the economic parameters. The method developed a defect size scale that is used to estimate the condition of the pipeline after rehabilitation. The condition scale that was developed by El-Abbasy et al. (2014_b) was applied to estimate the required action of intervention based on the condition of the pipeline.

Average deterioration rate was estimated based on the deterioration profile that was developed by El-Abbasy et al. (2014_b) according to the historical inspection data of pipelines in Qatar. The research also gathered some cost data on various sizes and types of interventions that were estimated to be performed during the service life of the pipelines. The research has developed a robust method on the LCC assessment of oil and gas pipelines. However, it did not propose any specific method to select the inspection method. It suggested two main plans namely; risky and conservative to choose the intervention action based on the condition estimation of the pipeline. The model does not offer a method to select between these two plans. It needs an assessment of the risk of failure to distinguish between the pipelines with high, medium, and low risk of failure.

2.5 Selected Research Techniques

In this research, a variety of techniques will be utilized to achieve its main objectives. Such techniques include but are not limited to Bow-Tie analysis, Probability Theory, Artificial Neural Networks (ANN), Regression Analysis (RA), Neuro-Fuzzy technique, Adaptive Neuro-Fuzzy Inference System (ANFIS), and Monte Carlo Simulation (MCS).

2.5.1 Bow-Tie analysis

Risk analysis of oil and gas pipelines is a difficult task as a result of the complexity of the factors leading to the failure. The uncertainty of the behavior of these products in case of failure of the pipeline adds to the complexity of risk models of such infrastructures. Bow-tie analysis is a new technique for the risk assessment of industrial systems especially the safety analysis of the industrial processes. This technique combines the Fault Tree (FT) with Event Tree (ET) models, which allows the analysis of different scenarios and the estimation of the probability and consequence of failures. Top event of the FT becomes the starting event of an ET.

Figure 2-6 presents a schematic view of the Bow-tie diagrams. The technique has been proved to be advantageous as it simplifies the complicated mechanism of industrial process failures. Combination of Bow-tie with the other techniques such as fuzzy set theory or statistical analysis (Parvizsedghy and Zayed 2015$_a$; and Shahriar et al. 2012) can lead to the estimation of the probability of failure and may provide an image of the possible scenarios of failure.

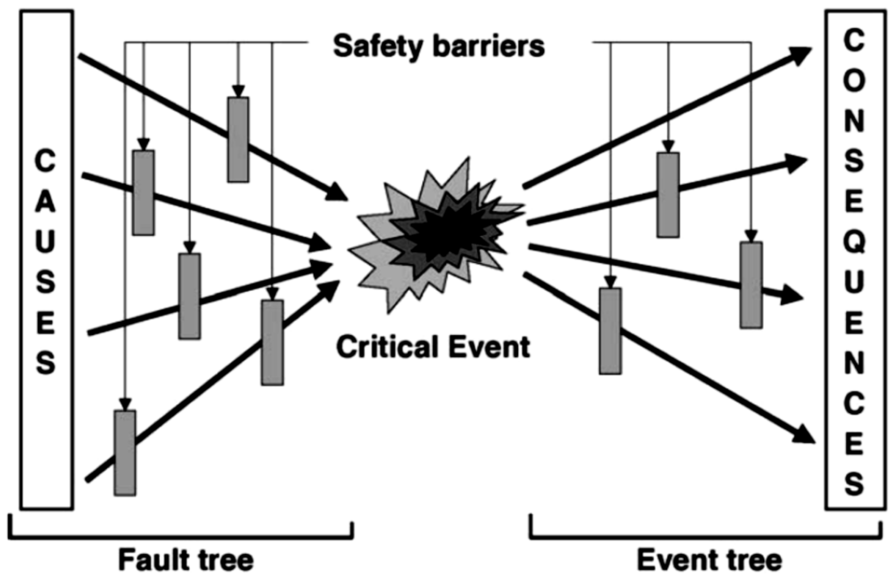


Figure 2- 6: Generic Bow-tie Model (adapted from Dianous & Fievez 2006)

The FT explores the potential causes of the top event or the risk factor of a system. Causes of the top event are expanded at different levels based on the existence of data. Basic events are the lowest level of the causes that can lead to the failure of the system and their estimation is possible according to the existing data. Detailed causes are connected with logical relationships (i.e. AND/OR) (Mokhtari et al. 2011). ET models the major hazards, which are controlled by the safety barriers. The barriers are demonstrated on the bow-ties, and their performance indicates the probability of happening of each major hazard (Dianous and Fievez 2006). As a result, different scenarios of a failure are identified and analyzed. Different scenarios indicate the success or failure of each safety barrier. The probability of the success or failure is multiplied by the probability of the occurrence of the top event to compute the occurrence frequency of each scenario of failure. Bow-ties are graphical diagrams of presenting the logical relationships between various factors responsible for the failure and the major consequences of a failure. Figure 2-7 depicts the key symbols of a fault tree each of which indicates a logical relationship.

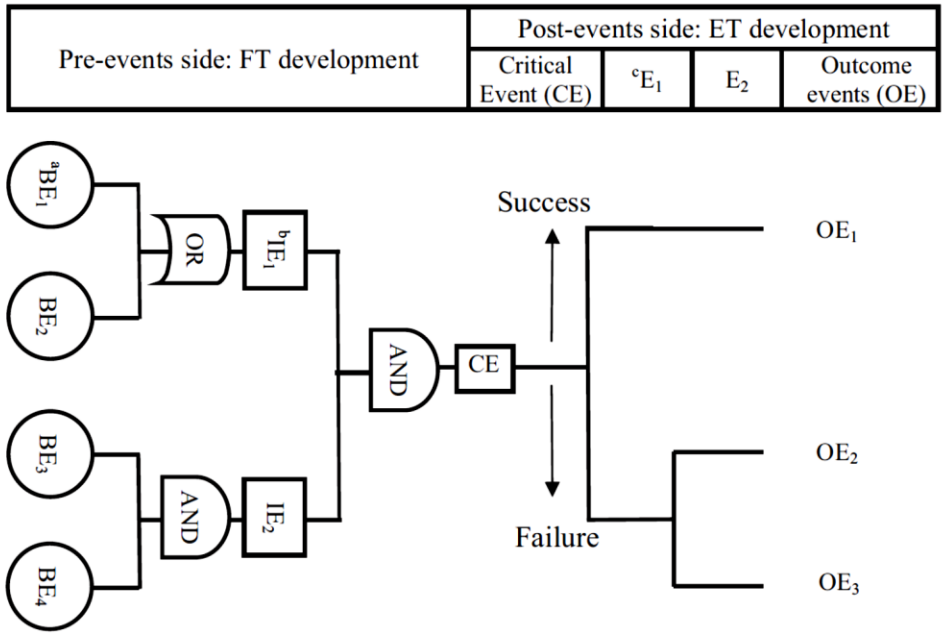
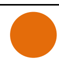


Figure 2- 7: Elements of a Bow-tie model (adapted from Ferdous et al. 2012)
BE-Basic Event; IE-Intermediate Events; CE- Critical Event; OE-Outcome Events

ARAMIS project developed structure of risk assessment through Bow-tie analysis; however, in the implementation phase they encountered several problems. One of the problems was mentioned as defining the frequency of occurrence of dangerous events, as well as the leading causes. In the previous works, a generic form of probability distributions was used, and the safety systems were not identified very clearly (Dianous and Fi´evez 2006). The shapes of various components of the Bow-tie diagrams follow a standard set of rules. A summary description of the components of fault tree and the defined shapes are depicted in Table 2-17. Traditional Fault-tree models analyzed the probability of failure of the top event of the fault tree by assigning crisp values to the basic events. Then, in the analysis phase, the logical relation of the basic events with the top event was considered, and the computation of the failure probability was performed.

Table 2- 16: Description and shapes of Graphical symbols used in Fault tree models (adapted from Ferdous 2006)

Graphical symbol		Shape name	Representing Event
Fault tree event symbols		Rectangle	Applied for representing Intermediate event or top-event.
		Circle	Represents the basic event
		Diamond	Undeveloped Event
		Oval	Conditional event use for representing any conditions
		House	External Events
Fault tree gate symbols		AND Gate	AND gates combine the input events, all of which has to occur simultaneously for the output event to occur.
		OR Gate	OR gates combine the output event that occurs if at least one of the input events occurs.
		INHABIT Gate	Input event produces output event when a conditional event occurs.
		TRANSFER Gate	Transferring gate information or event information under a sub-tree.

Yuhua and Datao (2005) described the process of quantitative analysis as follows:

1) Probability of occurrence of each basic event should be obtained from experts or the historical data;
2) All of the minimal cut-sets of the diagram should be identified;

3) Finally, the probabilities are calculated multiplying probabilities of occurrence of all included basic events in each minimal cut-set.

The computation would be performed in a reasonable time if the fault tree were not huge; however, the problems would arise if the tree is enormous, and the number of cut sets is too much. In that case, Equation 2-2 might be used to calculate the probability of occurrence of the top event.

$$P(T)=P\left(\bigcup_{j=1}^{n} Kj\right)=\sum_{i=1}^{n} P(Ki) - \sum_{i<j=2}^{n} P(KiKj) + \sum_{i<j<k=3}^{n} P(KiKjKk)$$

$$+ \ldots+(-1)^{n-1} P(K1K2\ldots Kn) P(Kj)= \prod_{i\in Kj} Fi(t) \qquad (2\text{-}1)$$

Where:

K1, K2,..Kn: the minimum cut-sets,

N: the total number of cut-sets

Fi(t): the probability of the basic event Xi.

2.5.2 Artificial Neural Networks (ANN)

There are several predictive supervised learning approaches, which can be employed to recognize the existing pattern among the input and output variables. Neural network points to several learning techniques; the most popular one is the back-propagation approach, which is very useful in the construction management research. Christodoulou (2004) applied neural networks for optimum markup calculation, Hegazy (1993) applied neural network for bid preparation, Siqueira (1999) for cost estimating. Attalla and Hegazy (2003) applied ANN for “Predicting Cost Deviation in Reconstruction Projects,” and Al-Barqawi and Zayed (2006) in condition rating of water mains and Zayed &

Halpin (2005) to develop a model to estimate the productivity of pile construction. Achim et al. (2007) predicted the remaining life of water pipes, applying neural networks. Parvizsedghy and Zayed (2013) applied ANN to develop a model for the prediction of the consequences of the failure of oil and gas pipes.

The neural network trains itself through data entries and finds the relationship between the input and output data. ANN imitates the function of a human brain, and it is very "fault tolerant" and, it is able to generalize; hence, these properties make it suitable for construction management issues. This technique provides a suitable platform for risk management research since construction problems carry much uncertainty. Zayed and Halpin (2005) mentioned that ANN is composed of two phases namely: learning or training and recalling. The function to find the relationship between variables through the neural network is called the learning phase, which is controlled based on the error of the produced network. The second function is called recalling that inserts the inputs to the trained network and creates predictive responses. Moreover, if the the output is available within the entry data of the training phase, it is called supervised otherwise it is entitled unsupervised.

Artificial neural networks have different layers, there are several processing elements (PE) in each layer, which mimic the act of neurons, and thus it is called "neural network". Figure 2-8 shows a Typical Artificial Neural Network that includes one hidden layer. It is very important to design the architecture of the network and define the learning elements including the transfer function, the learning rate, and the number of epochs. The simplest network would have one input, one hidden and one output layer, the number of hidden layers may increase according to the complexity of the problem. Neurons of each layer are connected to the neurons of the next layer through the connection lines each of which has a weight that is used to be multiplied by the inputs transferred from the previous layers. In the end, they are summed up with bias value to represent the neuron "NET" (Moselhi et al. 1991). The transfer or activation function is used to create non-linear relationships between inputs and outputs. Sigmoid (logistic), hyperbolic tangent (tanh), the sine or cosine and linear function are the most frequently used transfer functions. The sigmoid function is the most commonly applied to construction problems.

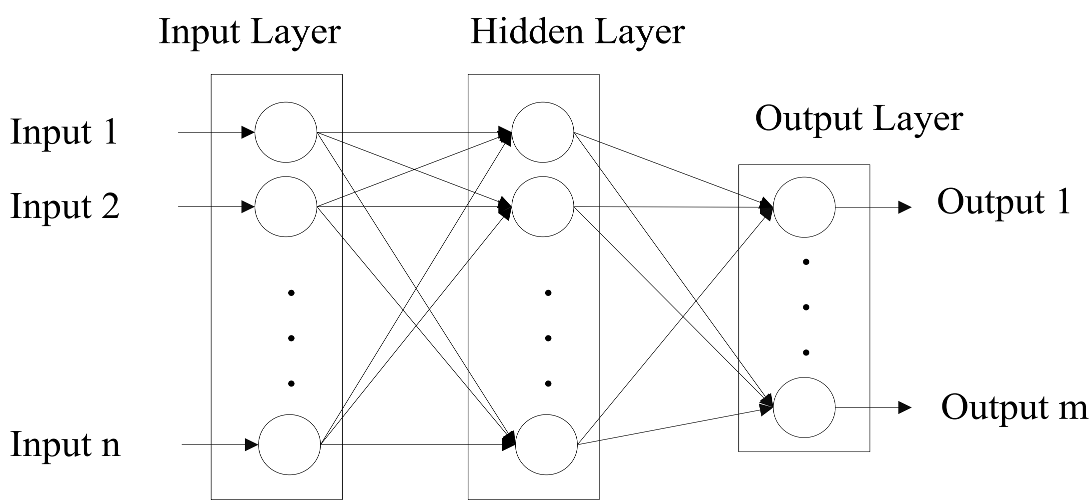


Figure 2- 8: Typical Artificial Neural Network (Parvizsedghy and Zayed 2013)

The performance of a network will be enhanced if the learning process is stopped sooner. Therefore, the network checks the pattern at the stopping points called epochs, to stop training at the point that the error starts to increase. Hegazy et al. (1994) reviewed the literature on backpropagation ANN and identified their problems. A summary of the challenges have been introduced as followed:

1) The representation of the knowledge and the structure of the problem is not well-defined;

2) Speed of the training is slow, and the performance is highly sensitive to the initial weights of the components;
3) Optimum design is not very well-guided; and
4) The black box nature of the method prohibits interpretation of the weights of the produced network.
5) Hegazy et al. (1994) tried to find some solutions and developed guidance to address these problems. For the first problem, in case of having more than one output the study suggests to construct and design smaller networks as it needs less computing time. However, it is mentioned that in case of having only one network the efficiency of the network would be higher due to a large number of interconnections and PEs. This research also defined the parameters of the network that should be determined by the user. These parameters are depicted in Table 2-18.

Table 2- 17: Parameters of back-propagation method (Hegazy et al. 1994)

1. Type of inputs and outputs
2. Transfer function
3. Number of hidden layers
4. Number of PEs in hidden layers
5. Connectivity
6. Learning algorithm
7. Learning rate (η)
8. Momentum coefficient (α)
9. Number of training cycles
10. Halting conditions (acceptable error)

Zhang et al. (1998) proposed to standardize data of each set before training since non-linear transfer functions restrict data to a limited range. Moreover, for the number of neurons in two hidden layer networks, Khaw et al. (1995) proposed to have (2n+1) neurons in the first hidden layer and (2n+1)/3 in the second one.

2.5.3 Fuzzy Set Theory

Historical data on the failures of different infrastructure is imperfect. Sources of imperfection are uncertainty and imprecision. Uncertainty arises where the confidence associated with data is less than one and imprecision is related to the vague and ambiguous data (Smets 1997). One of the approaches to deal with the vagueness of data is fuzzy sets. Zadeh (1965) introduced the fuzzy set theory that assigns a membership function to the imprecise components to deal with their vagueness. The functions define the degree of membership of each object to a set of pairs. Different type of membership functions can be assigned to the set of objects such as triangular, trapezoidal, Gaussian and Sigmoid (Ammar et al. 2013). Triangular membership functions are the most commonly used functions on account of the absence of enough information. Fuzzification and defuzzification are the two primary parts of the fuzzy models. Fuzzification is the process of transforming linguistic terms or numerical values into fuzzy membership functions. Fuzzy inference system is composed of a set of fuzzy rules that maps the inputs to the outputs. Rules are all defined by fuzzy membership functions. This process includes five main steps as described below (Mathworks 2013):

Step 1: Fuzzification of inputs

The first step is to obtain the inputs and transform into a set of fuzzy numbers. These fuzzy numbers determine the degree of membership of the input to the appropriate fuzzy sets (Mathworks 2013).

Step 2: Apply fuzzy operator

In this step, the membership functions attributed to the input parameters in addition to the related fuzzy operations define a set of fuzzy If-Then rules (Mathworks 2013).

Step 3: Weighting the rules

In this step, the proper weights are assigned to each rule. Weights are defined as a number between zero and one (Mathworks 2013).

Step 4: Aggregation of the Outputs

In step four, all pre-defined rules are aggregated to provide the final fuzzy set. The input of this step is the result of implication application as is defined in the previous step (Mathworks 2013).

Step 5: Defuzzification

The input of this step is the aggregation step's output, and the output is a crisp value that is computed through different defuzzification methods. These methods include centroid, bisector, middle of maximum (the average of the maximum value of the output set), largest of maximum, and smallest of maximum (Mathworks 2013). The centroid is considered to be the most prevailing and naturally attractive method used in the defuzzification process of fuzzy inference systems (Pappis and Siettos 2005).

2.7.3 General Theory of Uncertainty

Uncertainty is an unavoidable character of information. Uncertainty is traditionally noticed as the probability in science. The General Theory of Uncertainty (GTU) broke this notion with viewing the uncertainty in a broader context (Zadeh 2005). This theory combined the probability and fuzzy logic in a platform to overcome the limitations of each. In fact, this method helped to summarize the probability distribution functions in granular intervals. Figure 2-9 presents an application of the granular theory to a distribution function (Zadeh 2008). The probability distribution function is divided into equal intervals, and attributed probabilities are assigned to each interval.

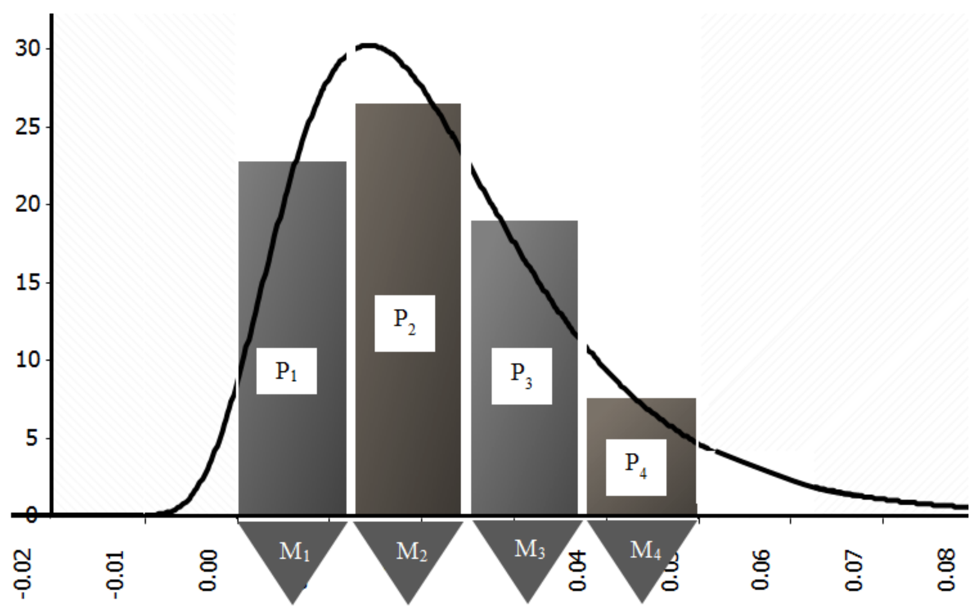


Figure 2- 9: Application of granular theory to a distribution function

P_i is granular value of p_i, i=1,.., n
(P_i, M_i), i=1,.., n

2.5.4 Neuro-fuzzy

ANN and fuzzy logic are two powerful techniques each of which has advantages and disadvantages. Disadvantages of ANN can be covered by fuzzy logic and the vice versa. The combination of two methods results in the neuro-fuzzy technique, which was used in resolving different research problems in construction management. Parvizsedghy and Zayed (2015_b) applied Neuro-Fuzzy to develop a Consequence of Failure prediction model for oil and gas pipes. Zayed and Mahmoud (2014) employed the Neuro-Fuzzy technique for productivity estimation of horizontal drilling activities. Hsiao et al. (2012) developed a neuro-fuzzy model to estimate the cost of se*miconductor* hookup construction. Jin (2011) developed a model to allocate the risk between various parties of public-private partnerships applying the neuro-fuzzy technique. Sinha and Fieguth (2006) developed a neuro-fuzzy model to classify the defects of the pipes.

In the training process of Neuro-Fuzzy, the membership functions of variables are fine-tuned to obtain better results. A version of neuro-fuzzy was titled ANFIS that was first introduced by Jang (1993). ANFIS aimed at developing a method that can best transform human knowledge or experience into a set of fuzzy rules while fine-tuning the membership functions of fuzzy sets. ANFIS applies Takagi and Sugeno method in the fuzzy modeling step due to the advantages of this system. Jang (1996) illustrated ANFIS function in a graphically presented example as is presented in Figure 2-10 and Figure 2-11. The example demonstrates the most simple inference mechanism in a first order Sugeno type that contains two fuzzy rules namely; rule1 and rule 2.

- Rule 1: If X is M_1 and Y is N_1 then ($f_1=p_1x+q_1y+r_1$)
- Rule 2: If X is M_2 and Y is N_2 then ($f_2=p_2x+q_2y+r_2$)

Figure 2-10 presents the inference system to compute output as a result of two inputs (i.e., x and y) to the system. ANFIS facilitates the process of inference system shown in Figure 2-11.

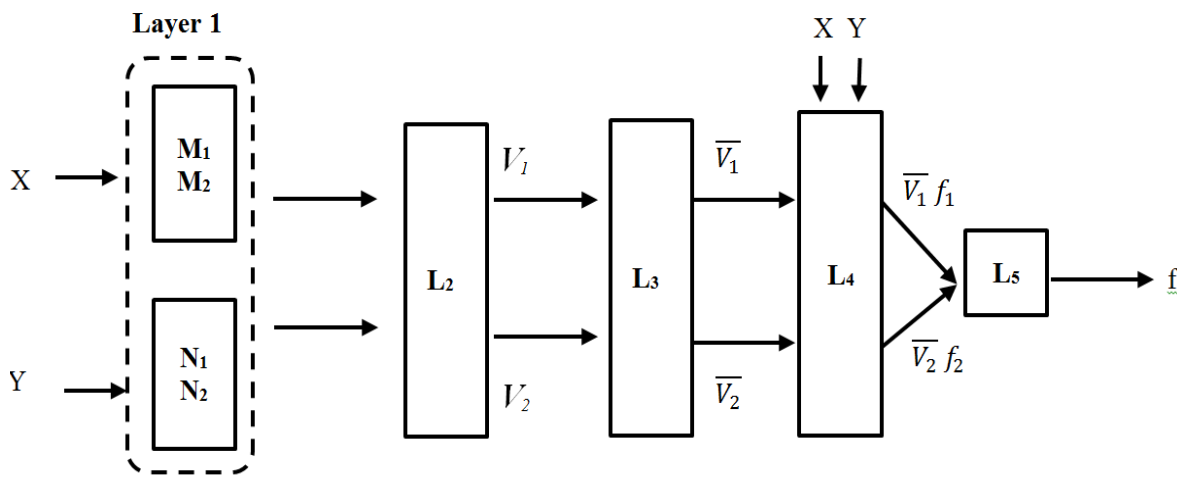


Figure 2- 10: First Order Sugeno fuzzy model

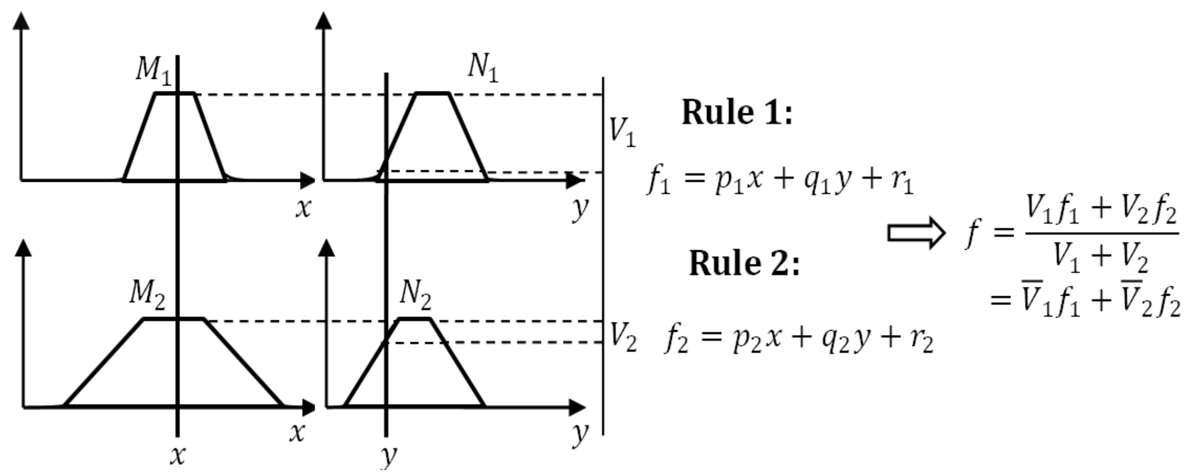


Figure 2- 11: ANFIS architecture

ANFIS has five layers and the nodes of each layer implement similar functions as are described below:

Layer1: The nodes in this layer obtain the linguistic terms as the inputs and produce the corresponding membership grades. Jang (1993) suggested applying the bell-shaped membership function in the range of zero to one. Equation 2-2 shows the result of this layer (Jang 1996).

$$O_i^1 = \mu A_i(x) \tag{2-2}$$

Where: O_i^1 is the membership function of linguistic input, $A_i$is the linguistic term to the model and x represents the input to the ith node of the model (Jang 1996).

Layer2: Nodes in this layer specify the "firing strength" of the rules through Equation 2-3 (Jang 1996):

$$O_i^2 = w_i = \mu A_i(x) \times \mu B_i(x), \text{ i=1,2} \tag{2-3}$$

Layer3: In this layer, the ratio of the firing strength of i_{th} rule is computed with respect to total firing strengths as shown in Equation 2-4 (Jang 1996).

$$O_i^3 = \overline{wi} = \frac{wi}{w1+w2}, \text{ i=1,2} \tag{2-4}$$

Layer4: Contribution of i_{th} rule toward the final output is calculated in this layer in node "i". Equation 2-5 describes the computation components of each node in this layer (Jang 1996).

$$O_i^4 = \overline{wi} * fi = \overline{wi} \times (pix + qiy + ri) \tag{2-5}$$

Where; the $\overline{wi}$ is the output of previous layer and fi represents the function applied on a set of parameters $\{p_i, q_i, r_i\}$.

Layer5: In this rule, the results of the previous layer are summed up in a single node in order to compute the final output of the model (Jang 1993). Equation 2-6 presents the output and inputs of this layer.

$$O_i^5 = \sum_i \overline{wi} \times fi = \frac{\sum_i \overline{wi} \times fi}{\sum_i \overline{wi}} \qquad (2\text{-}6)$$

Data is loaded into a neuro-fuzzy machine in three sets including training, testing, and checking datasets. Training dataset is part of data that is used to recognize the existing pattern among the inputs and outputs. Generalization capability of the model is checked using the testing dataset. The checking dataset is used to look for the over-fitting in the training process. The trained rules are utilized in the checking process to compute the predicted outputs. Forecasted outputs are compared with the actual outputs, and the error is computed via this comparison. The error of the model should be decreased during the training process. However, after certain points the error starts increasing. Consequently, continuing the training process results in over-fitting in the points called epochs (Mathworks 2013).

2.5.5 Monte Carlo Simulation

Monte Carlo simulation is a very powerful technique that can consider the uncertainties that exist in construction management problems. Considering the uncertainty of economic data and cost of operations traditional methods are not enough to calculate the life cycle cost of operations. The situation becomes clearer when it is about forecasting the future of infrastructures' life cycle. The Monte Carlo simulation model includes the relationship between input variable with known uncertainty. Instead of assuming a crisp value for the variables, a range of value is considered. The target or output variable is defined, and the model becomes iterated for a certain number of times. The output is computed for the specified times, and the probability distribution function is calculated. Consequently, the mean, maximum, and minimum values of output are calculated. This technique was applied in the life cycle cost assessment models to support the maintenance decision process of water mains (Shahata and Zayed 2008; 2012; and 2013).

2.6 Findings, Limitations, and Research Gap

There has been extensive effort to address the risk, and failure assessment of oil and gas pipelines and some researchers have tried to develop risk-based inspection planning models. However, literature review attests that the existing research works neither developed an integrated objective model for the risk assessment of such pipes nor a comprehensive maintenance planning method. Most of the previous studies concentrated on one of the aspects of the risk assessment of such pipes. Some considered one of the failure types of oil and gas pipelines such as corrosion. The others have concentrated on only the probability of failure. The existing comprehensive models lacked objectivity or developed physical models. While the models that obtain expert opinion are criticized by the subjectivity, implementation of the physical models is time-consuming and expensive. Modeling the consequences of failures was the subject of some other studies. Similarly, the existing models on the consequences of failure were either subjective, which needed the expert opinion, or needed data on the post-failure events such as the amount of product that is released to the environment. Consequently, current models were limited in their applications and could not predict the financial consequences of the pipe failures.

Moreover, physical models obtained data from inline inspection tools that is very expensive and is not possible to be frequently performed. Besides, at the beginning of the project or even before construction when there is a need for a model to assess the risk of failure in such pipelines none of the previous studies is helpful. Some of the pipes are not piggable, and it is not possible to apply inline inspection tools to measure the metal loss or deterioration growth. As a result, there is a certain need for an integrated risk assessment model that applies statistical analysis methods obtaining the available historical data on oil and gas pipeline properties and the surrounding environment.

In the literature review, several powerful techniques were found that can well suit the risk assessment of such pipes. For example, it was found that Bow-tie analysis is a strong graphical method that can be applied for the failure probability assessment. This method would be more powerful when it is combined with another analytical method. The historical data of the failures of oil and gas pipelines can be used to develop an objective model of the failure probability assessment. Also, Neuro-Fuzzy was found an effective pattern recognition method that can be applied to evaluate the failure consequences. This technique can be used in recognizing the existing pattern among the input and output variables and generates rules to forecast the failures of similar pipelines in analogous situations.

CHAPTER 3: RESEARCH METHODOLOGY

3.1 Overall Research Methodology

The overall flow of the research process for this study is shown in Figure 3.1. The research starts with a comprehensive literature review on the available studies on the risk and failure models of oil and gas pipelines. It continues with an overview of the maintenance and inspection options that were suggested for different situations and under specific circumstances. The appropriate techniques for the development of the proposed model are then identified and studied. Upon the completion of the literature review, the required historical data is gathered, to be used for the development of the models proposed in this study. The Risk-based maintenance planning model for oil and gas pipelines developed in this research is designed to overcome the shortcomings and limitations of the previous studies. Additionally, it is organized to build a structured platform for the maintenance planning of oil and gas pipelines.

This research comprises the development of several sub-models, each addressing specific research sub-objectives, as explained in the first chapter. First, different types of failures and the contributory variables are identified, and the main hazards and consequences of failures are detected. Separate models are then developed for the assessment of failure probability and the prediction of each failure's consequences. An integrated fuzzy risk index evaluates the risk of failure based on the calculated probability and consequence of failure for such pipes. The available inspection tools that can be used to inspect pipelines for different sources of failures are identified. The tools are selected based on the risk of failure. Their accuracy and detection capability indices are then used to introduce a new index called the risk reduction index. The risk-based inspection plans are developed and ranked based on their Risk-cost indices. Finally, the deterioration profile of the pipeline's service life is predicted and developed based on a risk growth profile. This profile is used to forecast the required rehabilitation actions during a pipeline's service life. Various rehabilitation scenarios are developed and ranked based on their life cycle cost, calculated using a Monte-Carlo simulation.

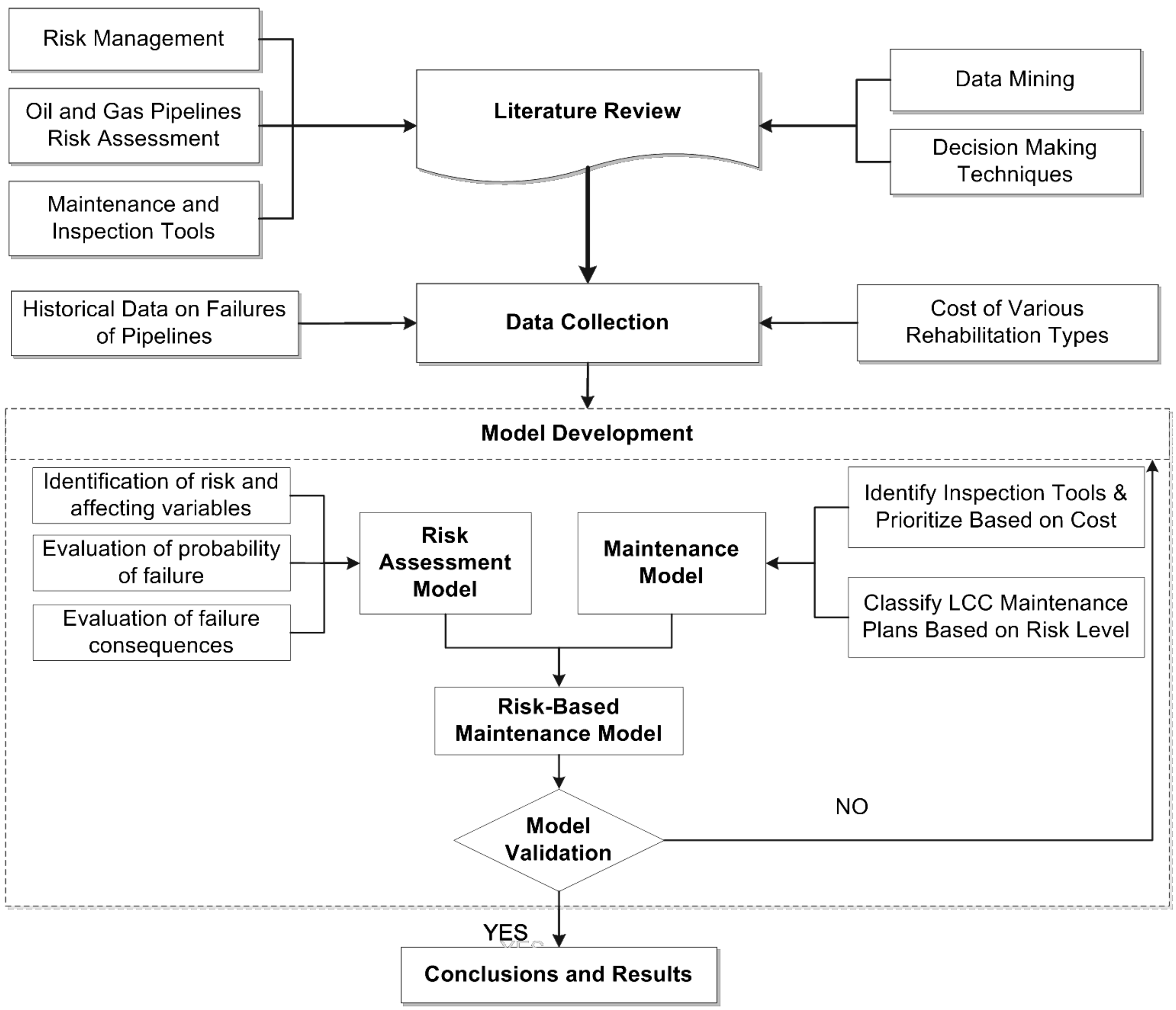


Figure 3- 1: Overall Model Flowchart

3.2 Risk Assessment Model

The development of the risk assessment model includes several stages. It starts with the identification of the main failure sources and the contributing variables. In this step, the sources of failure are categorized so that their assessment helps in the inspection and maintenance planning of oil and gas pipelines. Post-failure events are identified, and a model is developed to assess the probability of failure based on the identified contributing factors. The model also estimates the probability of post-failure events and evaluates their probability of occurrence. Another model is developed to assess the consequences of the risks. This model takes into account the preliminary identified factors and optimizes them based on the analysis results.

3.2.1 Identification of Failure Sources and Contributing Variables

Figure 3.2 shows the overall flow of this section. The methodology developed to identify the risk factors and related variables, as well as the hazards associated with the failure of oil and gas pipelines are described in this section.

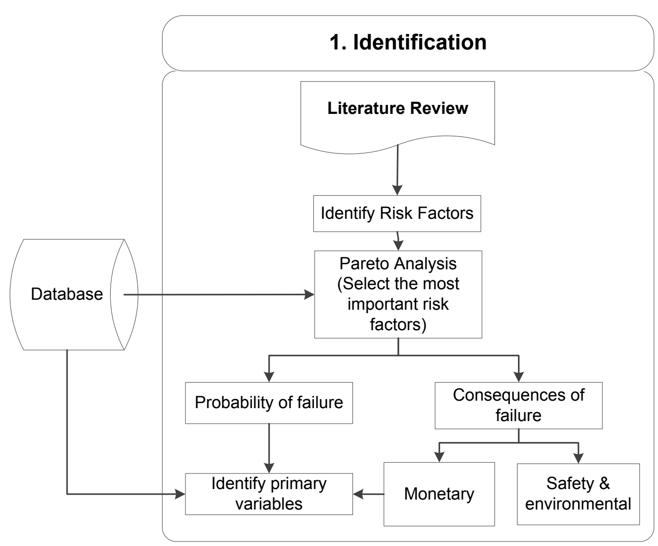


Figure 3- 2: Overall Flow of Identification Phase

In the literature review, various studies that developed a model to forecast the POF in oil and gas pipelines were summarized in several tables, in Section 2.3.4. The risk factors or failure types that were used most frequently in the literature are identified in this section. The frequency of failures due to the identified types is checked using the historical data. The historical data on the failures of oil and gas pipes in the US is applied to perform this analysis.

The most frequently-cited risk factors, as shown in Tables 2-5~2-7, are external corrosion, internal corrosion, material and construction defect, third party actions, incorrect operation, natural hazards and poor design. All of the above-mentioned factors have been reported as the causes of failure, although there have been occasional variations in the applied terminologies and categorizations by different researchers.

This research considers the sources of failures as an important factor in their classification, as different sources of failure affect oil and gas pipelines in different ways. Overall, the probability of post-failure events varies with respect to different identified failure sources. Finally, the vulnerability to different sources of failure should be taken into account when planning the maintenance and inspection of such pipelines. With this background and based on the study of the most important and most frequently reported sources of failures, a flowchart is developed, as shown in Figure 3.3. Risk factors are classified into physical and environmental categories, where the former refers to the sources of failure whose probability of occurrence increase with time, and the latter comprises those sources of failure whose probability of occurrence is not dependent on time or on a pipeline's age, but rather are related to the environment of the pipe and its operational condition. The physical factors include three major sources of failure as listed below:

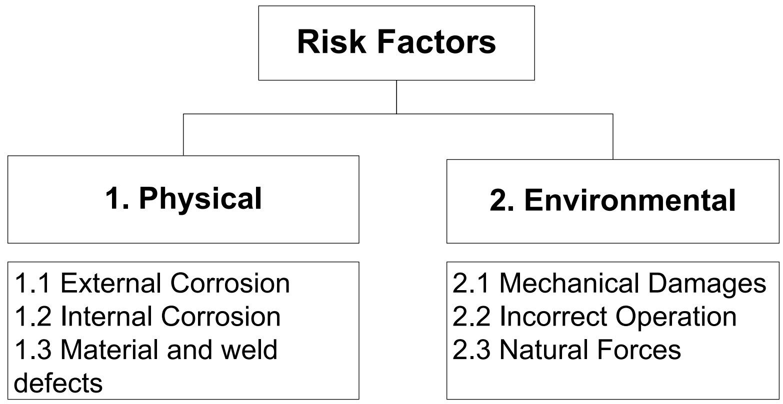


Figure 3- 3: Classifications of Identified Risk Factors

1. **External corrosion**: This type of risk is due to the oxidization of irons when the external surface of a pipeline is exposed to the environment, and can eventually lead to structural disintegration. Cathodic protection and pipeline coating are protective measures that can reduce the probability of this type of risk ($PHMSA_a$ 2014).
2. **Internal corrosion**: Internal corrosion occurs as a result of the chemical reaction of a pipe's material with corrosive products, whether water or other chemicals, leading to the loss of pipe material from the inside. There are a number of mitigation actions that can be taken to prevent this type of risk, such as the injection of inhibitors and the application of internal coatings ($PHMSA_a$ 2014).
3. **Material and weld defects**: Although modern steel production has made many advances, some impurities remain in pipes and may lead to pipe defects that could lead to failure. Consequently, the younger the pipeline, the more reliable it should

be. Nevertheless, inconsistencies persist in the materials and welds applied to connect pipes together.

The second group of risks covers the environmental sources of failure. These risks may happen as a result of excavation, incorrect operation, or natural forces, and consists of the following risks:

1. **Mechanical damages:** Failures caused by excavation vehicles or motor vehicle accidents are grouped under the category of mechanical damage in this research. These damages may occur as a result of the activities of a third party or on the part of the operators' employees.

2. **Incorrect operation:** Improper operations and activities by the operator's or the contractor's personnel may lead to a failure that is categorized under incorrect operation.
3. **Natural hazards:** Heavy rains, flooding, lightning, extreme temperatures, and high winds fall within this classification as causes of environmental failure.

After defining the risks, the variables that contribute to the occurrence of each failure type are identified. Similar to the identification of risks, the most frequent parameters in the literature are studied. Then, they are checked with the historical data to find the exact or similar factors that can help build a model to forecast the probability of failure of such pipes. Table 3-1 shows the variables identified from the reviewed studies. For example, cathodic protection effectiveness, coating type, and soil corrosivity are identified as factors that contribute to external corrosion failures. Soil corrosion itself is affected by soil resistivity, pH, and redox potential. For internal corrosion failures, the application of an inhibitor, the product’s corrosivity, and the inspection frequency are variables that contribute to the failure probability.

Table 3- 1: Common variables identified in previous studies

Failure type	Variables
External Corrosion	CP effectiveness, Coating (type, age, visual inspection) Soil corrosion (soil resistivity, pH, redox potential) pipe wall thickness
Internal Corrosion	Inhibitor application, Product corrosivity, Inspection
Material and weld defect	Maximum operating pressure, Hydrostatic testing pressure, pipe age, seam factor, weld
Third party	Depth of cover, activity level, one call system, Right of Way, Patrol frequency
Incorrect operation	SCADA effectiveness, Drug testing, safety program, equipment malfunction
Natural hazards	Earthquake, Flood, Subsidence

In the next step, the historical data of pipeline failures is studied to (1) identify the similar and measurable factors, and (2) evaluate the effects of these factors on the probability of occurrence of each failure type. Figure 3-4 illustrates the selected factors based on the study of the historical data of pipeline failures. External corrosion is affected by the soil properties including the acidity (pH), resistivity, and the Redox potential. The effectiveness of the cathodic protection used to reduce the impact of soil corrosion on the pipe has a direct implication on the external corrosion. The coating type and its efficiency also has an influence on the failures in this group.

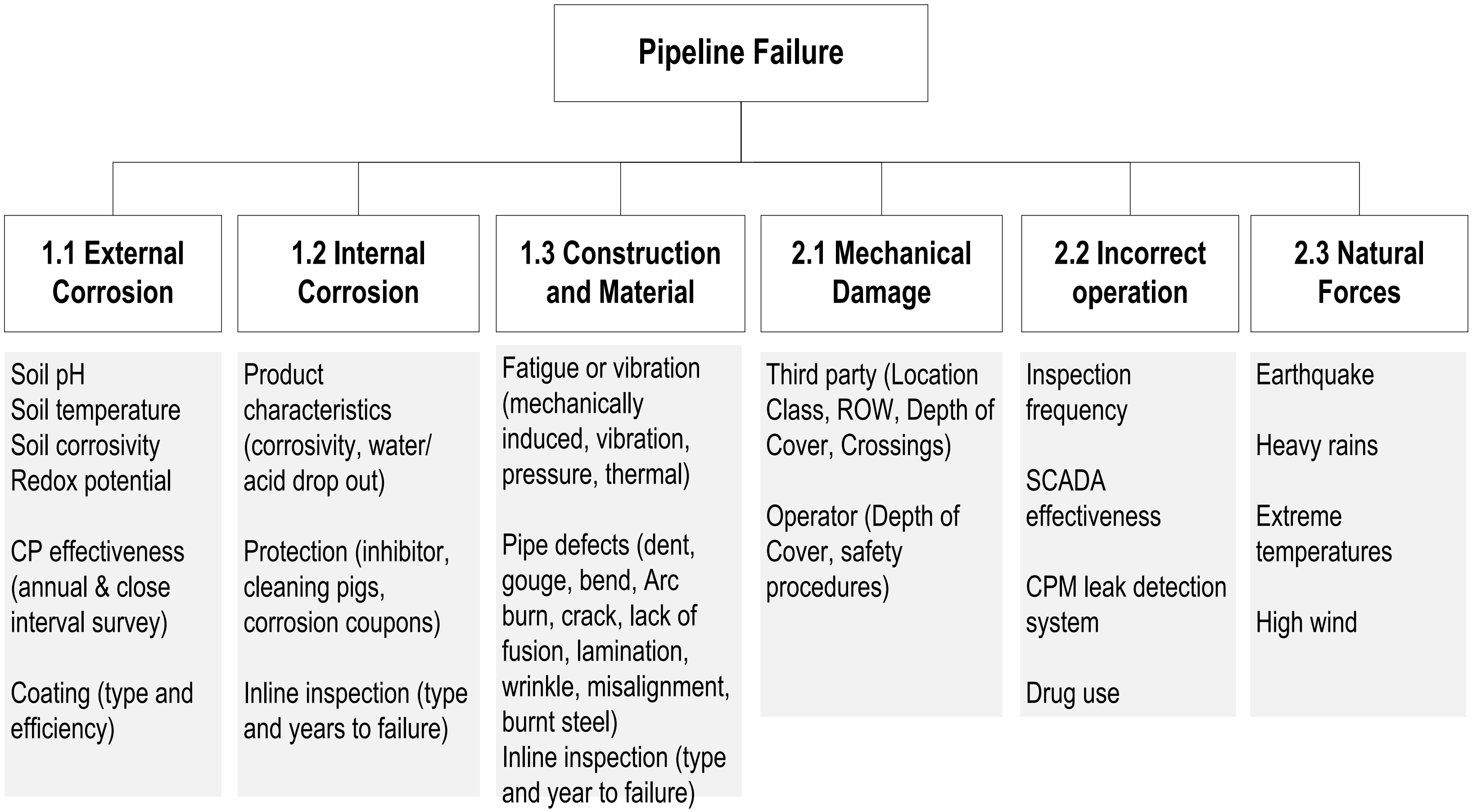


Figure 3- 4: Identified factors affecting each failure type

3.2.2 Probability of Failure Model

The probability of failure is one of the two main parameters of risk assessment. Figure 3-5 depicts the process of developing the failure probability model in this research. As shown in the figure, the development of this model includes three main steps: (1) Building the Bow-tie model, (2) Data analysis of the fault tree, and (3) Data analysis of the event tree. Due to the complexity of the behavior of oil and gas products and the existence of different pipeline failure scenarios, the Bow-tie model is recognized a suitable tool for the development of a failure probability model. Bow-tie models are the graphical representations of the possible scenarios of failure that start from the basic events leading to different causes of failures. The failure causes in this research are the sources of failures, such as external corrosion. The failure sources are then connected to the top event of the Bow-tie model or the product release.

The release is classified into different types based on the size of the hole that is formed in a pipe. Next, the top event is connected to the post-failure events. The Bow-tie model can be presented in two parts: the Fault Tree (FT) and the Event Tree (ET). The fault-tree model includes all of the basic causes, the failure sources and the top event of the tree. The event tree starts from the failure of the pipe and ends in the post-failure events.

Phase 1: The Bow-tie model is constructed based on the literature review results. All the factors and the failure sources identified in the previous section are used. The identified factors and failure sources are compared to the existing historical data from the Pipeline and Hazardous Materials Safety Administration of the US ($PHMSA_a$ 2014) database.

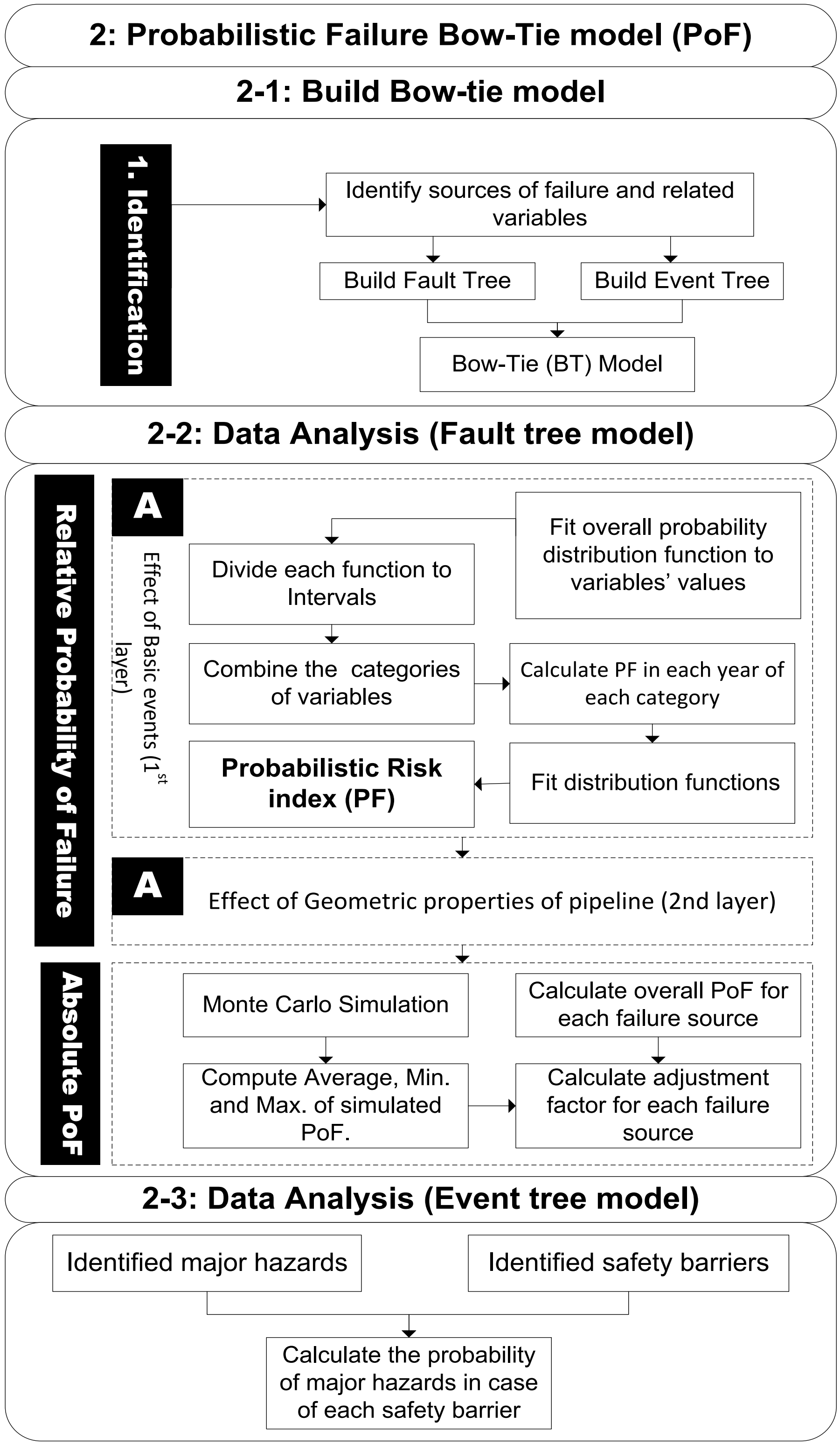


Figure 3- 5: Flowchart to develop the probability of failure model

The objective of this part of the study was to study the availability of historical data on the identified variables. First, a statistical analysis is performed to identify the most important failure sources. The variables associated various sources with the available historical data are selected. The fault tree part of the model is developed based on the results of this study. The Bow-tie model connects the identified variables that have an effect on different sources of pipeline failure, to their respective sources. In addition, the major after-failure events are identified from the history of the pipelines' failures. These events constitute the major elements of the event tree. The central point is the top event of the fault tree, which can be the failure of a pipeline or the release of the product that is being transported by the pipeline. The major pre-failure events are connected to the central point, or, in other words, to the pipeline failure.

This research proposes some modifications in the fault tree as presented in Figure 3-6 to extract the existing patterns and knowledge on the failure probabilities from the historical data. The changes are implemented at the basic events level, as well as on an additional, new level, which tracks the effect of the basic parameters of pipelines on the probability of failure. At the basic level, the basic variables are clustered based on the available data. These clusters include the specific properties of the pipelines with respect to related variables. In the new layer, this study proposes an investigation of the effect of the general properties of the pipelines on the failure probability. The result will be the calculation of the probability of failure with respect to each failure source.

Phase 2: The second phase of the model development analyzes the historical data on the failures of oil and gas pipelines in order to provide a comprehensive index for the assessment of their probability of failure. The analysis phase on the fault tree part is categorized into two main steps: 1) develop an index to calculate the relative probability of failure; and 2) obtain the conversion factors to compute the absolute probability of failure.

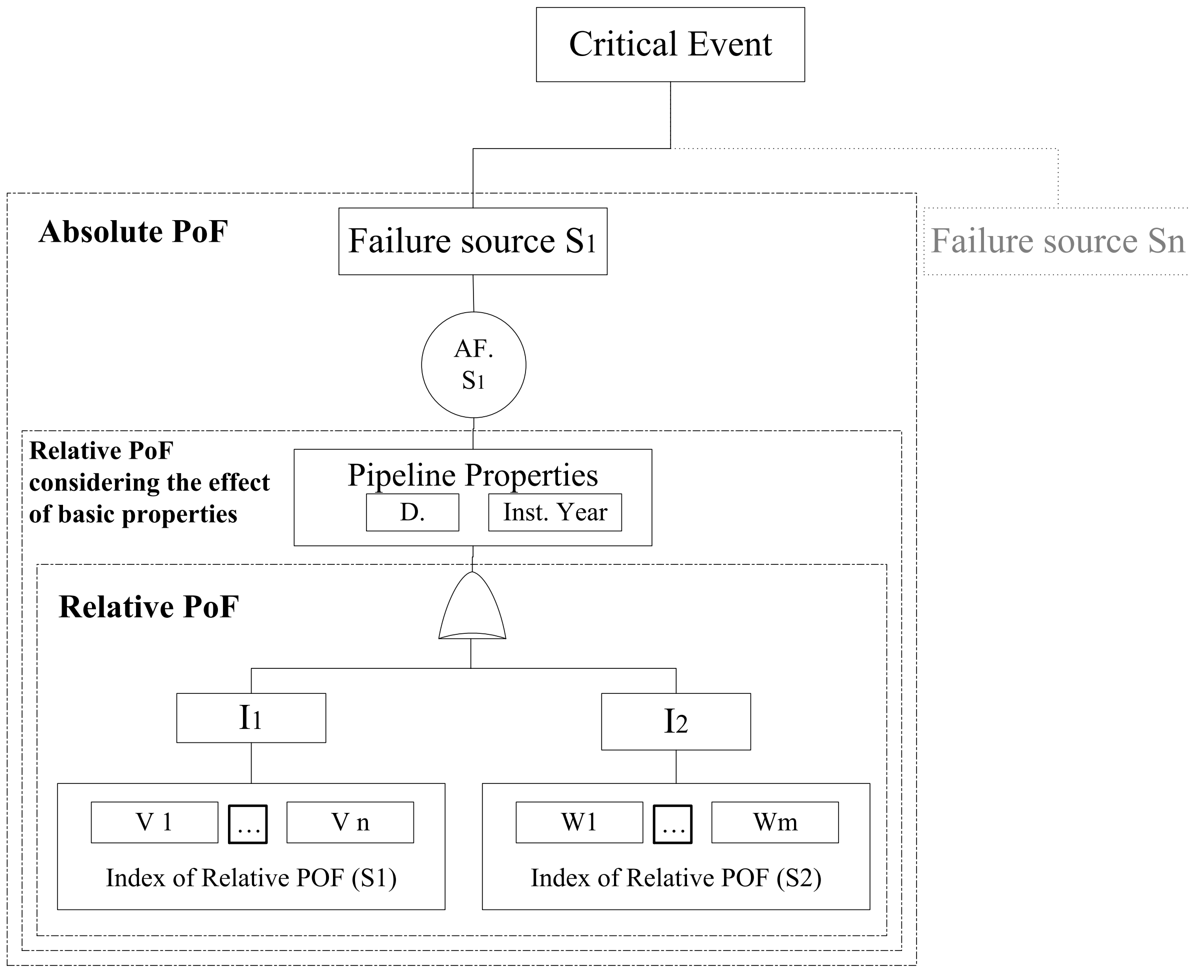


Figure 3- 6: Modified sample fault tree

Step 1-layer one: In the first step, the identified variables are divided into a number of categories. For quantitative variables, first the historical data on the failed pipes is fitted to the best probability distribution function, which is then divided into equal distances. For the qualitative variables, a study is performed to categorize them based on the available classifications. For some of these variables, the pipeline's installation period is used to identify the classification of the categories. After classifying the ranges of data for each variable, the number of pipes that failed in each year of the reporting period is calculated. In each category of each variable, the proportion of the failed pipes to the total number of failed pipes under each failure source is computed. Then, the distribution function that best fits the calculated data is determined for each category of the basic events with respect to each failure source. Data is preprocessed before the analysis. In this process, the incomplete data points, i.e. data points with missing data on the required variables, are removed, and the accuracy of data is investigated. The distribution function that best fits the remaining data is then determined. @RISK 6 (Palisade 2013) is applied to determine the function that best fits the historical data. In each of the categories, the number of failed pipes in each year of the reporting period is counted, and a table is formed based on these values. Equation 3.1 is applied to calculate the contribution of the basic causes to the failure of a pipe:

$$C_{k-i_j} = \frac{s_{k-i_j}}{\sum_{m}^{i=1}\sum_{n}^{j=1} s_{k-i_j}} \tag{3.1}$$

where; "C_{k-i_j}" is the contribution of the "i" th category of basic cause "S_k" in year "j" to the failure of pipes with respect to failure source "k", n is the number of years in the reporting period applied for analysis, and m is the number of categories determined for the classification of basic cause "k".

The software reports the results through six goodness-of-fit statistical tests, the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Chi-Squared, Kolmogorov-Smirnov (KS), Anderson-Darling (AD), and Root-Mean Squared Error

(RMSErr). Each of these statistical fit tests indicates how well a distribution function fits the data. The smaller the value of these statistics, the better the fit is. Some of these fit tests are applied to limited types of data: RMSErr is only used for cumulative and density data; AD and KS are only applicable to continuous data; and the others can be used for both continuous and discrete data. In this research, the selection of the best fit for most of the selected functions is based on the first rank of the sorted distributions based on the Anderson-Darling (AD) test. This test does not need to specify the number of bins, as opposed to the "Chi-Squared" test. Also, it considers the properties of the tail of the input data, whereas the KS test concentrates on the middle point of the inputs. As a result, the AD test can consider the effects of the maximum and minimum data on the best fit.

The selection of the best-fit distribution function is performed through the comparison of the results of the AD test. If there are distributions with close fit results, then the best fit with the most commonly used distributions is selected. The 99% range of the confidence interval is found in the reported results of the selected distribution function. The confidence level determines the maximum and minimum of the range within which the data is selected for future analysis. This methodology is developed based on the application of the granular theory to a distribution function, as explained in the literature review.

Step 1-layer two: In the second layer of this step, the effect of the main general pipe properties that can be effective on estimating the failure probability are analyzed. A process to that of layer one is repeated. All of the indices that are calculated through this step serve to build the stochastic index with which to assess the relative probability of failure unique to a pipe's properties. The specific properties of each pipe are taken into account, i.e., diameter, location and the installation year, in order to develop the indices to forecast the unique probability of failure.

The existing categories in the mileage reports are used to calculate the effects of the pipe's diameter and installation year. The contribution of each category of diameter in each year of the reporting period is calculated according to Equation 3.2. The calculated values are applied to determine the PDF best-fitted to the corresponding diameter category. The unit of the calculated values is the number of failures/year-mile. The contribution of the installation year of the pipes in each category of the installation year is calculated from Equation 3.3. The coefficient of each category of the installation year is computed from Equation 3.4. The second equation assigns a value of one to the minimum calculated amount of the contribution, and computes the remaining amount compared to the actual value of that category's contribution. According to the reports for transmission gas pipelines from 2001-2009, the pipeline diameters are clustered into five categories.

$$D_{k-i_j} = \frac{s_{k-i_j}}{\sum_{n}^{j=1} M_{d-i_j}} \tag{3.2}$$

where D_{k-i_j} is the contribution of the "ith" diameter category in year "j" of the database with respect to failure source "k", M_{d-i_j} is the mileage of the related diameter category in year "j", and "n" is the number of years in the reporting period.

$$y_{k-i} = \left(\frac{s_{k-i_j}}{\sum_{n}^{j=1} M_{y-i_j}}\right)/n \tag{3.3}$$

$$IY_{k-i} = \frac{y_{k-i}}{\min\{y_{k-1},\ldots,y_{k-n}\}} \tag{3.4}$$

where; y_{k-i_j} is the contribution of the "ith" diameter category in year "j" of the database with respect to failure source "k", M_{y-i_j} is the mileage of the related category of installation decade in year "j", and "n" is the number of years in the reporting period, IY_{k-i} is the coefficient determining the contribution of the "i" th category of the installation year of the pipe with respect to failure source "k".

Step 2: This step determines the conversion factors for each category that convert the relative probability of failure to the absolute probability of failure. All the possible pipes are simulated, and their relative probability of failure indices are computed to calculate these conversion factors. The calculated amounts are compared with the maximum and average annual probability of failure values for each diameter category. The coefficient of conversion is calculated via this comparison, and this factor is recorded for each diameter category.

Phase 3: This is the data analysis part of the event tree. First, various potential hole sizes and post-failure events are identified. Applying the probability and the Bayesian inference theory, an index is developed for each of the failure sources. This index provides the contribution of each failure source to the pre-defined hole sizes. Then, another index is used to calculate the contribution of each hole size to the occurrence of post-failure events such as ignition. Three hole sizes are forecasted to develop after the pipeline failure, small, medium, and large. Small hole sizes are the equivalent of pinholes, medium holes result in the puncture of a pipeline, and large-sized holes produce ruptures. The most determinant factor in the risk of different types of ignition post-pipe failure is identified as the hole size and the failure source. An index is developed to calculate the probability of occurrence of different hole sizes after each type of failure source, as shown in Equation 3.5. Equation 3.6 is then applied to develop an index that determines the probability of each ignition type in the case of happening of each type of hole size. Equation 3.7 is applied to calculate the probability of each failure scenario's occurrence.

$$P(H_j|S_k) = \frac{N_{H_{j_k}}}{N_{S_k}} \tag{3.5}$$

where $P(H_j|S_k)$ is the probability of hole size "j" developing in association with failure source "k", $N_{H_{j_k}}$ is the number of pipes failed under failure source "k" with hole size category of "j", and N_{S_k} is the total number of pipes failed under failure source "k".

$$P(Ign_i|H_j) = \frac{N_{ign_{i_j}}}{N_{H_{j_k}}} \tag{3.6}$$

$$P_{Sen.ijk} = P_{S_k} \times P(H_j|S_k) \times P(Ign_i|H_j) \tag{3.7}$$

where $P(Ign_i|H_j)$ is the probability of ignition type "i" happening when hole size type "j" occurs with failure source "k", $N_{ign_{i_j}}$ is the number of pipes failed under failure source "k" with a hole size category "j" and ignition type "i", and $N_{H_{j_k}}$ is the total number of pipes failed within failure source "k" with hole size "j".

Once all of the indices are developed and the related coefficients are computed, the equations developed in this section can be used to calculate the POF of each pipe. To compute the POF with respect to each failure source, Equations 3.8~3.11 are applied. Equation 3.8 computes the contribution of the basic events under an intermediate event with respect to each failure source. If two intermediate events exist under a single failure source, Equation 3.9 determines the maximum value and obtains it as the relative POF without applying the effect of the general properties of the pipe. Equation 3.10 is used to calculate the effect of the installation year and of the pipe diameter on the relative POF. Equation 3.11 calculates the absolute POF by applying an adjustment factor. The unit of the absolute POF is the number of failures/year-mile.

$$\widetilde{RP_{I_m}} = \sqrt[n]{\prod_{i=1}^{n} \widetilde{P_{x_i}}} \tag{3.8}$$

$$\widetilde{RP_{(I_1,I_2)}} = Max_{mean}\{\widetilde{RP_{(I_1)}}, \widetilde{RP_{(I_2)}}\} \tag{3.9}$$

$$\widetilde{RP_{S_k}} = \widetilde{RP_{(I_1,I_2)}} \times \widetilde{P_{D_a}} \times C_{IY_b} \tag{3.10}$$

$$\widetilde{P_{S_k}} = Mean\{\widetilde{RP_{S_k}} \times Af_{S_k(D_a)}\} \tag{3.11}$$

where; $\widetilde{RP_{I_m}}$ is the distribution function of the relative probability of failure with respect to an intermediate event, $\widetilde{P_{x_i}}$ is the distribution function of the basic events' contribution with respect to the intermediate event, $\widetilde{RP_{(I_1,I_2)}}$ determines the maximum distribution function correlated with two intermediate events under a failure source determined by comparing the mean values of the two, RP_{Ec} is the distribution function of the relative probability of failure with respect to the external corrosion, P_{D_a} is the distribution function of the contribution of the diameter category on the failure probability under a failure source, IY_{k-i} is the coefficient determining the contribution of the "I"th category of the installation year of the pipe with respect to the failure source "k", $P_{f(Ec)}$ is the distribution function of the absolute probability of failure with respect to the external corrosion failure source, and $A\widetilde{f_{Ec(D_a)}}$ is the adjustment factor with respect to the external corrosion in the correlated diameter category of the pipe.

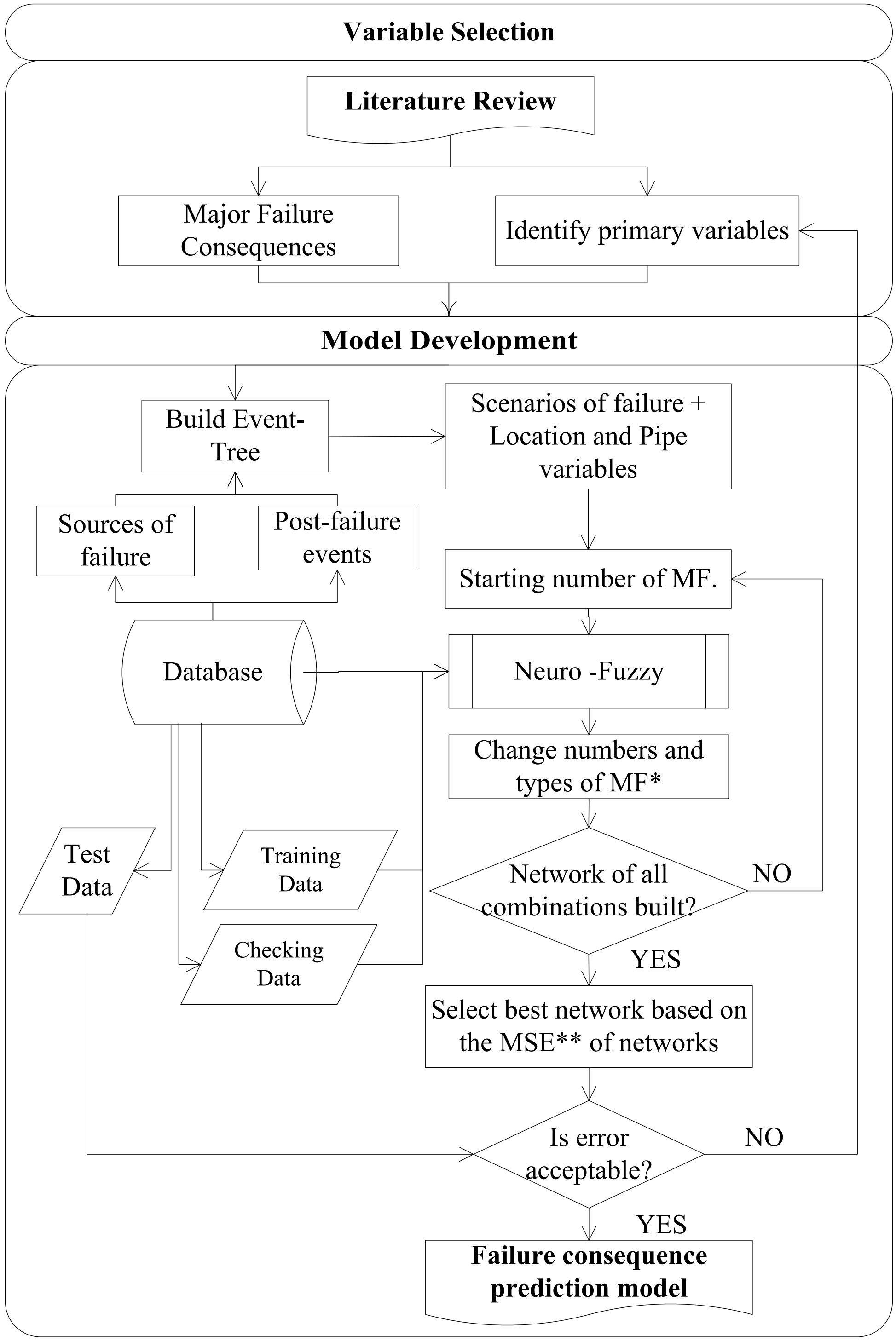
3.2.3 Consequence of Failure Model

The other parameter that is required for risk assessment is the consequence of failure, which can be estimated from various perspectives including individual, social, environmental, and physical damages to properties. All damages result in financial consequences that are difficult to estimate because of the sensitivity of failures' severity to their type and source. The lack of data about underground pipelines pre-failure adds to the complexity of the estimation. This research develops a failure consequence estimation model that can forecast the consequence level without the application of inspection or subjective data. The model development process is shown in Figure 3-7. According to this figure, the major consequences of a failure, as well as the primary variables that affect the failures' severity are identified. The pre-identified failure sources and post-failure events are used to define the failure scenarios.

The components of failure scenarios (i.e. FS) are extracted from the Bow-tie model, and include the failure sources, release type, and post-failure events. The components of the failures are combined through the application of Equation 3.12 to compute the value of a failure scenario that is composed of 63 different scenarios.

$$FS_i = R_i + C_i + I_i \tag{3.12}$$

where FS_i is the failure scenario for data-point "i", R_i is the release type of data-point "i", C_i is the cause of failure of data-point "i", and I_i is the post-failure event, including the ignition type of the data-point.



* MF: Membership Functions, ** MSE: Minimum Square Error

Figure 3- 7: Model Development Process

The location-related variables are those that are related to the location of the pipe and its surrounding environment, which can affect the severity of the failures. This variable group includes three variables: its onshore/ offshore location, the class location of the pipe, and whether the pipe is located in a high consequence area or not. The combination of all these variables is used to form a new variable called the location category (i.e. LC). Equation 3.13 is applied to build this variable and calculate the associated values for the historical data-points.

$$LC_i = OL_i + CL_i + HCA_i \tag{3.13}$$

where LC_i is the location category of the pipe or data-point "i", OL_i is the pipe's onshore/offshore location, CL_i is the class location of the pipes at data-point "i", and HCA_i is a variable that indicates whether the pipe is located in an onshore or offshore location.

The location category and failure scenario are considered as fixed variables and are required for the final model; while the combinations of different pipe properties are tested to optimize the model error. Various combinations, including two to four variable sets, are built to compare their prediction capability. Different neuro-fuzzy networks for each combination of the variables are produced. For each combination, a various number of and different types of membership functions are tested. Since there is no previous knowledge about the properties of the inputs and outputs, either of the two methods of clustering, namely subtractive clustering or grid partitioning can be used. Subtractive clustering is a rapid algorithm for clustering data that initiates clusters based on the initially-recognized fuzzy clusters. The fuzzy membership functions are then optimized based on the data properties during the training phase, and the best mode is embedded into the final model. This method uses the same number of membership functions, as well as the same types of membership functions, for all of the variables. However, some of the variables in this research do not require a large number of membership functions. Consequently, in this research another method, the more-flexible grid partitioning is used. The results of this method are more accurate than those of subtractive clustering.

The grid partitioning method of clustering, which is used in this research, considers all of the possible combinations of the clusters of input variables to generate fuzzy if-then rules. The number of data points is limited in the historical database, and the missing data adds to this shortage. Equation 3.14 presents the number of modifiable parameters for each neuro-fuzzy network, which is applied to find the starting number of the membership functions. A large number of parameters should be modified in this method, and this number must be smaller than the number of data points. Consequently, a large number of membership functions cannot be used in this method due to the limitations in the number of datapoints in the historical database.

$$Modifiable\ parameters = \prod_{i=1}^{n} V_i + \sum_{i=1}^{n} MF_{p_i} \qquad (3.14)$$

where V_i is the number of membership functions for each of the input variables, n is the number of the input variables and MF_{p_i} is the number of parameters for the selected type of membership functions for each of the input variables, which is three for triangular membership functions and four for trapezoidal membership functions.

In order to start the learning phase with an optimized number of membership functions, the starting number of the membership functions and their types are determined to develop the model. The error produced in all of the datasets is recorded, and the surface view in the generated network is checked. The average error of each network is calculated from Equation 3.15.

$$AE_i = \sum_{j=1}^{j=3} P_j \times E_{ij} \tag{3.15}$$

where AE_i is the average error in trial number "i", P_j is the percentage of data in dataset "j", and E_{ij} is the error produced in dataset "j" in trial "i" of the modelling phase.

After determining the starting number of membership functions, the historical data on the failures of pipelines are divided into three sets of training, checking, and testing datasets. The training dataset is obtained to train the model and produce the neuro-fuzzy network. The error of the produced network is checked versus the checking dataset in steps called epochs, and if the error starts to increase, the learning phase stops. The testing dataset is used to measure the error of the final network and test the validity of the model. In this research, 15% of data is allocated to each of the testing and checking datasets, and the remaining is obtained for training.

The surface view checks the relationship of one or two of the input variables versus the output variable. If the produced output is negative in all or most of the surface view of the produced network, the produced network is deemed ineffective. The sensitivity of the output variable versus all of the input variables is also checked. The networks that result in a constant output value versus the changes of one variable in its whole range are also removed from the consideration of the final model. Models with the use of various membership functions and different combinations of variables are generated, and the produced results are recorded. The best network is selected based on the error of the networks in all the datasets and in the surface view checks. Table 3-2 summarizes the variables that are used in the numerical models found in the literature. These studies aim to develop a model for pipeline failure consequences. However, as mentioned before, given that the geometric properties of the pipelines are not considered, the analysis of the failures' consequence in the literature is limited. Moreover, the input variables are not known for specific pipelines before failure and could be more suitable for scenario analyses.

Table 3- 2: Variables used in the numerical models developed for the failure consequence prediction models

Reference	Variables
Resterpo et al. (2009)	Occurrence of ignition and/or explosion, amount of product loss, the location specifications (i.e. offshore versus onshore, and HCA versus non-HCA), the system part involved, and the cause of the accident.
Simonoff et al. (2010)	Cause of the incidents and incident types.

In this research, some variables from previous studies by Resterpo et al. (2009) and Simonoff et al. (2010) are applied. These include the occurrence of ignition and/or explosion and the accident causes. However, the amount of product loss is not used, as it is not predictable at this stage before a failure occurs. Some other variables are suggested as the primary variables, such as the geometric properties of pipelines, which include the pipe diameter and wall thickness. Also, the importance of the Specified Minimum Yield Strength (SMYS) of a pipe and its maximum operating pressure (MAOP) are studied in the model. The other failure mode that will be examined in analyzing the model's efficiency is the existence of rupture, puncture or leakage. For this failure mode, only the probability is calculated in the event tree of the Bow-tie model.

The age of the pipeline is considered in the input variables, as it may affect the failure consequences. The failure consequences model forecasts the severity of the failures of oil and gas pipelines. Various failure consequence types were discussed in the literature review. They are classified into three groups of safety, environmental, and economic consequences. The amount of property damage includes the economic damages and can represent the severity of a pipeline's failure.

The primary variables that are used in this research are shown in Table 3-3. As indicated, the variables are categorized into three groups. Group one includes the variables that are directly related to the properties of the pipe. These properties include the pipe diameter (DI), pipe wall thickness (WT), the Maximum Allowable Operating Pressure (MAOP) and the Specified Minimum Yield Strength (SMYS). Various combinations of these variables are tested to optimize the results of the model. Group two of the variables includes those that are related to the scenarios of failure, obtained from the Bow-tie model. In addition, databases report values on the parameters including those that indicate the location of the pipe with respect to the number of buildings and people around the pipe and the existence of ecologically-sensitive environments such as rivers and lakes. The former is recognized by a variable known as class location, and the latter is identified with a variable that determines if the pipeline is located in a high consequence area or not. All the possible failure sources are extracted from this model.

Table 3- 3: Primary input variables

Variable Type	Variable	Value		
		Min.	Max.	Unit
Pipe Properties	Pipe Diameter	1	48	Inch
	Pipe Wall Thickness	0.02	1.25	Inch
	Specified Minimum Yield Strength (SMYS)	16,000	70,000	mpa
	Maximum Operating Pressure (MAOP)	60	7,100	psig
Failure Scenario (FS)	Release type	1	4	-
	Failure cause	1	7	-
	Ignition or leakage	0	1	-
Location Category (LC)	Onshore or offshore	0	1	-
	Class location	1	4	-
	Pipe located in high consequence area (HCA) or not	0	1	-

A new variable is constructed, which indicates the failure scenarios. The new variable is built by assigning 1000s, 100s, and 10s codes in order to be able to differentiate between various scenarios with one variable. Presenting the failure scenarios with one value will help to greatly decrease the number of input variables, which will reduce the computational time for the neuro-fuzzy system. For this purpose, a thousands' code is allocated to each of the failure sources offered in Table 3-4. The ignition variable obtains a hundreds' value of 100 to 300 based on the possibility of an ignition, an explosion or none. Release types are given a value of 10 to 30 based on the possible sizes of the leakage, ranging from a small hole to a large rupture.

3.2.3.1 Neuro-fuzzy model training

After the variable selection, the second step of the model development is training, optimization, and validation. The ANFIS is applied to the development of the model, as it is a very powerful pattern recognition technique that also considers the uncertainties of the accuracy of the historical data. ANFIS is a Mamdani fuzzy inference system that maps a set of inputs to a set of membership functions and maps the membership functions to the rules. The rules are first mapped to a set of output membership functions, which are later transformed into a crisp output using de-fuzzification techniques (Mathworks 2013). The historical data on the failures of oil and gas pipelines in the US are used to develop the model. This database includes enough parameters to develop this model. The database is preprocessed, and the related variables are obtained. It is randomly divided into training and checking datasets. The checking dataset should be carefully selected as it should contain enough features of the whole database. If it does not contain the natural features of the historical data, the validation may result in an unacceptable amount of error.

After dividing data into training and checking datasets, the training data is divided into two sets; training and testing, and the Fuzzy Inference Structure (FIS) is built. There are three methods in ANFIS for generating an FIS. First, the user can build the membership functions by using the previous knowledge from the existing data. However, if there is not enough knowledge regarding the database and its properties, either of the two methods of optimizing the FIS, namely, subtractive clustering or grid partitioning, can be used. As mentioned earlier, subtractive clustering is a fast algorithm for clustering data and for recognizing the possible membership functions within input and output data. As a result, the generated fuzzy membership functions are optimized based on the properties of data during the training phase, and the best mode is embedded into the final model. This method initiates the construction of the model based on the initially-recognized fuzzy clusters.

Data points are used as the candidates of the cluster centers in subtractive clustering, while in grid partitioning the grid points are considered as the candidates. This makes subtractive clustering perform faster in the computation process than grid partitioning, although grid partitioning is more accurate. Moreover, the grid partitioning method is more flexible as it can assign a different number of membership functions to various variables. Equation 3.16 is applied to measure the density of data around each point (Hammouda and Karray 1997). The data point with the highest density is chosen as the first cluster center. The density value is then revised by applying Equation 3.17. The data point with the highest revised density is chosen as the next cluster center, and the process continues until a sufficient number of clusters is obtained.

$$D_i = \sum_{j=1}^{n} exp\left[-\frac{\|x_i - x_j\|}{(r_a/2)^2}\right] \tag{3.16}$$

$$D_i = Di - D_{c1} exp\left[-\frac{\|x_i - x_{c1}\|}{(r_b/2)^2}\right] \tag{3.17}$$

where:

x_i: the existing data points

r_a: a positive constant that presents the radius of a neighborhood

r_b: a positive constant which defines a neighborhood with “measurable reductions in the density”.

X_{c1} is the first cluster center, which is the data point with the highest density (D_{c1}) as calculated by Equation 3-6 (Hammouda and Karray 1997).

In the training phase, several parameters should be determined, such as the training mode, which can be hybrid or back-propagation. The hybrid method of training combines the least squares method with back-propagation. These methods are applied to recognize and optimize the fuzzy inference system parameters based on the training data. Figure 3-8 shows the generic Mamdani fuzzy inference system (FIS), the parameters of which are optimized in the training phase. Figure 3-9 shows a sample FIS structure with four input variables. This structure shows the triangular membership functions assigned to the defined inputs to develop the FIS. The efficiency of the training phase is then checked against the testing dataset at several data points called epochs. As mentioned in the literature review, the error of a model trained by Neural Networks and Neuro-Fuzzy systems increases at some points as a result of over-fitting. These points are called epochs, and the system verifies the trained network in the checking dataset at each epoch, and whenever the error starts increasing, the training is stopped. Continuing the training would not help the system's learning task or its generalization capability.

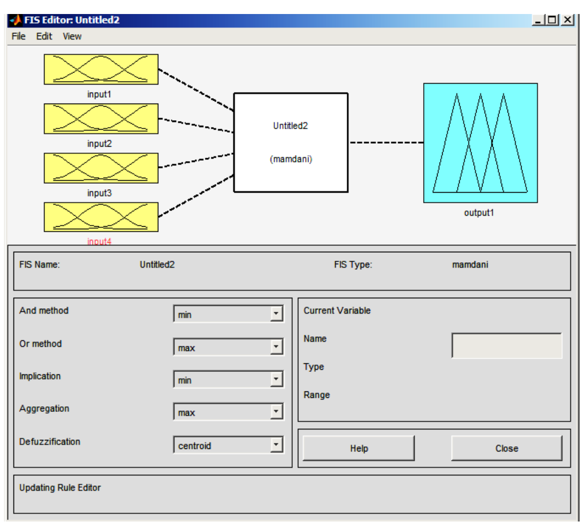


Figure 3- 8: Mamdani Fuzzy Inference System (Mathworks 2013)

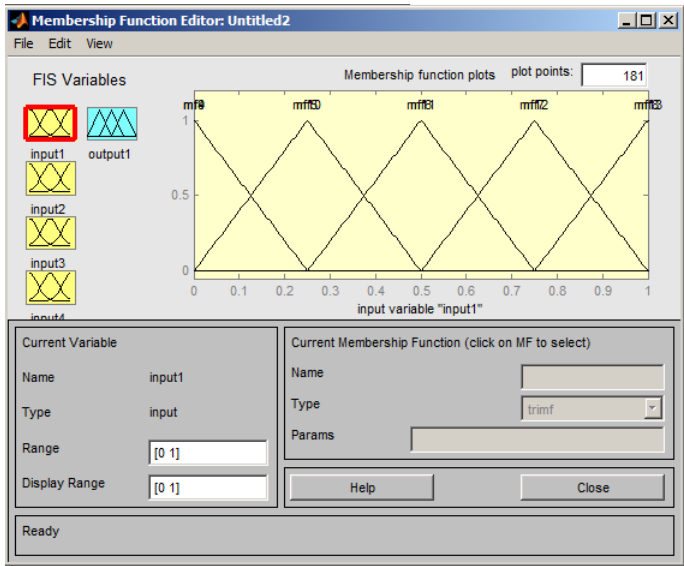


Figure 3- 9: Sample FIS structure with four input variables (Mathworks 2013)

In this research, the number of input variables is optimized based on the error of the trained model, which is checked against the validation dataset. For this purpose, different combinations (i.e. *m* of *n*) of input variables are generated. The model is built for each set, and the error of the developed network against the testing dataset is recorded. The error is obtained by comparing the neuro-fuzzy-estimated outputs with the actual data. The Mean square error (MSE), which applies Equation 3.18, is used to measure the average of the squares of the errors in each dataset. Consequently, the models with the least amount of error are recognized. If the errors are very close, the validation dataset is used to select the best combination of the variables. The validation dataset is embedded into the trained system, and the forecasted consequences are predicted via the model. Figure 3-10 shows the inputs, output, and fuzzy rules of a sample fuzzy inference structure. As shown, different membership functions are assigned to each input and output. The rules are defined and used to predict the output.

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(E_i - A_i)^2 \tag{3.18}$$

where: n *is* the number of data points in each dataset, E_i is the estimated output, and A_i is the actual output.

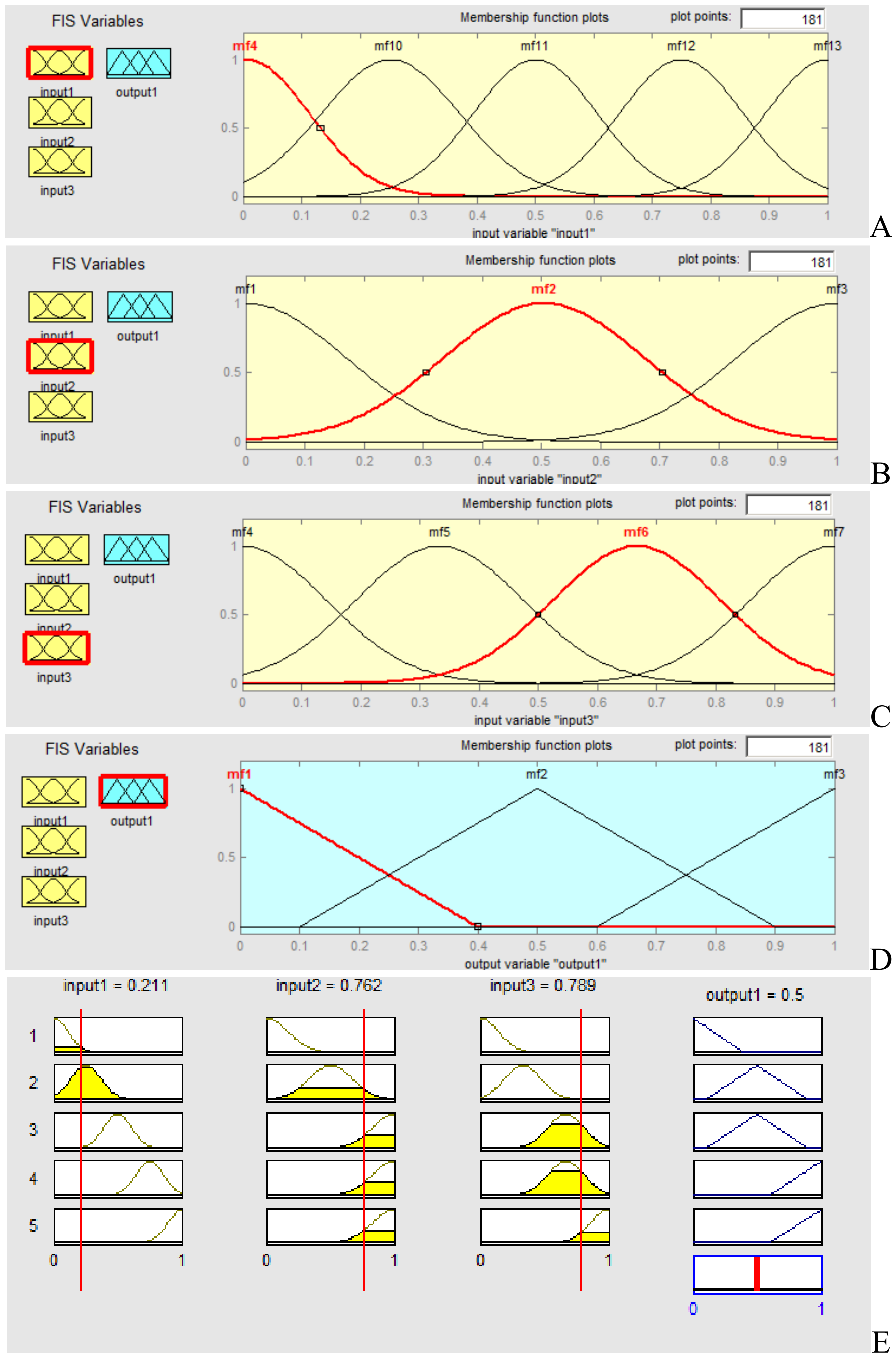


Figure 3- 10: Sample fuzzy inference structure and output rules
(A: Input 1, B: Input 2, C: Input 3, D: Output, E: Rules of the model predicting output)

3.2.4 Validation of the POF and COF Models

In order to validate the probability of failure and the consequence of failure assessment models, part of the databases are separated, and the error measuring methods are used to evaluate the accuracy of the models. The error measuring methods compare the estimated values of the output variables with their actual counterparts.

Equations 3.19 and 3.20 are used to calculate the Root Mean Square Error (RMSE) and the Average Invalidity Percentage (AIP), respectively. Equation 3.21 is applied to measure the Average Validity Percentage (AVP) of the model. In an accurate prediction, the value of the AIP should be closer to zero, while the value of the AVP should be closer to one. The Mean Absolute Error (MAE) is presented in Equation 3.22 and, as can be predicted, the closer the value of the MAE is to zero, the more accurate the prediction. The value of the modified absolute percentage error (Modified APE) is calculated as the median of the values obtained by Equation 3.23 (Hyndman & Koehler 2006).

$$\text{RMSE} = \sqrt{\sum_{i=1}^{n} \frac{(\text{Ci-Ei})^2}{n}} \tag{3.19}$$

$$\text{AIP} = \frac{\sum_{i=1}^{n} \left|1-\left(\frac{\text{Ei}}{\text{Ci}}\right)\right|}{n} \tag{3.20}$$

$$\text{AVP} = 100- \left[100 \times \left(\frac{\sum_{i=1}^{n} \left|1-\left(\frac{\text{Ei}}{\text{Ci}}\right)\right|}{n}\right)\right] \tag{3.21}$$

$$\text{MAE} = \frac{\sum_{i=1}^{n} |\text{Ci-Ei}|}{n} \tag{3.22}$$

Symmetric Absolute Percentage Error of period i (sAPE) = $\left|\frac{(Ci-Ei)}{\left(\frac{Ci+Ei}{2}\right)}\right|$ (3.23)

where Ci is the actual value of the probability of failure,

Ei is the estimated value, and n is the number of data-points in the testing dataset.

3.2.5 Integrated fuzzy risk evaluation model

There are two main methods for evaluating the level of risk of failure. The most commonly used method is the multiplication of the probability of failure by the consequences of failure. However, this method removes the differences of the risks of two pipes: one with a high probability of failure and a low consequence of failure, the other with a low probability of failure and a high consequence of failure. The risk of failure for both is evaluated with a single value. Therefore, this method is not recommended for this research. Another method used in many studies is the risk matrix. A sample risk matrix is shown in Figure 3-11 (Milazzo et al. 2015).

Once the probability of failure and consequence of failure is assessed using the pre-developed models, a scale is needed in this method in order to evaluate the level of risk assessment. Different guidelines offer various scales with which to evaluate the level of failure risk. The linguistic terms they attribute to the calculated amounts of probability of failure and consequences of failure, as well as the risk levels, vary from one set of guidelines to another. The calculated rates of failure probability and consequences are compared with this matrix to evaluate the level of risk of a pipeline.

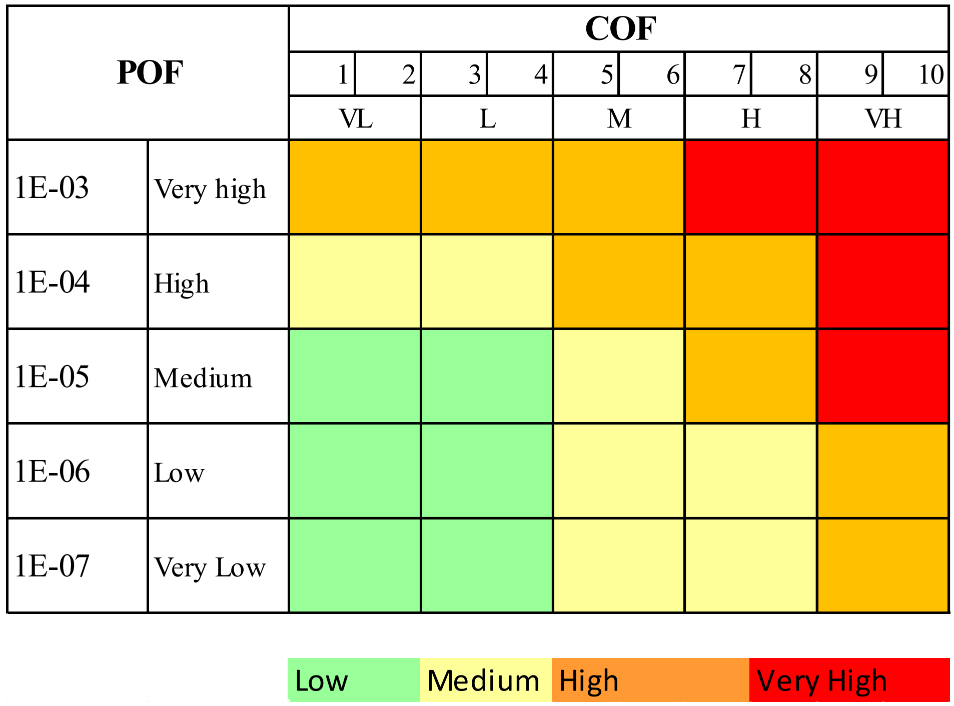


Figure 3- 11: A Sample Risk matrix

Table 3-5 presents some of the pre-defined scales of probability of failure evaluation. Besides the fuzzy nature of the level of risk evaluation, these scales do not consider the probability of failure of the pipes with respect to different sources of failure.

Table 3- 4: Probability of failure scale of evaluation

Linguistic term	DNV 2010	Milazzo et al. 2015
Very Low	$<10^{-5}$	$<10^{-6}$
Low	10^{-5} to 10^{-4}	$10^{-6}$to 10^{-5}
Medium	10^{-4} to 10^{-3}	$10^{-5}$to 10^{-4}
High	10^{-3} to 10^{-2}	10^{-4} to 10^{-3}
Very High	$>10^{-2}$	$>10^{-3}$

Due to the fuzziness of the level of risk and complexity of evaluation as a result of the existence of various values for different failure sources, this research suggests the application of a fuzzy expert system. This fuzzy expert system would evaluate the risk of failure with respect to each failure source. First, Equation 3.24 is developed to convert the computed probability of failure values to logarithmic grades, as the level of severity of pipeline failure probability is assessed on a logarithmic scale.

$$GP_{S_k} = 8 + \log(P_{S_k}) \tag{3.24}$$

where GP_{S_k} is the grade of probability of failure with respect to failure source “k”, and GP_{S_k} is the absolute probability of failure with respect to failure source “k”.

Developing the fuzzy expert system that evaluates a pipeline’s risk index is composed of three steps, as listed below:

1- Fuzzification of the inputs: To fuzzify the inputs, 5-grade fuzzy membership functions are assigned to evaluate the calculated value of the probability of failure. Similarly, the computed consequence of failure and the output are fuzzified. The thresholds of the membership functions are mainly defined based on the findings from the literature review and experts’ opinions.

2- Defining the rules: These rules map the relationship between the inputs, here the probability and consequence of failure, with the output or the risk index. The rules are defined based on the available guidelines and the experts’ opinions.

3- Defuzzification: The fuzzy inference system developed in this research applies the Mamdani model, which is intuitive and suitable for human inputs (Mathworks 2013). This model aggregates inputs and outputs with the attributed fuzzy rules and calculates the defuzzified output, which is the level of risk of failure, using the centroid method of defuzzification.

3.3 Maintenance Model

After the risk assessment and the associated determination of the pipeline's level of risk, a maintenance model is developed. In this model, decisions are taken in two steps, at inspection and rehabilitation planning, as described in the following sections.

3.3.1 Inspection Planning

The failure probability and consequence analysis models help identify the level of risk of the pipelines being evaluated. The pipelines' inspection plans are optimized based on the risk of failure. Based on a pipeline's risk level, the inspection planning model suggests the most suitable tools for its inspection and the frequency at which they are to be used. Figure 3-12 depicts the process of the fuzzy inspection tool selection model development for such pipes. The inspection tools and techniques were studied in Chapter 2. There are varieties of inspection techniques that can be used for different purposes. However, a comprehensive structured model to recognize the most suitable inspection techniques and determine the frequency of running the tools for a specific pipeline could not be located within the existing works.

Choosing an appropriate inspection tool helps to detect the defects and sources of failure based on their level of risk. This model aims to recognize the most potential sources of failure for pipelines and proposes the optimum inspection technique accordingly. The failure probability model analyzes the probability of occurrence of each source of failure for the pipelines. It can also verify which types of failure sources are more severe. The level of probability of failure is applied in order to prioritize the most suitable list of inspection tools for each failure source. Based on the literature review, a list of inspection techniques is prepared for each failure source. The recommended range of inspection frequency for each group is studied via the guidelines and inspection manuals. Table 3-6 presents a sample of the prepared list of inspection tools, their recommended inspection frequency and the cost of running each one. The different techniques of each list are ranked based on their average running or operating cost.

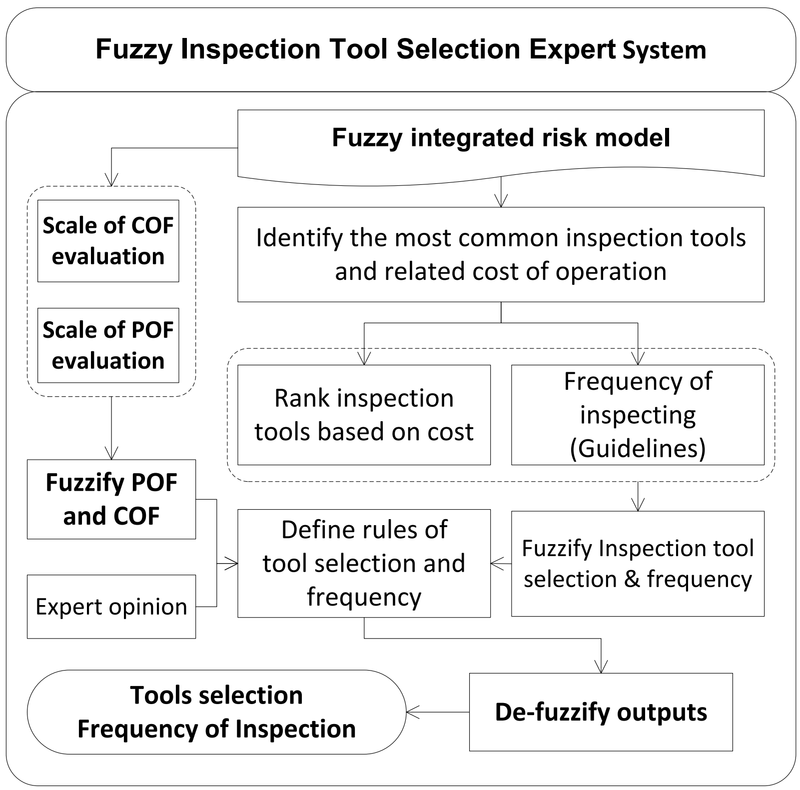


Figure 3- 12: Inspection planning model

Table 3- 5: Sample list of inspection techniques and their cost and recommended range of operation frequency

Inspection techniques		Frequency of operation	Cost of operation
No. 1	….	a_1-b_1	C_1
. .	. .	. .	. .
No. n	….	a_n -b_n	C_n

To be most effective, each inspection technique should be used in a range of frequencies. This range is identified from the literature. The range is developed to address the various levels of failure probability. Consequently, pipelines with a higher probability of failure are inspected more frequently. Consider as an example inspection technique No.1 from Table 3-6. This inspection is recommended to be conducted every a_1 to b_1 units of time. This range will be divided into five equal intervals using Equation 3.25.

$$I_1 = \frac{(b_1 - a_1)}{5} \tag{3.25}$$

where I_1: the calculated interval frequency

b_1: the upper bound of the recommended frequency, and

a_1: is the lower bound of the recommended frequency.

A table is then developed for each inspection type to determine the frequency of inspection with respect to different levels of the probability of failure. Table 3-7 depicts a sample index that will be developed. Next, the calculated frequency number is fuzzified to incorporate the uncertainty involved with the accuracy of decisions and the computed failure risk.

Table 3- 6: Sample index of inspection frequency based on the level of failure probability

Inspection techniques		Frequency of operation with respect to the level of failure probability				
		VH	H	M	L	VL
No. 1	….	a_1+I_1	$a_1+2\times I_1$	$a_1+3\times I_1$	$a_1+4\times I_1$	$a_1+5\times I_1$
. .	. .					
No. n	….	a_n+I_n	$a_n+2\times I_n$	$a_n+3\times I_n$	$a_n+4\times I_n$	$a_n+5\times I_n$

The inspection tool is selected based on the list of the identified inspection techniques. These tools are prioritized based on the pipeline failure consequences. A pipeline with a higher consequence of failure is recommended to be inspected with a more expensive inspection technique such as a high-resolution Inline inspection. The consequence level of a pipeline failure is estimated in the range of 1 to 10, which is divided into five levels of severity. The severity levels are titled: Very Low, Low, Medium, High and Very High.

For the low consequence failures, the lower-cost inspections, such as low resolution inline inspections and further distances of digging for direct assessment are assigned. The high resolution inspection techniques and extra-high resolution techniques are prescribed for the high and very high failure consequences. When the list of the available inspection techniques is generated, the next step is to develop the inspection scenarios, which constitutes the second part of inspection planning.

After developing the general rules for selecting inspection techniques, the risk-based inspection maintenance expert system is developed. The methodology for developing this model is shown in Figure 3-13. This model is developed based on the growth of the pipeline risk, and it considers the costs of various inspection scenarios over the life cycle of a pipeline. The capability of the detection of the selected inspection tools and their accuracy of detection is identified. By combining these two values, the risk reduction index of each inspection technique is calculated. After the inspection tools have been selected and their optimal run frequency determined, a risk growth profile is developed. This profile should forecast how the risk generally grows during the service life of a pipeline. In order to develop the cumulative risk growth profile, the individual probability of pipeline failure in each year of its life span is calculated using Equation 3.26. The individual probabilities of failure for previous years are then summed to achieve the cumulative probability of failure for one year, as indicated in Equation 3.27. The cumulative probability of failure growth at year “i” represents the probability of a pipeline failure before that age.

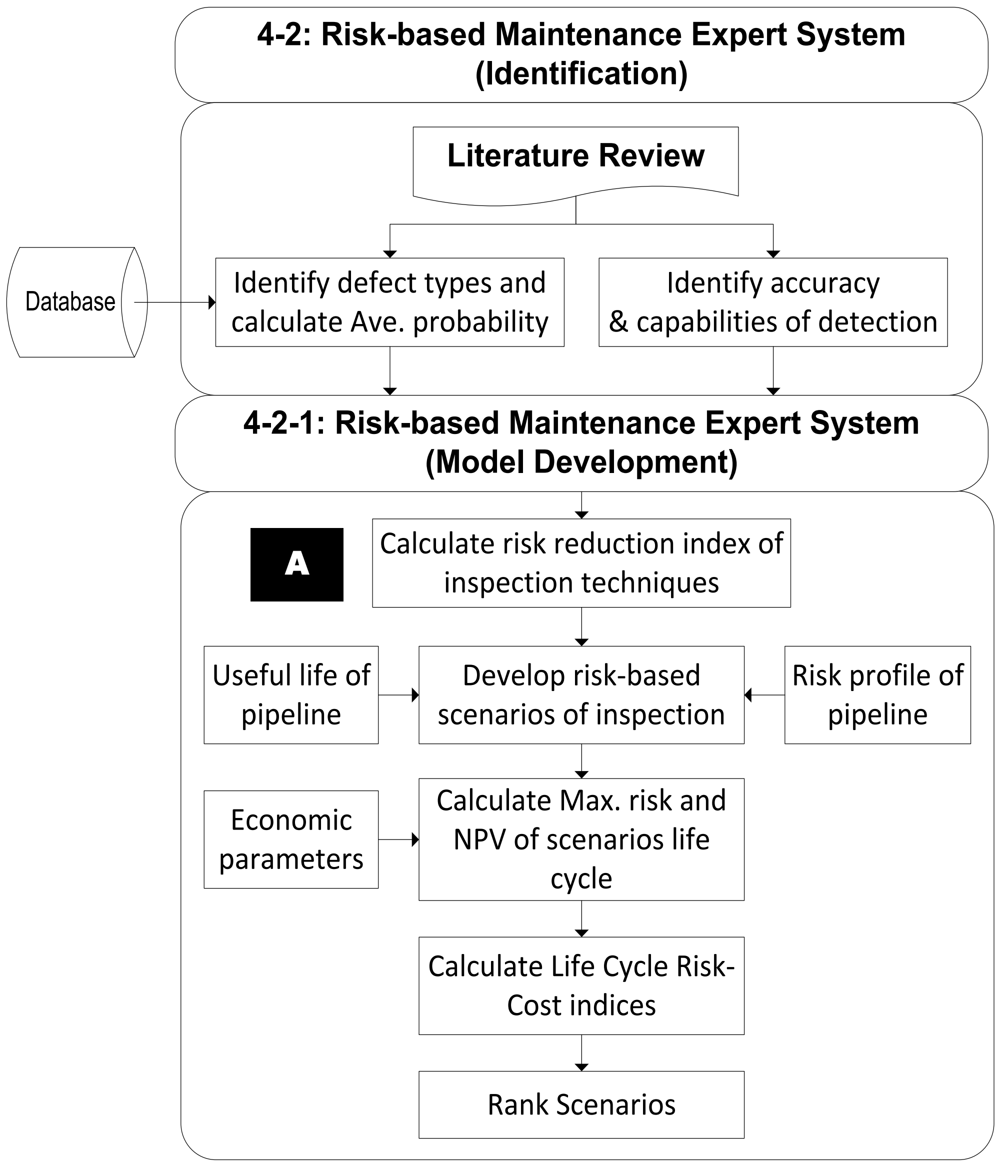


Figure 3- 13: Risk-based inspection model development

$$PoF_i = \frac{Number\ of\ pipelines\ failed\ in\ year\ "i"}{Total\ \text{number of pipelines failed}} \tag{3.26}$$

$$Cumulative\ PoF_{(i+1)} = PoF_{(i+1)} + Cumulative\ PoF_{(i)}\ [1] \tag{3.27}$$

where: "i" represents the year in which the probability of failure will be calculated.

, An after-inspection risk profile is developed for each scenario. The maximum failure risk, which is in the last year of the service life, is then determined from the risk profile. The pipeline's inspection cash flow for each scenario is developed after embedding the cost data of the inspection operations. The net present value of the developed scenario is calculated after defining the economic parameters, including the interest rate(s) and inflation. Net present value is more commonly used to compare different scenarios' economic equivalency; however, it cannot be used for alternatives with different service lives. Monte Carlo simulation is applied to consider the uncertainties that exist in the cost of running the inspection tools and the economic parameters. The annual worth of each scenario is computed from Equations 3.28~ 3.30 (Parvizsedghy et al. 2014) :

$$\widetilde{NPV} = \sum_{t=1}^{n} \widetilde{Ct}\ (P|F, \tilde{\imath}, t) = \sum_{t=1}^{n} \widetilde{Ct}\ * \frac{1}{(1+\tilde{\imath})^{t}} \tag{3.28}$$

$$\widetilde{EUAC} = \widetilde{NPV}\ (A|P, \tilde{\imath},\ n) \tag{3.29}$$

$$(A|P, \tilde{\imath},\ n) = \frac{\tilde{\imath}(1+\tilde{\imath})^{n}}{(1+\tilde{\imath})^{n}-1} \tag{3.30}$$

where $\widetilde{NPV}$ is the probability distribution function of the net present value of the cash flow under evaluation;

$\widetilde{Ct}$: The probability distribution function of total cost elements in year *t,*

---

[1] *Assuming: Cumulative* $PoF_1 = PoF_1$

n: The service life of the pipeline in years,

$\tilde{\iota}$: The probability distribution function of the forecasted interest rate for the planning horizon of the pipeline's service life, and

$(A|P, \tilde{\iota}, n)$: The probability distribution function of conversion factor from present worth to equivalent uniform annual worth.

In order to perform a pipeline's inspection planning, its risk profile is developed, considering the effect of inspection on the risk of failure. After selecting the inspection technique or the combination of inspection techniques for a scenario, the risk reduction index is calculated for those techniques. The risk reduction index is computed from Equations 3.31 and 3.32.

$$DC_i = \frac{\sum_{j=1}^{6}(P_j \times \overline{C_{j_i}})}{\sum_{j=1}^{6} P_j} \tag{3.31}$$

$$RR_i = DC_i \times A_i \tag{3.32}$$

where P_j is the probability of failure with respect to the failure source "j", $\overline{C_{j_i}}$ is the fuzzified capability of detecting the failure source "j", DC_i determines the detection capability of inspection tool "i", A_i: the accuracy of that inspection tool, and RR_i: represents the risk reduction percentage of inspection technique "i".

The accuracy percentage of each inspection tool is computed using Equation 3.33. This variable measures the accuracy of the tool.

$$A_{p.i} = mean. \left| \frac{\widetilde{\widetilde{DS} + \widetilde{A_i}}}{\widetilde{DS}} - 1 \right| \tag{3.33}$$

where A_i is the accuracy percentage of inspection tool "i", $\widetilde{DS}$ is the distribution function of the defect size that can be detected with inspection tool "i", and $\widetilde{A_i}$ is the distribution function of the accuracy of inspection tool "i".

After calculating the inspection life cycle cost and developing the pipeline's risk profile, the most effective inspection scenarios are proposed based on their Risk-Cost index. The risk-cost index of each scenario is calculated from Equation 3.34. The lower the index of a scenario the better it is.

$$\text{Risk-Cost index } (S_i) = \text{Max risk- } S_i \times (\text{Mean EUAC-}S_i) \tag{3.34}$$

where S_i is Scenario "i" of the inspection plan,

Max Risk S_i is the Maximum risk of scenario "i" found in the risk growth profile, and

Mean EUAC S_i is the Average uniform annual cost of scenario "i".

3.3.2 Rehabilitation Planning Model

The overall methodology to develop the rehabilitation planning model is shown in Figure 3-14. The model development started with a comprehensive review of the rehabilitation and maintenance types. The rehabilitation techniques are selected after reviewing the maintenance manuals and guidelines for the operation of oil and gas pipelines. The maintenance of oil and gas pipelines is categorized based on their type (i.e., regular maintenance, inspection, remedial actions, repair, and replacement). They are further categorized according to their sizes. Based on the assumption that there is a direct reverse relationship between risk growth and a pipe's condition during its service life, a risk-based deterioration profile is developed. As a result, the risk growth profile that is developed in the inspection planning model is reversed to forecast the deterioration of pipes before intervention. This profile is then used to select the required actions of rehabilitation during the life cycle of such pipes.

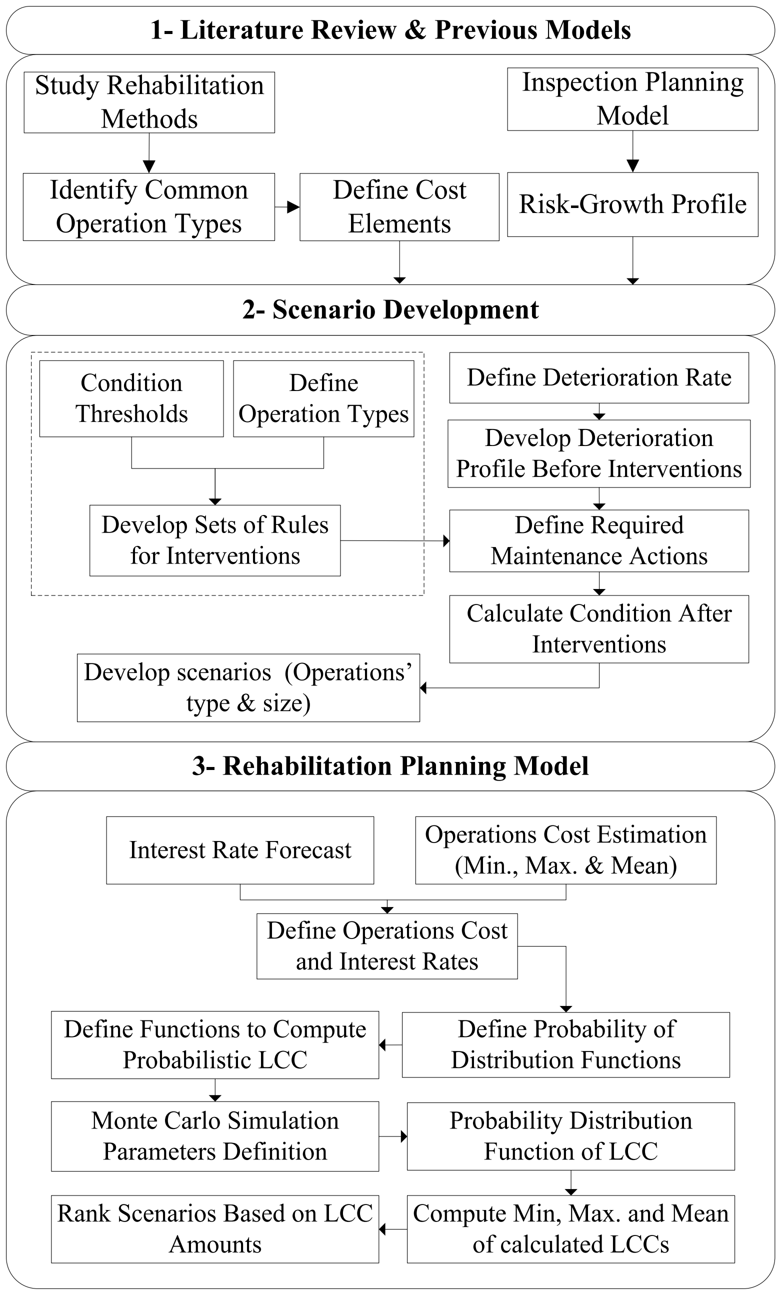


Figure 3- 14: Rehabilitation planning model development flowchart

The impact of each rehabilitation type and size on the pipe condition after intervention is studied and a methodology is developed to calculate pipeline condition after rehabilitation. The related cost data is either gathered from previous studies or calculated using the available cost estimates of various repair types. Several combinations of maintenance operation types are considered in the development of the maintenance scenarios. A set of rules are developed to define condition thresholds for the execution of maintenance operation types.

Two types of plans, conservative and regular, are specified. The regular plans impose a set of rehabilitation condition thresholds for different operation types (e.g., coating, repair, replacement) that are lower than those imposed by the conservative ones. Thus, it is the conservative plans that should be used for high-risk pipelines. It is worth noting that the maintenance operations in a conservative plan start sooner than those in a regular one. Each plan is composed of three groups of scenarios. Each group of scenarios is composed of certain types of maintenance operations (i.e., repair and recoat) of various sizes. The condition thresholds specify the time and the type of the necessary maintenance operations. Three groups of maintenance scenarios are considered in each plan. Each scenario group consists of several maintenance scenarios based on the size of the defect. Each maintenance scenario is defined by the following parameters: 1) scenario group; 2) size of the defect; and 3) repair type (i.e., sleeves or clamps).

The required maintenance actions are forecasted by considering the condition of a pipeline before the rehabilitation action and the set of rules for each scenario group. A method is developed to calculate the pipeline condition after each rehabilitation type. The size of the repair or replacement not only affects the cost of the maintenance technique, but also the increment of the condition, which is the improvement in the overall pipeline condition due to a maintenance action. Equations 3.35--3.37 estimate the condition increment of every size of recoat, repair, and replacement, respectively.

$$CI_{\text{recoat}} = 0.5 \times (10\text{-OC}) \times \frac{S_n}{10} \tag{3.35}$$

$$CI_{\text{repair}} = 0.7 \times (10\text{-OC}) \times \frac{S_n}{10} \tag{3.36}$$

$$CI_{\text{replacement}} = (10\text{-OC}) \times \frac{S_n}{10} \tag{3.37}$$

where "CI" = condition increment for the maintenance operation, "OC" = current overall condition of a pipeline section, and "Sn" = size of the maintenance operation. The term "10 - OC" represents the difference between the current overall condition and the maximum condition of a pipeline, namely, "10" (i.e., the condition of a newly constructed pipeline).

Determining the maintenance operations and their execution time over the life cycle of the pipeline requires the development of deterioration profiles after the rehabilitation interventions for each scenario. Consequently, a profile defines a maintenance scenario and determines the time and type of the maintenance operations that need to be carried out each year. The collected operations' costs are then used to forecast the cash flow of the pipeline's maintenance over its life cycle.

Finally, the cash flows of the maintenance scenarios are calculated using Microsoft Excel (Microsoft Group 2010). A Monte Carlo simulation is used to compute the Net Present Value (NPV) distribution function of each maintenance scenario. The probability distribution functions of the maintenance operation costs and the interest rates are defined using @Risk 6 (PALISADE 2013). The probability distribution functions are used to address the uncertainties in the estimation of the maintenance operation costs and the future interest rates. The distribution functions are defined as triangular functions. The standard parameters of triangular distribution functions are the minimum, maximum, and most likely values, which are defined in the model. After defining the distribution functions of the maintenance operation costs and interest rates, the NPV of each scenario is calculated. For each scenario, the computations on the simulated model are iterated for 1,000 times. The distribution function that best fits the calculated NPV amounts is determined, and the minimum, maximum, and mean values of each scenario are reported. This process is repeated for each scenario. The obtained NPV mean values are used to rank the scenarios. Finally, the scenarios with the lowest NPV values are selected as the optimum maintenance scenarios during the service life of the pipeline.

CHAPTER 4: DATA COLLECTION

Several countries have recorded data of the failures of oil and gas pipelines, and a few have published data. Some have reported processed data on the causes and consequences of failures periodically, and some have published raw data on each failure. Among published databases, authors found the database of the pipeline and hazardous materials safety administration ($PHMSA_a$ 2014) of the US Department of transportation the most complete one. It contains data on various types of pipelines in different classifications. This database has divided data according to the classification of pipelines (i.e. gas transmission and gathering, gas distribution and hazardous liquid pipelines). It has recorded general data of each failed pipeline, location-related data of incidents, and information related to the operators. Furthermore, it provides detailed data about each failure: the cause of the failure, the cost and the environmental consequences of the incident, and the overall inspections that have been done during the pipeline's operation. Installation year of pipelines, date of failure, maximum allowable operating pressure, SMYS have been recorded exactly as a numerical value while there are some linguistic or binary values for some inspection related parameters.

Rules of defining failures have been changed through the time. Also, the recorded data has been modified over the years. Consequently, the database is divided into several date periods each of which reports different parameters of failures and pipelines. Data includes date ranges from 1970 to 1984, 1986 to 2001, 2002 to 2009 and 2010 to 2013. Each dataset includes different categories of the failed pipelines. For example dataset of gas pipelines which has recorded failures from 1970-1984 has data on soil properties. This data will be helpful in determining the effect of soil properties on the failures of oil and gas pipelines. Consequently, in each part of the model the parameters that are needed are studied to select the most appropriate ones. Table 4-1 shows sample data existed in the dataset of the gas transmission and gathering pipes that is recorded on the failure of 2010 to 2014. Appendix A shows all existing data variables in the same dataset.

Table 4- 1: Sample data excel sheet (PHMSA$_a$ 2014)

OPERATOI	Operator NAME	IYEAR	LATITUDI	LONGITUD	COMMODITY	RELEASE	FATAL	INJURI	IGNITE	EXPLODE	ON_OFF	DEPTH_OI	CROSSING
18516	SOUTHERN NATURAL GAS CO	2010	33.11	-89.15	NATURAL GAS	41176	0	0	NO	NO	ONSHORE	60	NO
31711	SOUTHERN STAR CENTRAL GAS PIPELINE,	2010	37.94	-98.26	NATURAL GAS	91089	0	0	NO	NO	ONSHORE	40	NO
32341	SOUTHEAST SUPPLY HEADER, LLC	2010	31.86	-90.33	NATURAL GAS	239	0	0	NO	NO	ONSHORE	108	NO
1007	KM INTERSTATE GAS TRANSMISSION CO	2010	40.49	-98.55	NATURAL GAS	2535	0	0	NO	NO	ONSHORE	41	NO
12696	CYPRESS GAS PIPELINE COMPANY	2010	29.00	-91.00	NATURAL GAS	4101	0	0	NO	NO	ONSHORE	2	NO
31286	ONEOK GAS TRANSPORTATION, LLC	2010	35.68	-96.95	NATURAL GAS	42800	0	0	YES	NO	ONSHORE	48	NO
4070	EAST TENNESSEE NATURAL GAS CO	2010	36.48	-82.55	NATURAL GAS	100	0	0	NO	NO	ONSHORE	30	NO
4280	EL PASO NATURAL GAS CO	2010	31.92	-104.43	NATURAL GAS	9	0	0	NO	NO	ONSHORE	30	NO
26330	ENOGEX LLC	2010	35.12	-96.20	NATURAL GAS	6	0	0	NO	NO	ONSHORE	42	NO
19570	WILLIAMS GAS PIPELINE - TRANSCO	2010	27.51	-97.98	NATURAL GAS	4	0	0	NO	NO	ONSHORE	65	NO
3	ACADIAN GAS PIPELINE SYSTEM	2010	29.92	-91.12	NATURAL GAS	6838	0	0	NO	NO	ONSHORE	36	YES
13750	NORTHERN NATURAL GAS CO	2010	44.49	-93.22	NATURAL GAS	1000	0	0	NO	NO	ONSHORE	84	NO
31728	GULF SOUTH PIPELINE COMPANY, LP	2010	29.80	-91.33	NATURAL GAS	188	0	0	NO	NO	ONSHORE	72	NO
405	ANR PIPELINE CO	2010	29.84	-93.05	NATURAL GAS	0.01	0	0	NO	NO	ONSHORE	36	NO
32099	ENERGY TRANSFER COMPANY	2010	29.86	-97.22	NATURAL GAS	208458	0	0	NO	NO	ONSHORE	42	NO
13120	NATURAL GAS PIPELINE CO OF AMERICA (	2010	37.00	-100.48	NATURAL GAS	1	0	0	NO	NO	ONSHORE	30	NO
4070	EAST TENNESSEE NATURAL GAS CO	2010	35.09	-85.21	NATURAL GAS	50	0	0	NO	NO	ONSHORE	30	NO
4070	EAST TENNESSEE NATURAL GAS CO	2010	35.11	-85.17	NATURAL GAS	50	0	0	NO	NO	ONSHORE	30	NO
32513	AMEREN ILLINOIS COMPANY	2010	39.56	-90.65	NATURAL GAS	48299	0	0	NO	NO	ONSHORE	24	NO
31728	GULF SOUTH PIPELINE COMPANY, LP	2010	30.98	-89.22	NATURAL GAS	24320	0	0	NO	NO	ONSHORE	36	NO
405	ANR PIPELINE CO	2010	29.86	-93.07	NATURAL GAS	1000	0	0	NO	NO	ONSHORE	36	NO
22655	WILLISTON BASIN INTERSTATE PIPELINE C	2010	48.52	-102.88	NATURAL GAS	5230	1	0	NO	NO	ONSHORE	40	NO
2564	COLORADO INTERSTATE GAS CO	2010	38.73	-102.93	NATURAL GAS	313870	0	0	NO	NO	ONSHORE	30	NO
19160	TENNESSEE GAS PIPELINE CO (EL PASO)	2010	29.53	-96.14	NATURAL GAS	69908	0	0	NO	NO	ONSHORE	39	NO

DIAMETEF	THICKNES:	SMYS	PIPE_SPEC	SEAM_TYI	PIPE_MAI	COATING_	RELEASE	CLASS_LOCATION	HCA	DAMAGE (2013 $)	MOP_PSIG	CAUSE
24	0.25	52000	API 5L OR	DSAW	1952	COAL TAR	RUPTURE	CLASS 2 LOC	NO	399798	750	CORROSION FAILURE
26	0.281	60000	API - 5LX 6	LONGITUL	1967	COAL TAR	RUPTURE	CLASS 1 LOC	NO	974110.3	900	MATERIAL FAILURE OF PIPE OR WELD
42	1	70000	API 5L GR	DSAW	2007	FUSION B	LEAK	CLASS 1 LOC	NO	599603.7	1200	MATERIAL FAILURE OF PIPE OR WELD
16	0.25	35000	API 5L - GI	OTHER	1929	COAL TAR	RUPTURE	CLASS 1 LOC	NO	57002.02	720	MATERIAL FAILURE OF PIPE OR WELD
16	0.344	42000	API 5LX	LONGITUL	1952	OTHER	RUPTURE	CLASS 1 LOC	NO	586480.6	903	CORROSION FAILURE
26	0.25	52000	X-52	FLASH WE	1950	COAL TAR	RUPTURE	CLASS 1 LOC	NO	808915.8	600	CORROSION FAILURE
12.75	0.25	42000	API-5L	LONGITUL	1953	COAL TAR	LEAK	CLASS 2 LOC	NO	127563.5	706	EXCAVATION DAMAGE
26	0.303	52000	API 5L OR	DSAW	1947	COAL TAR	LEAK	CLASS 1 LOC	NO	114330.1	825	CORROSION FAILURE
8.625	0.188	42000	API 5L	LONGITUL	1981	COAL TAR	LEAK	CLASS 1 LOC	NO	12332.68	827	CORROSION FAILURE
24	0.281	52000	TGTC-1A	DSAW	1950	COAL TAR	LEAK	CLASS 1 LOC	NO	60967.76	878	CORROSION FAILURE
12.75	0.25	42000	API 5LX	LONGITUL	1964	OTHER	LEAK	CLASS 1 LOC	NO	378268.3	909	OTHER INCIDENT CAUSE
30	0.375	75000	API 5L	SINGLE SA	2008	FUSION B	LEAK	CLASS 1 LOC	NO	138410	1000	INCORRECT OPERATION
30	0.5	52000	API 5L	FLASH WE	1951	ASPHALT	LEAK	CLASS 1 LOC	NO	365946.5	936	MATERIAL FAILURE OF PIPE OR WELD
6.625	0.28	35000	API	OTHER	1955	COAL TAR	LEAK	CLASS 1 LOC	NO	54329.23	1090	CORROSION FAILURE
36	0.438	60000	API 5L	DSAW	1969	ASPHALT	RUPTURE	CLASS 1 LOC	NO	1866432	1050	OTHER INCIDENT CAUSE
26	0.25	52000	AO SMITH	OTHER	1948	COAL TAR	LEAK	CLASS 1 LOC	NO	158534.5	712	MATERIAL FAILURE OF PIPE OR WELD
12.75	0.25	42000	API-5L X-4	LONGITUL	1950	COMPOSI	LEAK	CLASS 3 LOC	NO	62167.54	823	MATERIAL FAILURE OF PIPE OR WELD
12.75	0.25	42000	API-5L X-4	LONGITUL	1950	COMPOSI	LEAK	CLASS 1 LOC	NO	64837.72	823	MATERIAL FAILURE OF PIPE OR WELD
8	0.188	35000	GRADE B	LONGITUL	1966	COAL TAR	MECHANI	CLASS 1 LOC	NO	321151.9	400	EXCAVATION DAMAGE
20	0.25	46000	API-5L	LONGITUL	1949	COAL TAR	RUPTURE	CLASS 1 LOC	NO	178704.9	550	MATERIAL FAILURE OF PIPE OR WELD
8.625	0.25	35000	API	OTHER	1956	COAL TAR	LEAK	CLASS 1 LOC	NO	73340.06	1090	CORROSION FAILURE
8.625	0.188	42000	API 5L	LONGITUL	1961	COAL TAR	MECHANI	CLASS 1 LOC	NO	42717.19	700	EXCAVATION DAMAGE
20	0.312	41000	API 5L OR	LONGITUL	1947	COAL TAR	RUPTURE	CLASS 1 LOC	NO	169221.6	920	MATERIAL FAILURE OF PIPE OR WELD
24	0.5	40000	API 5L OR	OTHER	1947	COAL TAR	RUPTURE	CLASS 1 LOC	NO	678168.2	750	CORROSION FAILURE

Figure 4-1 presents distribution of the failure sources in hazardous liquid pipelines during 1986-2013. Failures due to the external corrosion have received the first rank of the failures by frequency. Third-party failures stand in the second place followed by the failures due to the material and weld defect. Also, a considerable number of failures have been due to the internal corrosion, while equipment failures have caused the pipeline failure by 11%. Incorrect operations and natural forces stand after equipment failures. Natural forces, third party non-excavation, and operator excavation are the least likely causes of failure.

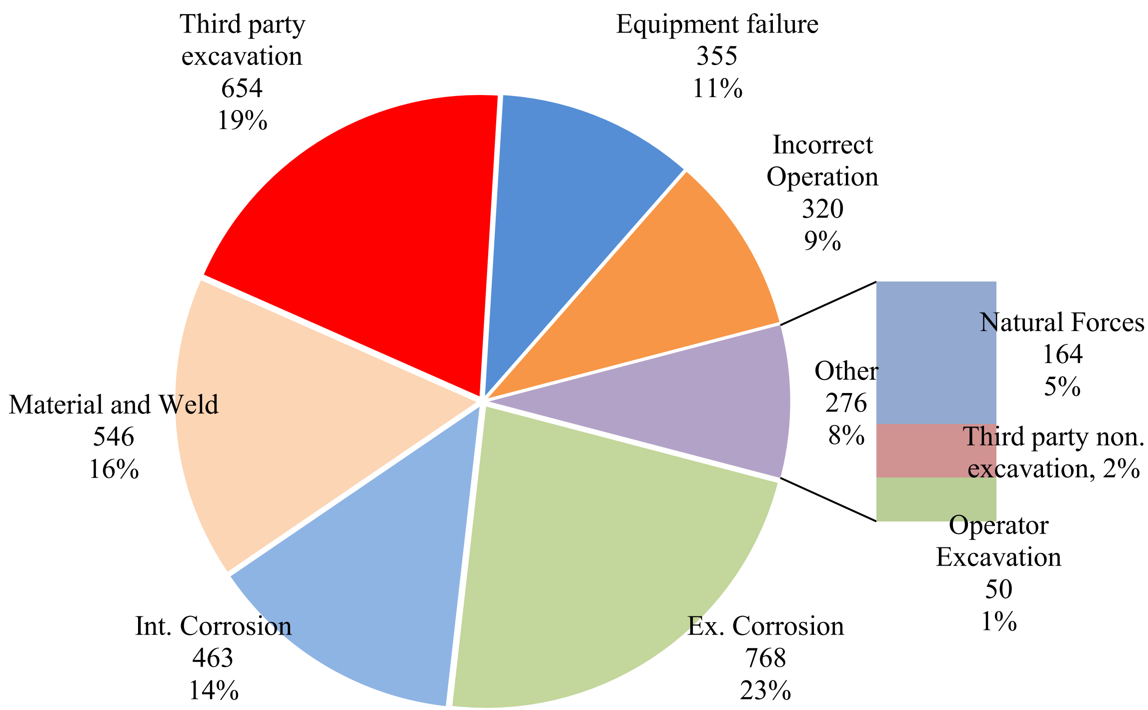


Figure 4- 1: Distribution of Failure Sources (1986-2013)

The risk assessment model in this research is developed mainly based on the historical data collected on the failures of pipes from the Pipeline and Hazardous Materials Safety Administration ($PHMSA_a$ 2014). Historical data is gathered from 1970 until now; the criteria of recording data changed over this time. Data on Hazardous Liquid (HL) pipelines is reported in four main reporting periods: 1) from 1970 to 1986, 2) from 1986 to 2001, 3) from 2002 to 2009, and 4) from 2010 until now. Data on gas pipelines is classified based on the type of the pipes first including gas transmission and gathering in one classification and distribution pipes in another classification. Data on the Transmission and gathering pipes is reported in similar reporting periods as HL pipes, except the first period that expands from 1970 to 1984. Reported data in each of the reporting periods is different, but all includes the basic properties of pipes such as diameter and wall thickness. $PHMSA_a$ (2014) defines an incident on the failed pipes as an event that resulted in the gas leakage and met 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". ($PHMSA_a$ 2014).

The second set of data is collected on the mileage reports of the pipes in the US that report mileage of data in each year of the reporting period ($PHMSA_b$ 2014). Mileage data of pipes was reported in each year within different categories of pipe diameter, installation year and pre-defined classification of HL and transmission and gathering, as well as the distribution pipes. Failure sources are studied in this research and the ones with the highest contribution to the incidents are identified. The identified sources included External Corrosion (EC), Internal Corrosion (IC), Material and Weld defects (MW), Mechanical Damages (MD), Incorrect Operations (IO) and Natural Forces (NF). Historical environment data on the NF sources of failures are collected from the National Oceanic and Atmospheric Administration of the US Department of Commerce (NOAA

2015). Data on the surface temperature, soil moisture and the wind speed in the locations that have been subject to the natural hazard failures are extracted. Figure 4-2 shows the extracted mean temperature map for North America in the month of January 2011. The average temperature in the month that pipe has failed is collected for all of the pipes that have failed due to the extreme temperature causes. Related data is located from similar figures.

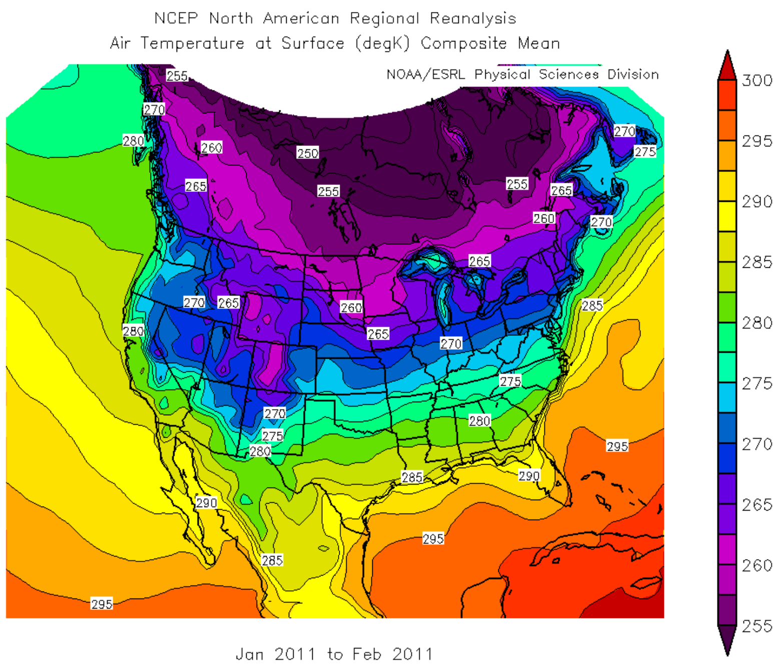


Figure 4- 2: Air temperature map of North America in January 2011 (NOAA 2015)

There is a possibility to zoom into the states of the US and locate the exact location of the incidents in the month of failure happening. The temperature data on the failure locations are obtained as a sample map is shown in Figure 4-3 that illustrates the map of Texas State in the month of January 2010. Figure 4-4 shows a sample data collection map of Texas State in the month of December 2014. Due to the importance of soil moisture on the failures after heavy precipitations, this factor is considered in the development of the indices for natural forces failure source. Related data is collected for every pipe that has failed due to high precipitation.

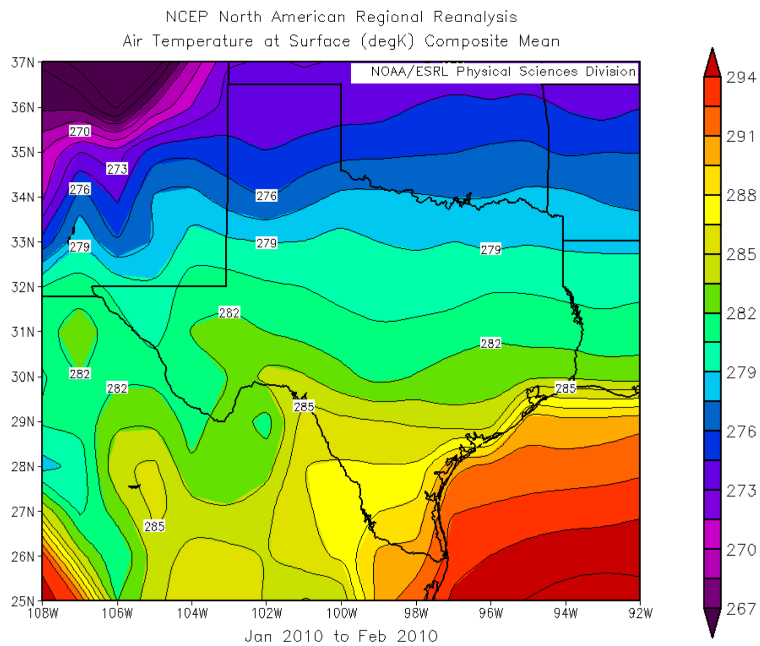


Figure 4- 3: Mean air temperature of Texas State in January 2010 (NOAA 2015)

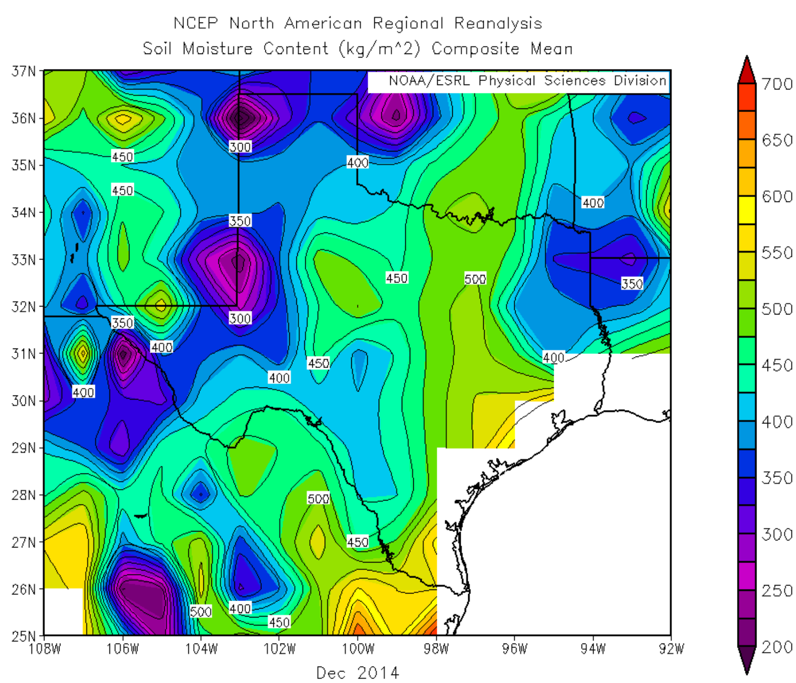


Figure 4- 4: Mean soil moisture content values for Texas State in December 2014

A sample wind speed map for the Texas State in the month of December 2014 is shown in Figure 4-5. Wind damage failures are the third source of natural force failures. Data on the actual wind speed is gathered in each failure location.

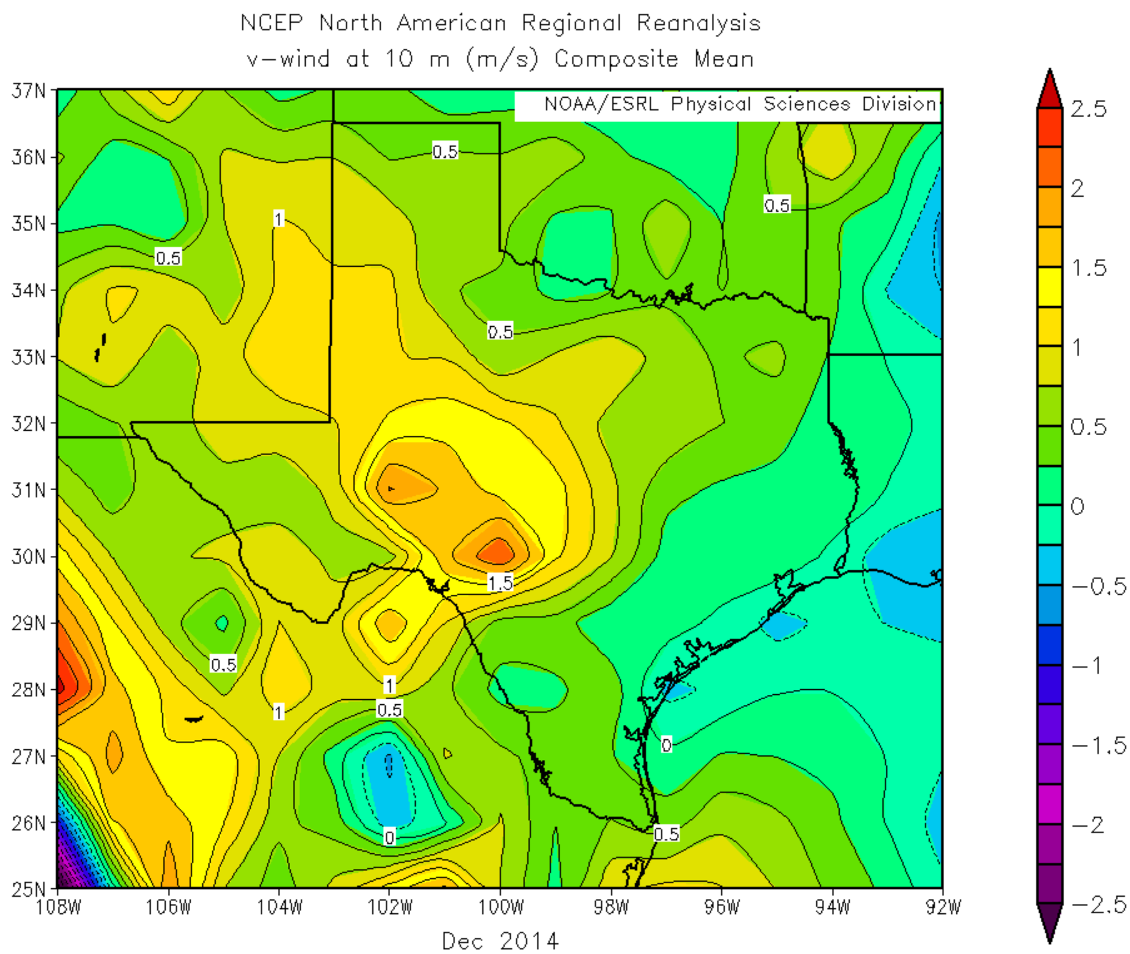


Figure 4- 5: Wind speed map for Texas State in December 2014

4.1 Frequency of Failure Sources versus Various Variables

In this section, the trend of frequencies for several variables will be studied against failure sources. Some variables have been selected as they may affect the failures of pipelines. These variables include age, pipe diameter, wall thickness, Maximum Operating (MOP) Pressure, Specified Minimum Yield Strength (SMYS) and coating type. Figure 4-6 shows how the frequency of failure sources changes in different age classes. From this figure, it is clear that frequency of failures due to external corrosion has increased by the age of pipelines. A similar trend happens to the failures due to internal corrosion in the first three decades of the pipelines' lives. Apart from the first age class, the number of failures due to the material and weld defects has been increased. However, the case is different for the failures with incorrect operation and equipment failure sources. The increasing trend for the first four decades of the failures due to third party excavation is also clear from the graph.

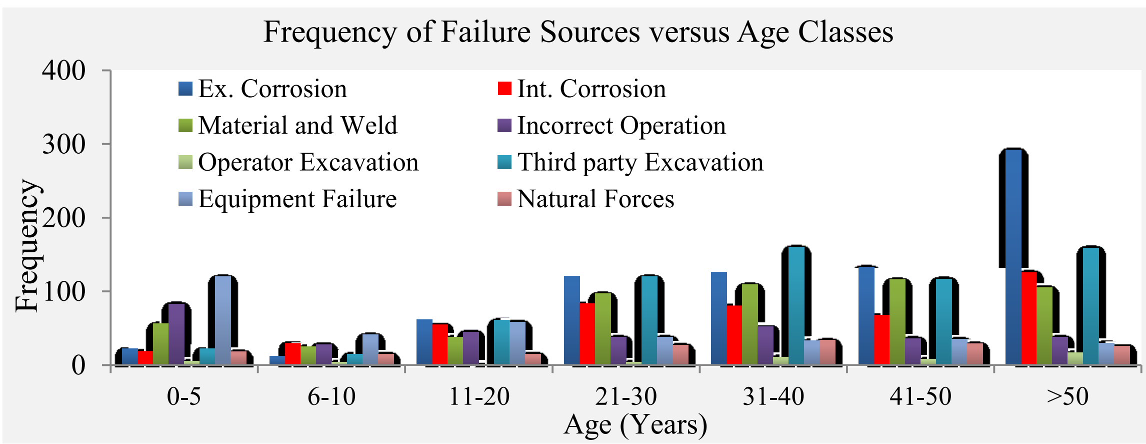


Figure 4- 6: Frequency of Failure Sources versus Age Classes (1986-2013)

Figure 4-7 depicts the distribution of failure sources in every pipe diameter class. For almost the entire failure sources, diameter class between five and eleven inches is the most frequent diameter class. After that, pipelines with a diameter between eleven and seventeen have devoted more failures to themselves. Another remarkable point of this graph is that the excavation failures have been more effective in smaller diameter classes than the larger ones. Whereas, corrosion-related failures have a higher percentage in the larger diameter classes.

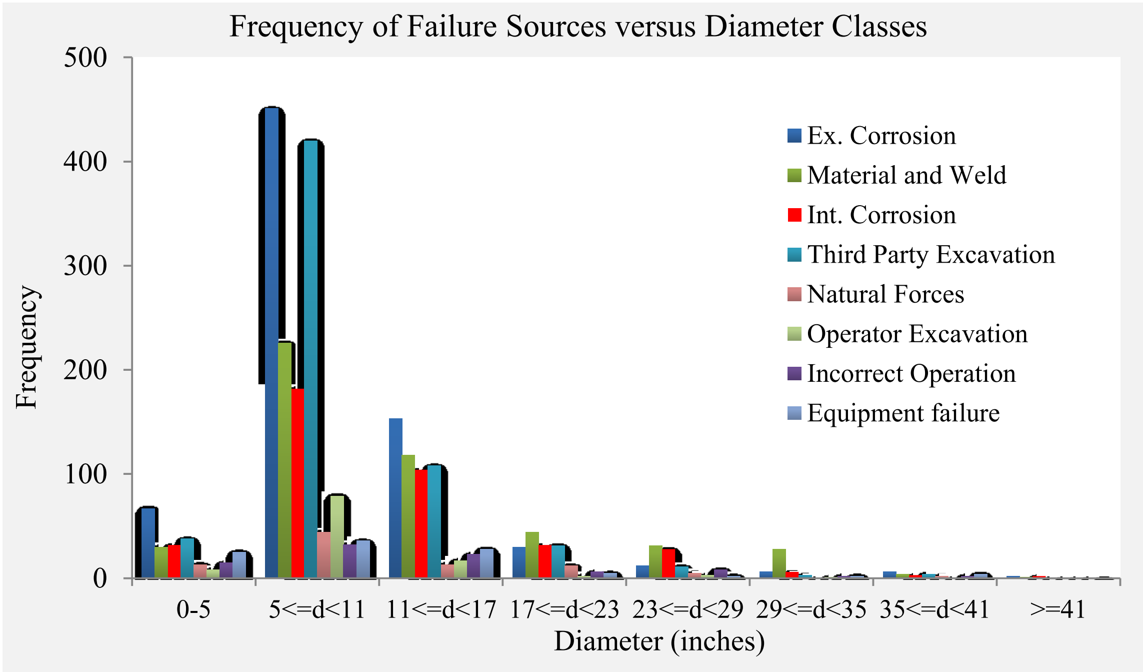


Figure 4- 7: Frequency of Failure Sources versus Diameter Classes (1986-2013)

Figure 4-8 shows the number of failure sources in each pipe wall thickness class. As shown in the figure, the overall number of failures decreases with increasing the thickness of pipelines.

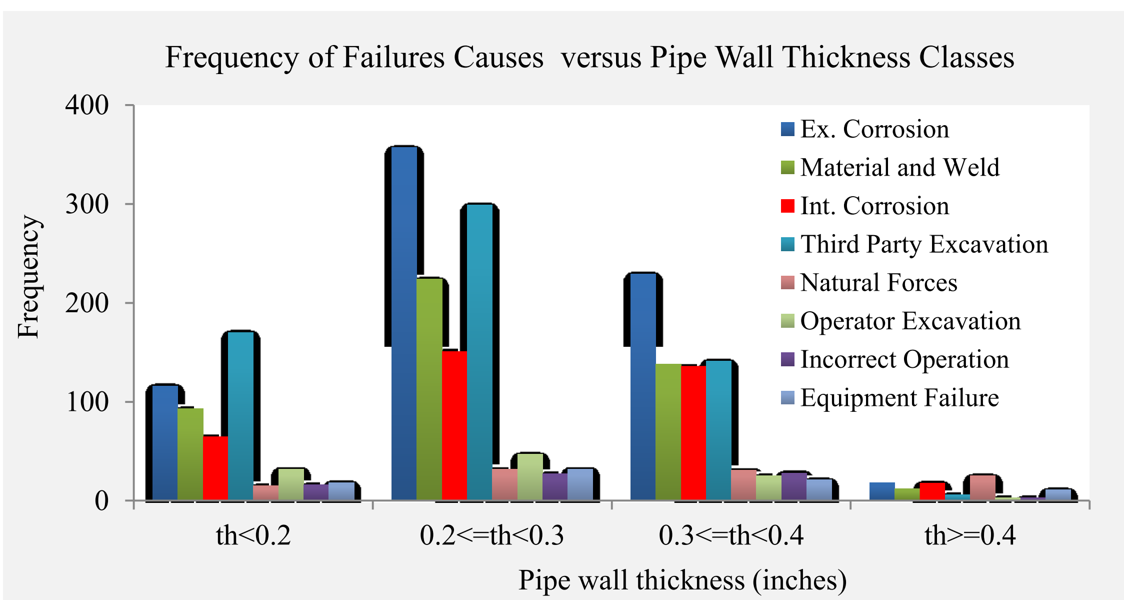


Figure 4- 8: Frequency of Failure Sources versus Pipe wall Thickness Classes (1986-2013)

Figure 4-9 presents the changes in the number of failure sources with respect to the Maximum Operating Pressure (MOP) of pipelines. Failures due to external corrosion, material and weld defects, and third party and operator excavation increase significantly with increasing the maximum allowable operating pressure of pipelines.

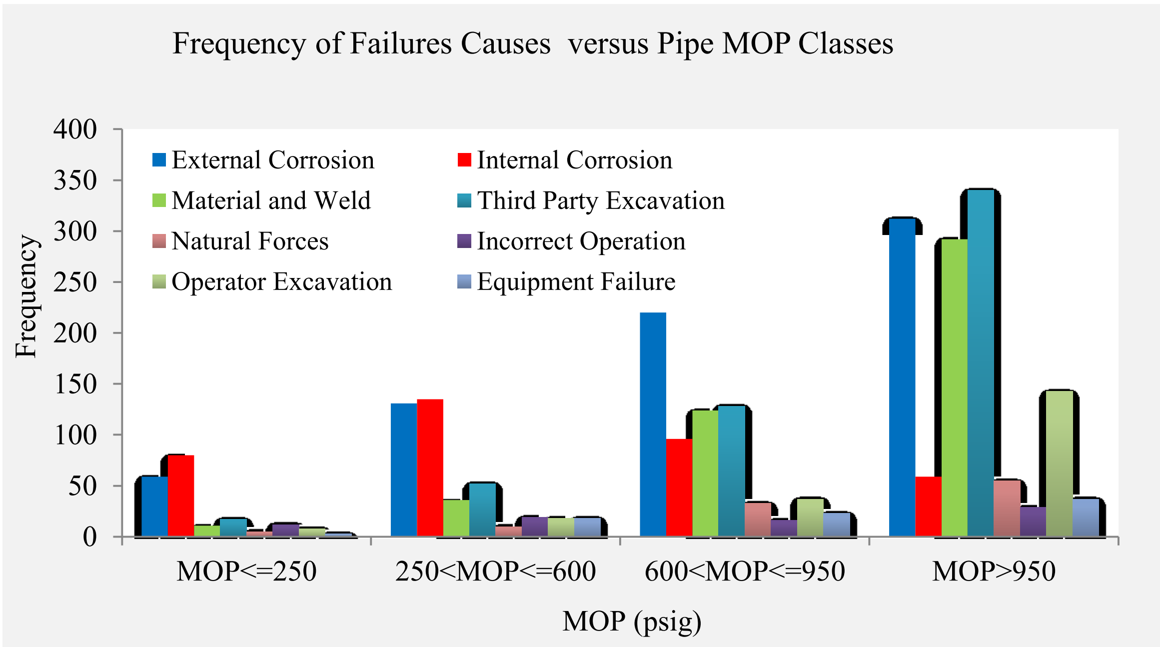


Figure 4- 9: Frequency of Failure Sources versus Pipe Maximum Operating Pressure (MOP) Classes (1986-2013)

Specified minimum yield strength also has a significant effect on the failures frequency as is evident from Figure 4-10. The number of failures due to internal corrosion regularly reduces as the SMYS of the pipelines goes up. The last class of SMYS, which is devoted to the pipelines with SMYS over 55,000, has the least number of failures in the entire failure sources. For the external corrosion, there is not a regular trend while most frequent failures happen in the first class of SMYS. However, material and weld failures are mostly attributed to the category of pipelines with SMYS between 45,000 and 55,000.

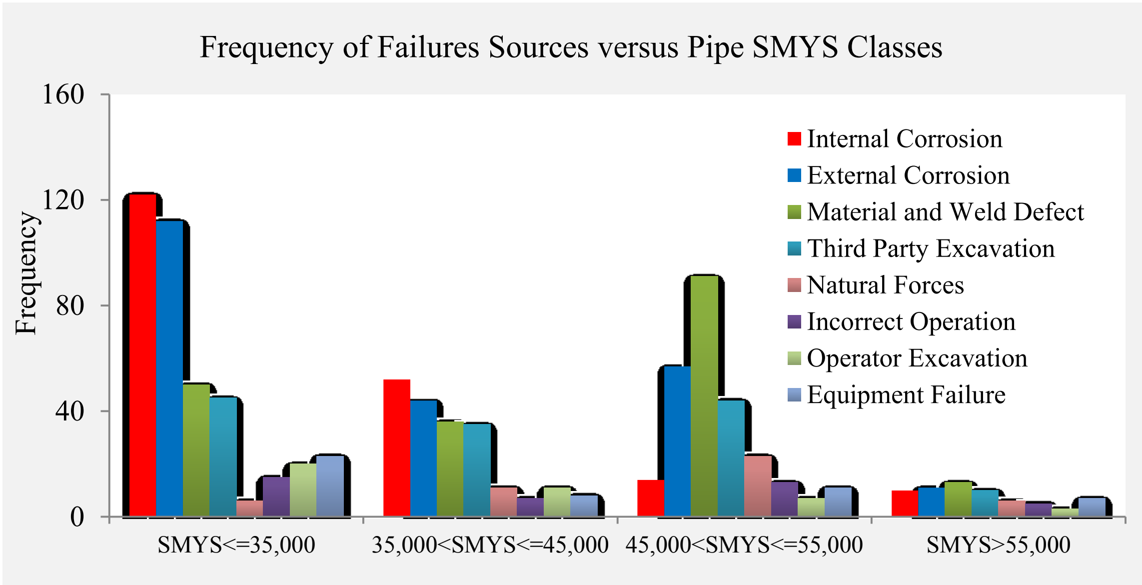


Figure 4- 10: Frequency of Failure Sources versus SMYS Classes (1986-2013)

Figure 4-11 depicts the number of failures for each coating type categorized by the failure sources. Cold tape, coal tar, and asphalt have been assigned the largest number of failures in almost all of the failure sources. Polyethylene and epoxy type of coating stand in the second place by the number of failures. Failures due to the external corrosion decrease exceptionally in the pipelines with polyethylene and epoxy coatings as well as "paint".

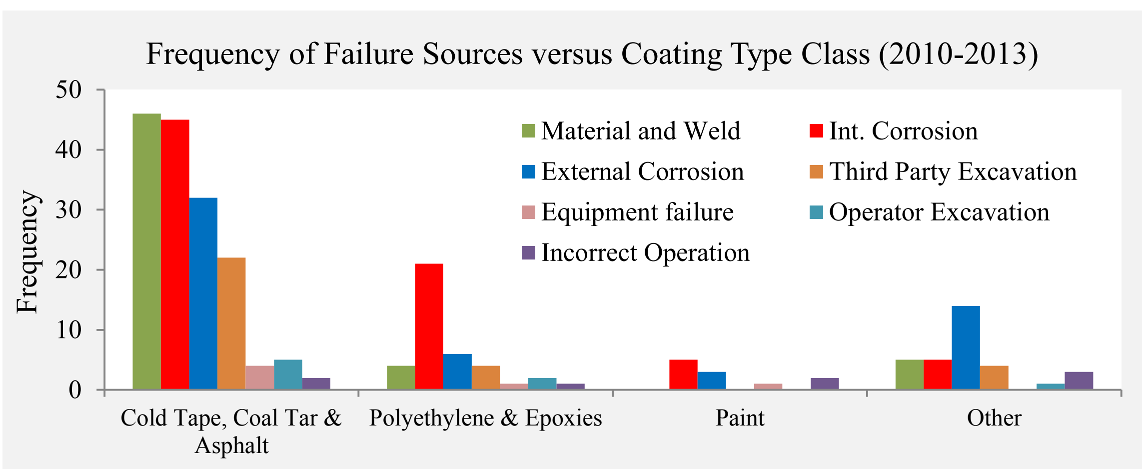


Figure 4- 11: Frequency of Failure Sources versus Coating Types (2010-2013)

4.2 Frequency of Failures in Monetary Consequence Classes

In this section, distributions of failures in three different monetary consequence classes are studied against several variables. Figure 4-12 studies the number of failures in monetary consequence classes versus the age of failure of pipelines. It can be seen that older pipelines result in higher monetary consequences. The number of failures with less than 10,000 US dollar consequences decrease for the first five decades of service life while it is increased in the last decade of study when the pipelines are older than 50 years old. However, except the first five years of pipeline service life the number of failures with consequences over 10,000 and 100,000 goes up over time.

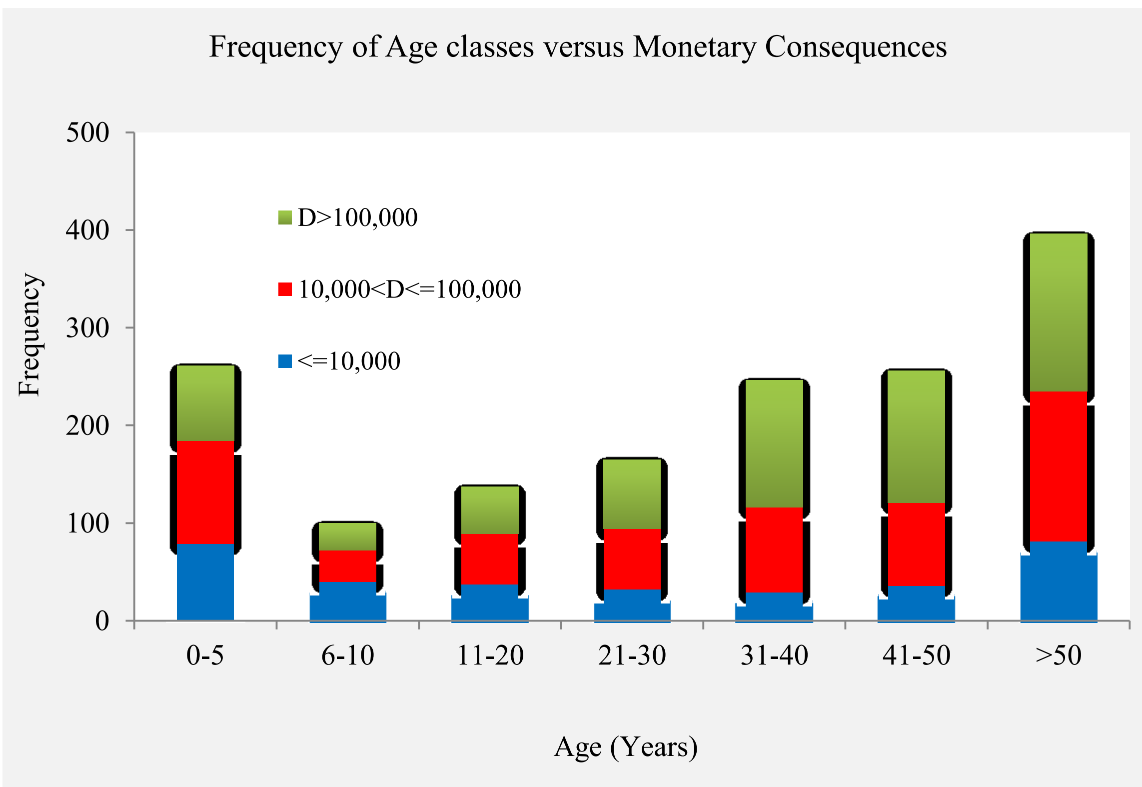


Figure 4- 12: Frequency of Age Classes versus Monetary Consequence Classes (1986-2013)

Figure 4-13 shows the number of failures in each monetary consequence class of failures against pipes' diameter classes. For the smallest diameter pipes, the monetary consequence is not huge. Failures result in similar consequence classes when the diameter of pipes is between five and eleven. However, the frequency of failures with higher consequences goes up for larger pipes while the percentage of the failures with small amount of consequences decreases in larger pipes. Figure 4-14 shows the frequency of failures in three pre-defined consequence classes versus pipe wall thickness classes. Overall, the number of failures with higher monetary consequences increases in pipes with thicker walls. The highest percentage of failures with consequences over 100,000 US dollar happens in the pipelines with a wall thickness between 0.2 and 0.3 inches.

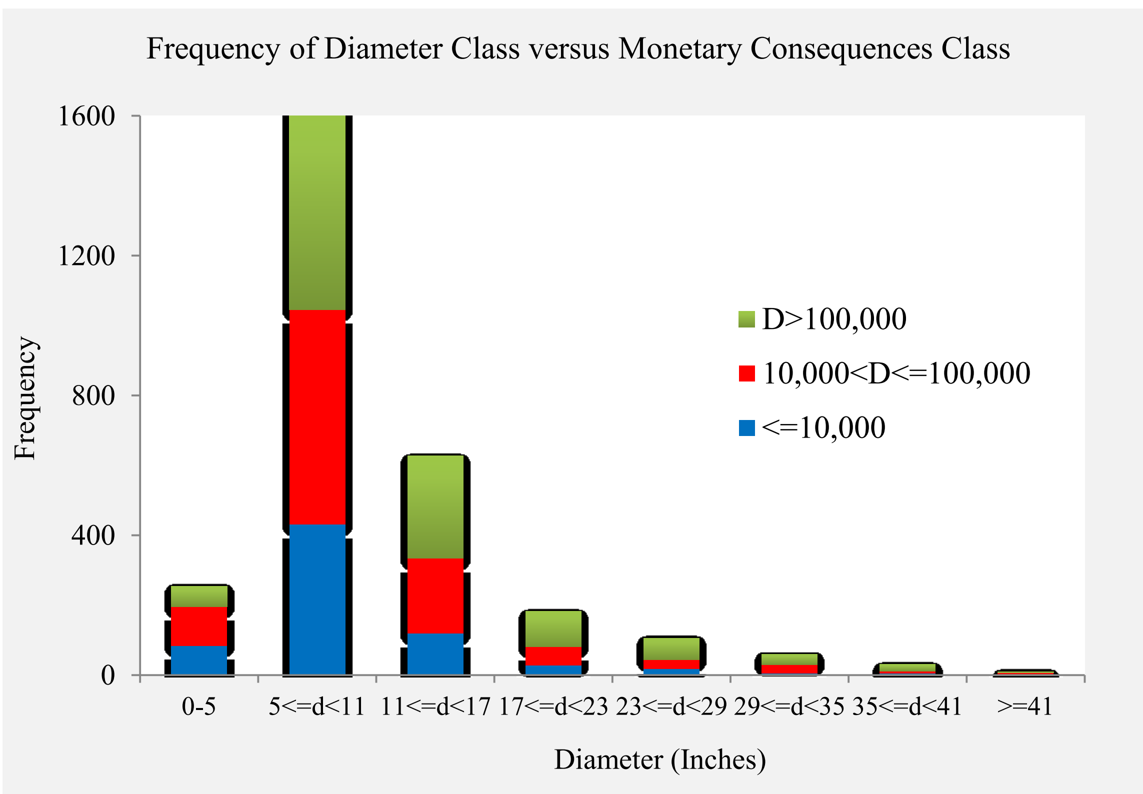


Figure 4- 13: Frequency of Diameter Classes versus Monetary Consequence Classes (1986-2013)

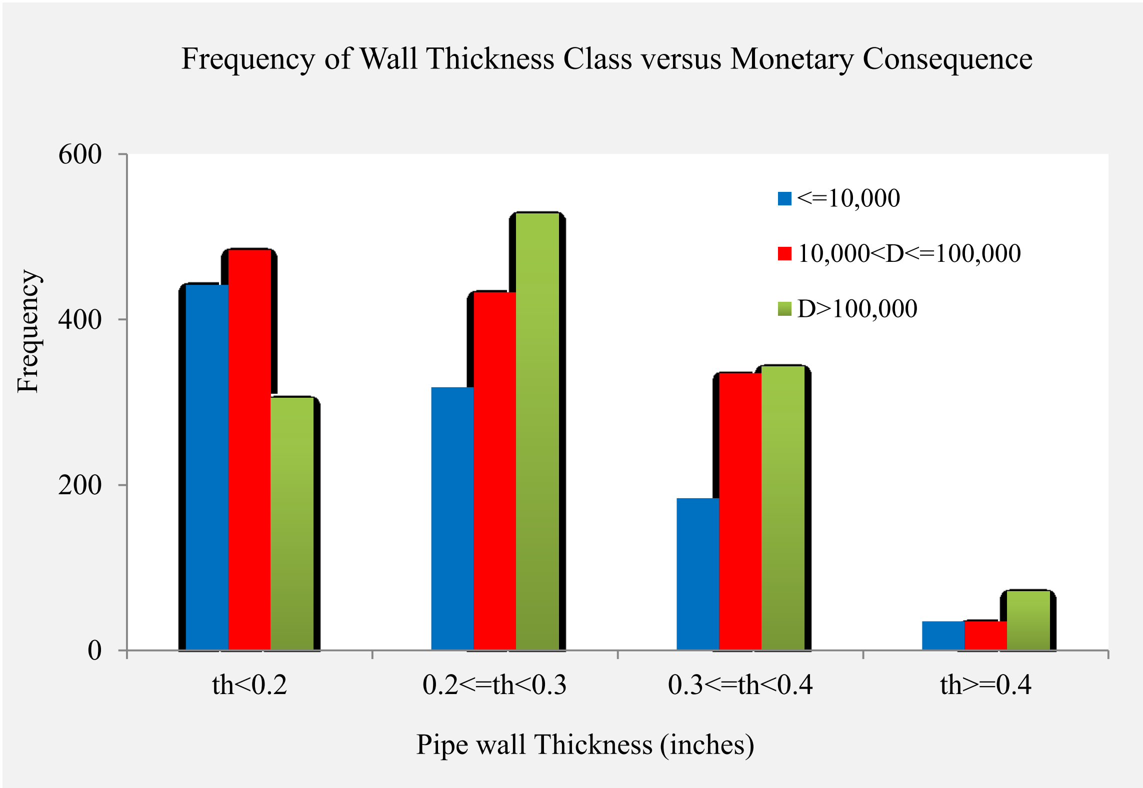


Figure 4- 14: Frequency of Wall Thickness Classes versus Monetary Consequence Classes (1986-2013)

Figure 4-15 depicts the number of failures with various consequence classes in different classes of the maximum operating pressure of pipelines. Overall, the consequences of failures in pipelines with higher pressures increase. Failures with over 100,000 US dollar consequences have the largest percentage of failures in pipelines with pressures more than 950 psig. This is not true for the pipelines with operating pressure limits. For example in the pipelines with pressure less than 250 and between 250 and 600, the failures with consequences between 10,000 and 100,000 have the highest percentage. Figure 4-16 studies the effect of the specified minimum yield strength on the failure consequences. The number of failures with less monetary consequences (i.e. less than 100,000 is decreasing when the SMYS of the pipes goes up. However, the failures result in higher consequences when the SMYS of the pipes are more than 45,000.

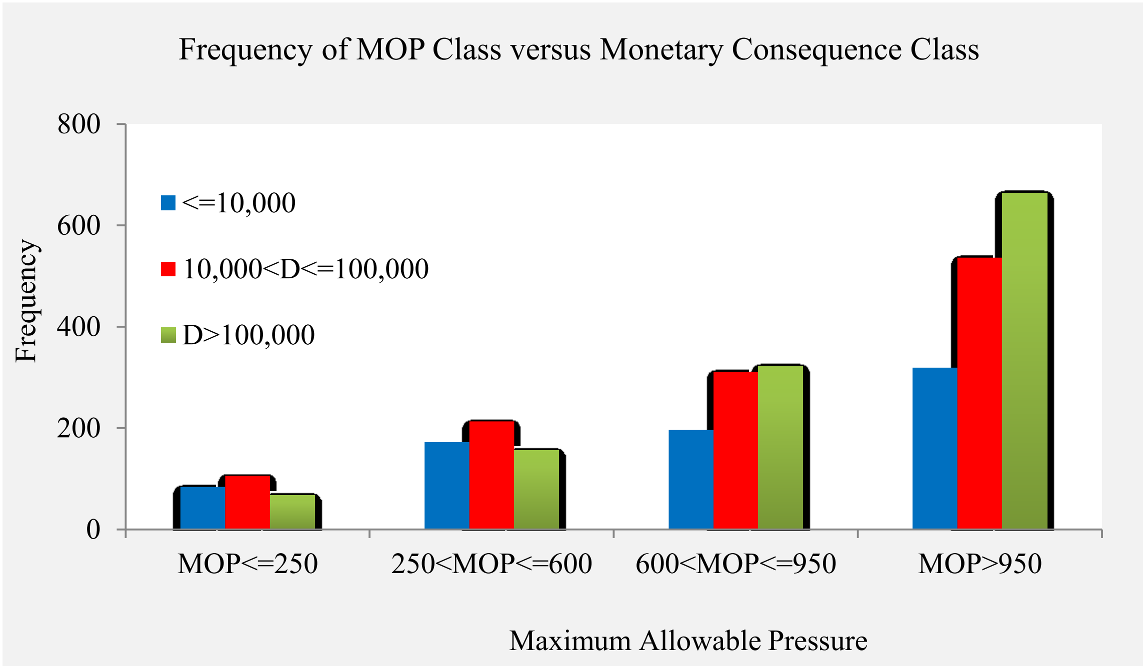


Figure 4- 15: Frequency of MOP Classes versus Monetary Consequence Classes (1986-2013)

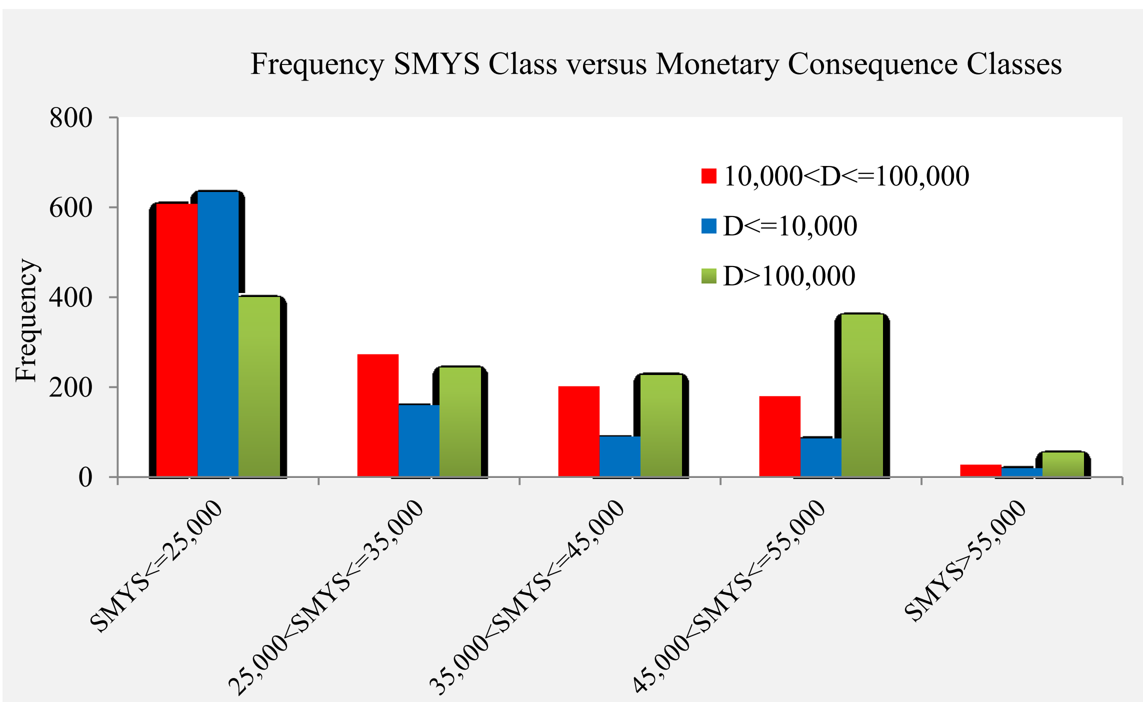


Figure 4- 16: Frequency of SMYS Classes versus Monetary Consequence Classes (1986-2013)

Studies present the effect of different variables on the number of failures and their monetary consequences. In the model development, the impact of different variables will be taken into consideration when the primary variables are needed to be identified.

4.3 Rehabilitation Cost Data

An extensive literature review was conducted to gather the data for the development of the life cycle cost model of oil and gas pipelines. The data includes the pipeline the economic factors during the pipeline service life. Life cycle cost models also require a set of economic factors such as maintenance operation costs and the interest and inflation rates. Menon (2005) detailed the most probable cost components during the construction and operation phases of gas pipelines. The research also detailed typical installation cost of pipelines with various diameters. The annual operating costs were estimated for a typical gas pipeline. Baker et al. (2008) summarized high and low cost per mile estimates of inline inspection for gas and oil pipelines. The costs were discounted using the historical inflation data published on the World Bank website (World-Bank, 2013) to convert to 2013 US dollars. The type of inspection, pipe diameter, wall thickness, and pipeline accessibility may change the cost of inline inspections. Repair cost data was gathered from a research conducted by the US Environmental Protection Agency (EPA, 2006). The study compared the repair and replacement cost of a 24” natural gas pipeline. The EPA’s research has detailed the repair and replacement costs of 6” and 24” pipeline defects. The assumptions and cost data used in the EPA’s research were used herein to estimate the cost of the different repair and replacement sizes. Table 4-2 shows the cost database that is used to implement the developed model.

Table 4- 2: Cost Data for Different Types of Rehabilitation Techniques (US $)

Operation Type	Minimum	Mean	Maximum
Regular Maintenance			
Regular Maintenance	22,500	25,000	28,750
Inspection			
Inline Inspection	3,500	4,000	4,600
Remedial Action			
Recoating S1	180,000	200,000	230,000
Recoating S2	324,000	360,000	414,000
Recoating S3	576,000	640,000	736,000
Recoating S4	630,000	700,000	805,000
Recoating S5	648,000	720,000	828,000
Recoating S6	720,000	800,000	920,000
Recoating S7	900,000	1,000,000	1,150,000
Repair			
Type B Sleeve S1	353,116	392,352	451,204
Type B Sleeve S2	369,021	410,023	471,526
Type B Sleeve S3	400,829	445,366	512,171
Type B Sleeve S4	464,447	516,052	593,460
Type B Sleeve S5	575,777	639,753	735,715
Type B Sleeve S6	655,299	728,110	837,327
Type B Sleeve S7	973,386	1,081,540	1,243,771
Bolt on Clamp S1	388,428	431,587	496,325
Bolt on Clamp S2	405,923	451,025	518,679
Bolt on Clamp S3	440,912	489,903	563,388
Bolt on Clamp S4	510,891	567,657	652,806
Bolt on Clamp S5	633,355	703,728	809,287
Bolt on Clamp S6	720,829	800,921	921,059
Bolt on Clamp S7	1,070,725	1,189,694	1,368,148
Replace			
Replace S1	675,000	750,000	862,500
Replace S2	810,000	900,000	1,035,000
Replace S3	1,440,000	1,600,000	1,840,000
Replace S4	1,575,000	1,750,000	2,012,500
Replace S5	1,620,000	1,800,000	2,070,000
Replace S6	1,800,000	2,000,000	2,300,000
Replace S7	2,250,000	2,500,000	2,875,000

The costs collected from the literature were discounted using historical inflation rates. The uncertainty in the cost estimation was also considered herein. The calculated and collected costs were considered in this study as average costs. These average cost values were then multiplied, respectively, by 0.9 and 1.15 to obtain the minimum and maximum operation costs for a 24” gas pipeline. The interest rate is expressed using a distribution function based on the interest rates in the USA between the years of 1992 and 2008. The function follows a triangular probability distribution with the minimum at 3%, the most likely at 4%, and the maximum at 6%.

CHAPTER 5: MODEL DEVELOPMENT AND IMPLEMENTATION

In this chapter, the methodology proposed in chapter 3 is applied to develop the model. Figure 5-1 shows the overall process of the model development and implementation process in the parts that need extensive data analysis or development. As shown, first a Bow-tie model is developed based on the identification of the basic events, causes of failures, and the after-failure events. Then, historical data is gathered from the Pipeline and Hazardous Materials Safety Administration ($PHMSA_a$ 2014) of the US department of transportation. Data is used to develop the risk assessment model and verify the validation of the developed methodology. In the probability of failure prediction model the identified variables are categorized, then a comprehensive index is developed that along with the developed equations can be used to predict the probability of failure of such pipelines.

For the consequence of failure assessment model, neuro-fuzzy is used to develop several Fuzzy Inference Systems (FIS) to minimize the error of the final model in the estimation of the financial consequence of failures. The selection of the final model is based on the error of the developed models and sensitivity analysis. Risk level is evaluated for each failure source developing a fuzzy integrated risk evaluation model. Inspection planning model uses the results of risk assessment to select the inspection tool and determine the frequency of running them. Various scenarios are developed for each of which an after-inspection risk growth profile is developed. The risk-cost index is the determining factor in ranking the scenarios of inspection. Rehabilitation planning model categorizes various rehabilitation techniques and develops different scenarios of rehabilitation considering possible defects' sizes. After-rehabilitation deterioration profile is developed for each scenario, and the life cycle cost is estimated using Monte-Carlo simulation. Top scenarios are those that are less expensive during the service life of the pipes.

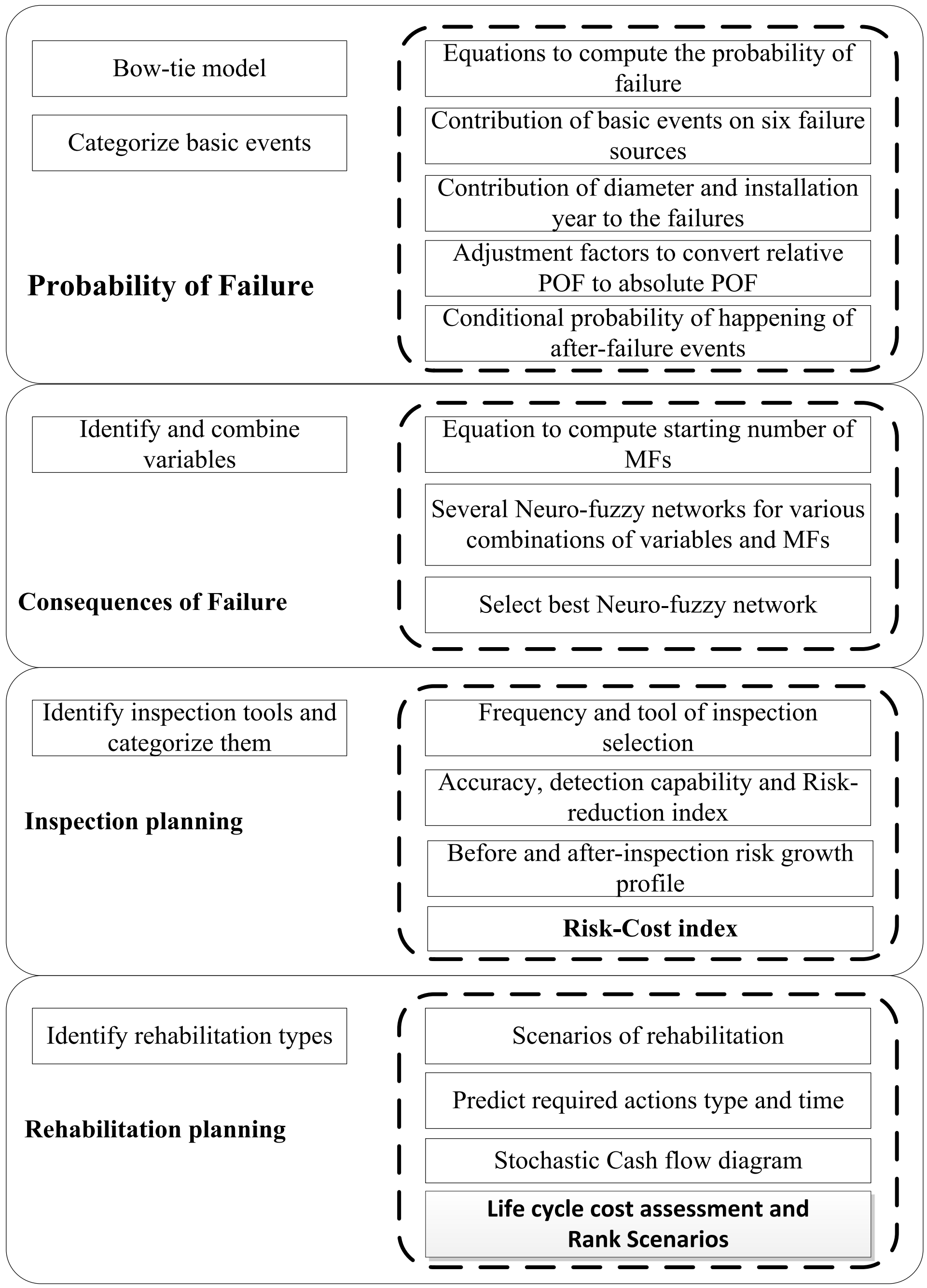


Figure 5- 1: Model development and implementation overall process

5.1 Bow-Tie

The identified variables and failure sources in the previous section are used to build the Bow-tie model. Fault tree is built with modifications on Dawotola et al. (2009), Yuhua and Datao (2005) and Shahriar et al. (2012) that is made by consulting with higher experts of oil and gas pipelines. Finally, the fault tree is developed, which is presented in Figure 5-2. The primary objective of applying the modifications to the fault tree was to increase the objectivity of the model by applying the available historical data on the failures of oil and gas pipelines.

The basic events are aimed to be measurable and hence to increase the objectivity of the model in this research depending on the availability of data in the database. Six main failure sources are considered to be evaluated in this model. Due to the unavailability of data on some variables in the database of oil pipes, computer-based inspection efficiency, notification of One-call system and marking of the pipes are excluded from the index of such pipes. According to the Bow-tie model, the basic causes of the failures are presented in the lowest level of the tree that lead to six main failure sources, which are connected to the top event of the tree. External corrosion failures are identified to be affected by the soil corrosion and protection measures. Soil corrosion itself is affected by the soil properties including soil acidity (pH), soil resistivity, and redox potential of the pipe. Each variable is supposed to have a contribution to soil corrosion intermediate event that can lead to the external corrosion of the pipe.

Protection measures are detailed into cathodic protection effectiveness and pipe coating types. Types of the product transporting through the pipe, inline inspection and protection measures are identified to affect the Internal Corrosion failures. For material and weld defect sources, the seam type of pipes, Specified Minimum Yield Strength (SMYS) and the inspection history are identified to have a contribution on the probability of failure. The fourth source of failure is identified as mechanical damages leading to the failures of pipes. The identified basic causes are identified as the location class, existence of computer-based inspection system (SCADA or CPM), existence of highly populated area, One-call center being notified before excavation and the accurate marking of the pipes. For incorrect operations, the identified variables are SCADA or CPM efficiency, qualification of the operator performing the task, operating pressure, and location of the pipes.

Natural forces are identified to happen as a result of heavy rains, extreme temperatures, and high winds. Consequently, temperature, precipitation and wind speed are identified to affect such failures. Heavy rain or precipitation is measured through the soil moisture in the locations that such failures have happened according to the historical database. In the next step, the major hazards that were identified in the previous section are used to develop the event tree. The event tree model is adopted from Parvizsedghy and Zayed (2015_b). Figure 5-3 presents the event tree, which presents the after-failure events. The center of the tree is the critical event of a pipeline failure that leads to the post-failure events containing the explosion, ignition, and leakages. Puncture, leakage, and rupture are three pre-failure events that cause the release of oil or gas in pipelines. Puncture is considered to be a medium size defect on the pipe, and pinhole represents small size defects leading to leakages. A rupture is a large size defect when the pipe is not serviceable anymore.

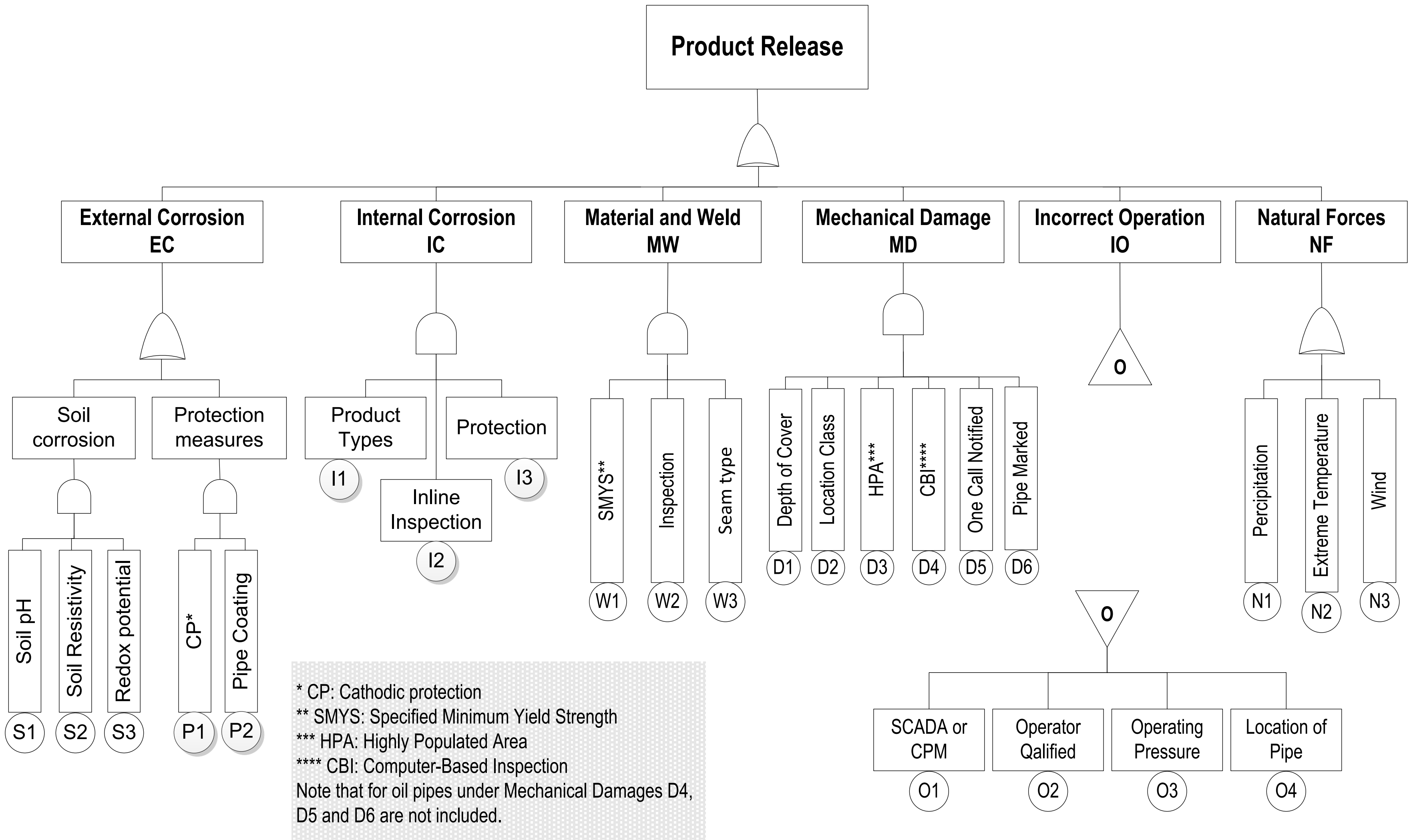


Figure 5- 2: Bow-Tie model (Fault tree part)

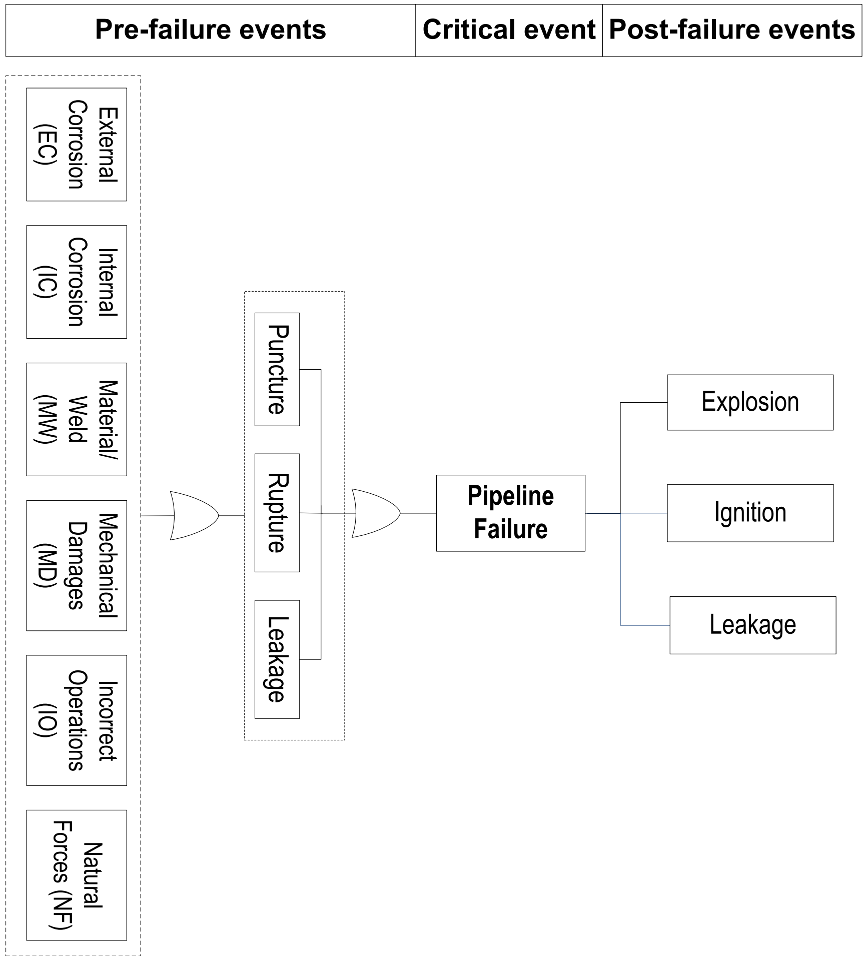
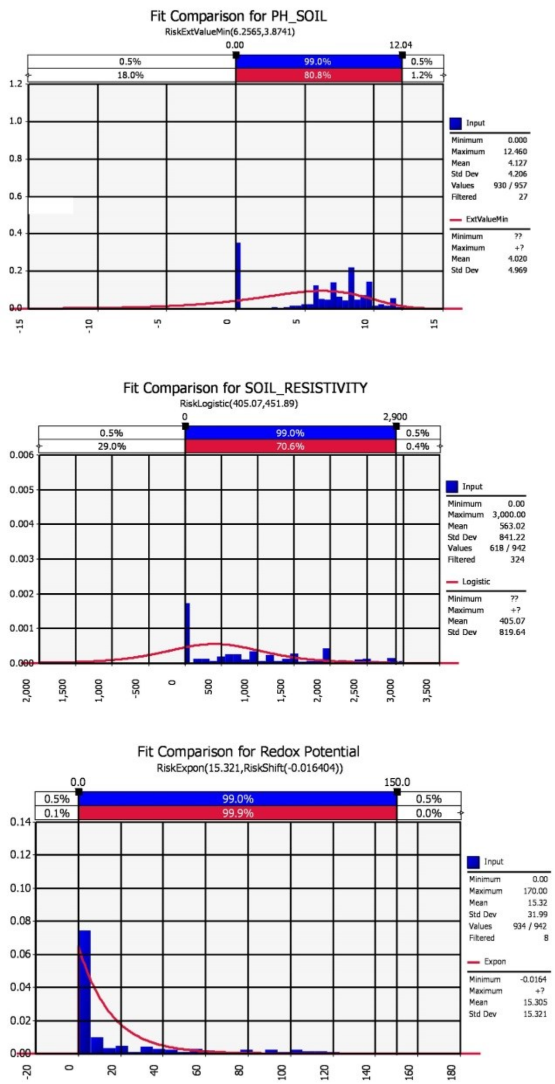


Figure 5- 3: Event tree part of Bow-tie model

5.2 Probability of Failure Prediction Model

The analysis starts after the development of the Bow-tie model. First, the identified variables or basic causes are categorized according to their characteristics. For quantitative variables such as the causes leading to soil corrosion, first the best PDF that fits the historical data of the failed pipes for each variable is determined. Then, the 99% confidence interval is divided into various categories. Different numbers of categories are tested to find the best number of categories that suits the variable. This is due to the existence of the missing data and errors that exist in the database and for some of the variables there is not enough data. Figure 5-4 shows the probability distribution function corresponding to the historical data related to the basic causes of soil corrosion for pipes that have failed due to the external corrosion. Part “A”, “B”, and “C” of the figure present the PDF related to the soil acidity (i.e. pH), Soil Resistivity (SR), and Redox Potential (RP). As shown, the 99% range of soil pH falls within zero to twelve, SR within zero to 2,900, and RP zero to 150. The ranges are then classified in the proper numbers of categories.



A

B

C

Figure 5- 4: PDFs associated with A: pH, B: SR, and C: RP historical data

For coating type and some other basic causes that are qualitative, the installation year of the pipes that exist in the database is used to determine the categories. Consequently, as shown in Table 5-1 coating type is categorized into 4 clusters. The first cluster belongs to the pipes with coal tar, asphalt, and paint coatings. Calculated values for each category of the basic causes are used to determine the best PDF that fits the contribution of that basic cause to the failure of the pipe. This process is performed applying @Risk 6 software. This process is repeated for each category of the basic causes, and the best PDFs are selected to represent the contribution of each category of the variables to the failure of pipes. The calculated amounts and PDFs are used to compute the relative probability of failures for each pipe in a particular environment and with specific properties.

Table 5- 1: Coating types categories

Category	Average year of Installation	Coating Types
1	1954	Coal Tar, Asphalt, Paint
2	1970	Cold Applied Tape, Composite
3	1998	Field Applied Epoxy, Fusion Bonded Epoxy, Extruded Polyethylene
4	1950	None

5.2.1 Data Analysis and Model Implementation

The steps of the probability of failure development model are followed to produce a comprehensive index to forecast the probability of failure of pipes specific to their properties.

Phase 1: Developing Bow-Tie Model

The fault tree and the event tree that was developed in the previous section build the Bow-tie model that is used to develop the POF prediction index.

Phase 2: Data Analysis of the Fault-Tree

Data analysis follows the model development process for the analysis of the fault tree part of the Bow-tie model, which results in an index to compute the probability of failure for oil and gas pipes. First, all of the variables or the basic causes are categorized. Categories of the variables contributing to the identified failure sources are shown in Table 5-2. As shown, the soil resistivity is categorized into five categories. Soil acidity is categorized into three categories: 1) Acidic soils that have a pH less than four, 2) Neutral soil that have pH between four and eight, and 3) Alcaic soils, which have a pH above eight. In addition, the soil around pipes is categorized from the point of view of the Redox Potential (RP). Low RP belongs to those soils which have RP less than 50 ohm.cm, high RPs belong to the soils with an RP over 100. As for the protection measures under external corrosion, there are two basic events, coating types and cathodic protection. Coating types is categorized in four categories as was explained before. Cathodic protection effectiveness is categorized into four categories increasing the efficiency from one to four. The highest efficiency belongs to the pipes with cathodic protection from beginning of the installation of the pipes and inspecting its efficiency frequently. As for the internal corrosion, the internal inspection is categorized into three categories representing the inspection frequency of the pipes. Internal protection is another basic cause contributing to such failures, which is categorized into three categories: 1) No-protection, 2) Inhibitor application only, and 3) Inhibitor application plus applying dewatering cleaning or lining. Material and weld defect failures are affected by three basic causes, namely Specified Minimum Yield Strength (SMYS) of the pipes, inspection frequency, and seam types. All basic causes are clustered into three categories. The seam types include High Frequency-Electric Resistance Welded Pipes (HF-ERW), Low Frequency-Electric Resistance Welded Pipes (LF-ERW), and other types.

Mechanical damages are affected by six basic causes, Depth of Cover (DOC), location class, high-populated area, one call system, and being accurately marked. The depth of cover is categorized into four categories: 1) less than 6 centimeters, 2) between 6 and 36, 3) between 36 and 66, and 4) over 66 centimeters. For the location class, there are two categories those pipes that are in location class one and two, and those that are located in classes three and four. Being/not being in a high populated area, notifying/not notifying the one call system and being/not being marked accurately are the other affecting factors to measure the POF with respect to the mechanical damages for gas pipes. The mechanical damages for oil pipes are affected by DOC, location condition, and being in a highly populated area. The changes of the basic causes are due to the unavailability of the data on location class, one call system notification, and being/not accurately marked. The depth of Cover is categorized into five categories the first four of which is similar to those of gas pipes plus one for the category of pipes with a cover of over 96 centimeters. Operator property and right of way (ROW) are the two categories of the location conditions. Being in a highly populated area or not is the last factor determining the POF with respect to the mechanical damages for oil pipes.

For the incorrect operations, there are three basic causes to consider: 1) Computer Monitoring System (CMS) efficiency, 2) Qualification of Operator, 3) Qualification of Operator, and 4) location of pipe. CMS is measured from one to three in terms of efficiency. The qualification of the operator that is performing an operation on a site affects the POF as shown. A low operating pressure versus a high operating pressure is a determining factor in computing the POF. Finally, being buried underground or above-ground is another cause of the failures with respect to the incorrect operations. For natural force damages, there are three main basic causes that determine the POF. Precipitation causes high soil moisture that leads to the movement of the pipe and failure. Soil moisture is categorized into three categories including the pipes within the soils with less than 250 kg/m^2, between 250 and 400 kg/m^2, and over 400 kg/m2. Extreme temperatures, especially in the coldest months of the year (i.e. December to February), is considered in four categories, temperatures of less than -4 belongs to the first category.

Table 5- 2: Categories defined for the basic causes

Failure source	Intermediate Event	Basic Cause	Category 1	2	3	4	5
External Corrosion	Soil corrosion	Soil resistivity	0-967	967-1933	1933-2900	2900 - 3867	>3867
		Acidity	0-4	4-8	>8	-	-
		Redox potential	0-50	50-100	>100	-	-
	Protection measures	Coating types	Coal Tar, Asphalt, Paint	Cold Applied Tape, Composite	Filed applied epoxy, Fusion bonded epoxy, Polyethylene	None	-
		Cathodic protection	1	2	3	4	-
Internal Corrosion		Product type	Crude Oil	HVL	Non-HVL	Gas	-
		Inline Inspection	No-inspection	1 year	2-5 years	-	-
		Internal protection	No-protection	Inhibitor only	Dewatering cleaning or lining	-	-
Material & weld defects		SMYS	<46,000	46,000-65,000	>65,000	-	-
		Inspection	0-1 year	2-5 years	>5 years	-	-
		Seam types	HF-ERW	LF-ERW	Other	-	-
Mechanical damages (Gas)		Depth of cover	<=6	6-36	36-66	>66	
		Location class	1,2	3,4	-	-	-
		Computer-based inspection	Yes	No	-	-	-
		Highly populated area	Yes	No	-	-	-
		One call	Yes	No	-	-	-
		Accurately marked	Yes	No	-	-	-
Mechanical damages (Oil)		Depth of cover	<=6	6-36	36-66	66-96	>96
		Location	Operator property	ROW	-	-	-
		Highly populated area	Yes	No	-	-	-
Incorrect Operation		CMS efficiency	1	2	3	-	-
		Qualification of Operator	Yes	No	-	-	-
		Operating pressure	High	Low	-	-	-
		Location of Pipe	Under-ground	Above-ground	-	-	-
Natural Forces		Precipitation (kg/m^2)	<=250	250-400	>=400	-	-
		Extreme Temperature (˚C)	Less than -4	- 4 to Zero	Zero to 4	Over 4	-
		Wind (m/s)	Less than 4	4-5	Over 5	-	-

A probability distribution function is assigned to each category of each variable that determines the contribution of the category of that variable to the failure of the pipes. Table 5-3 provides the parameters of the PDFs selected for the contribution of the identified basic causes to the EC failures. For each category, the function and its parameters are defined in the table. The distribution functions, as well as their parameters, are defined for each category of each basic cause.

There are two parameters for the distribution functions of Normal, Lognorm, and Laplace, namely mean value, and the standard deviation. The two defined parameters of Gamma, ExtValue, ExtValueMin, Weibul, and Logistic functions are alpha and beta. The LogLogistic distribution function is defined by three parameters, gamma, alpha, and beta. The exponential distribution function is defined by its beta parameter, while the Uniform PDF is defined through the minimum and maximum of the boundary.

There is a meaningful difference between the contributions of the various categories of each cause with respect to the mean values of the PDFs. Under the external corrosion failures for the soil resistivity, the highest contribution belongs to the first category that includes those pipes buried in soils with less than 967 ohm.cm of resistivity. The failure probability decreases considerably while the resistivity increases, and it is the lowest when the resistivity is larger than 4,000.

For the acidity of the soil, it is understood that the pipes within soils with pH lower than four have the highest probability of failure while the neutral soils deteriorate with the lowest rate. The POF with respect to external corrosion is the highest for those pipes buried in the soils with a redox potential of less than 50, and it is the lowest when the redox potential is over 150. There are two basic causes under the protection measures, coating types, and cathodic protection. The first category of pipes with respect to the coating type, that are coated with coal tar, asphalt, or paint has highest probability of failure, while the pipes with a field applied epoxy, fusion bonded epoxy, or polyethylene have the lowest rate of failure probability. The POF with respect to the external corrosion failures decrease significantly when the cathodic protection efficiency increases. Similar tables are developed for all of the failure sources as are shown in Tables A-1, A-2 and A-3 from the Appendix A.

Table 5- 3: Contribution of the identified basic causes to the EC failures

Basic causes			1	2	3	4	5
Soil corrosion	Soil resistivity	Function	lognorm	Gamma	Exponen	LogLogistic	Logistic
		parameter #1	0.047	7.358	0.006	(0.005)	0.00
		parameter #2	0.016	0.002	0.001	0.01	0.00
		parameter #3	(0.002)	(0.003)	-	6.31	-
	Acidity	Function	lognorm	lognorm	ExtValueMin	NA	NA
		parameter #1	0.020338	0.014815	0.025600	-	-
		parameter #2	0.021296	0.009634	0.011000	-	-
		parameter #3	0.013200	0.000357	-	-	-
	Redox potential	Function	Normal	Logistic	Logistic	NA	NA
		parameter #1	0.058	0.005	0.002	-	-
		parameter #2	0.018	0.003	0.002	-	-
		parameter #3	-	-	-	-	-
Protection measures	Coating types	Function	Normal	Lognorm	Normal	Lognorm	NA
		parameter #1	0.095	0.038	0.024	0.040	-
		parameter #2	0.063	0.017	0.019	0.06	-
		parameter #3	-	(0.008)		0.01	-
	Cathodic protection	Function	Logistic	Normal	ExtvalueMin	Normal	
		parameter #1	0.052934	0.030864	0.028509	0.0042735	
		parameter #2	0.013759	0.01322	0.0048658	0.0032051	
		parameter #3	-	-	-	-	

Similarly, the contribution of the diameter categories of pipes with respect to each failure source is computed. Table 5-4 demonstrates the contribution of the pipe diameter categories to the EC, IC and MW failure sources. Table A-4 in Appendix A shows the contribution of diameter classes to the MD, IO, and NF failure sources. Pipe diameter is categorized in five distinctive sizes including, pipes under 4”, between 4 and 10”, between 10 and 20”, between 20and 28” and larger than 28”. As shown, the smaller oil pipes are more susceptible to external corrosion failures, while the larger oil pipes are less likely to fail as a result of the external corrosion failures. However, there is not a considerable difference between the contributions of the diameter to the external corrosion for gas pipes. For internal corrosion failures, the contribution of the diameter category of less than 4” and between 20 and 28” is almost the same. The pipes between 4 and 10” are less likely to fail. However, the case is different for the gas pipes. These pipes are the most likely to fail as a result of an internal corrosion when their size is between 4 and 10 inches. The rate of failure constantly decreases by increasing the size of the pipes while it is the lowest for the pipes of larger than 28 inches. The material and weld defect failures are the most common among the pipes larger than 20” and smaller than 28”, on the other hand the smallest category of oil pipes are the least likely to fail due to the material and weld defects.

The available data on the Installation year of pipes were studied, and it is categorized into four technologically distinctive eras of installation. The categories of pipe installation years include those installed before 1950, between 1950 and 1970, between 1970 and 1990 and after 1990. Finally, contribution coefficients of the installation year categories for all failure sources are computed and shown in Table 5-5. In most of the failure sources, the older pipes show a larger contribution to the failure. However, in the oil pipes with respect to the internal corrosion failures there is not a significant difference between various categories of installation years in the POF. The material and weld defects for oil pipes between 1950 and 1970 is another exception, which shows a smaller coefficient compared to the pipes installed before 1950.

Table 5- 4: Contribution of the pipe diameter categories on EC, IC and MW failure sources

Basic causes			<=4"	4"-10"	10"-20"	20"-28"	Over 28"
External Corrosion	Oil	Function	Extvalue	Extvalue	Expon	Normal	NA
		parameter #1	0.00090378	0.00010944	0.00005038	0.00007228	-
		parameter #2	0.00041641	0.00003680	0.00004868	0.00005193	-
	Gas	Function	Logistic	Extvalue	Weibull	Lognorm	Logistic
		parameter #1	0.00001572	0.00001211	1.70230000	0.00007314	0.00001170
		parameter #2	0.00001748	0.00001215	0.00004652	0.00003177	0.00001074
		parameter #3	-	-	-0.00000404	-0.00003299	-
Internal Corrosion	Oil	Function	Normal	Lognorm	Laplace	Lognorm	Normal
		parameter #1	0.00018736	0.00021320	0.00013712	0.00030310	0.00010740
		parameter #2	0.00011963	0.00004484	0.00004276	0.00018332	0.00010291
		parameter #3	-	-0.00012909	-	-0.00010834	-
	Gas	Function	Normal	Logistic	Normal	Logistic	Logistic
		parameter #1	0.00001007	0.00001994	0.00002885	0.00001379	0.00000822
		parameter #2	0.00001854	0.00001096	0.00001445	0.00001159	0.00000754
Material and Weld	Oil	Function	NA	Extvalue	Normal	Normal	Normal
		parameter #1	-	0.00004411	0.00008870	0.00014256	0.00007326
		parameter #2	-	0.00001730	0.00005287	0.00008560	0.00010340
	Gas	Function	Logistic	Logistic	Lognorm	Normal	Uniform
		parameter #1	0.00003525	0.00001007	0.00003993	0.00006610	-0.00000711
		parameter #2	0.00002077	0.00000685	0.00002761	0.00004397	0.00008533
		parameter #3	-	-	-0.00000947	-	-

Table 5- 5: Contribution coefficients of the installation year categories all failure sources

Failure source		Before 1950	1950-1970	1970-1990	1990-2013
EC	Oil	5.4577	2.8698	1.8178	1.0000
	Gas	9.6251	7.1401	2.1142	1.0000
IC	Oil	1.8603	1.0000	1.7547	1.8267
	Gas	6.6121	3.7375	3.8713	1.0000
MW	Oil	3.5380	6.3275	1.8464	1.0000
	Gas	2.6298	1.8082	1.1449	1.0000
MD	Oil	1.4747	1.7553	1.0234	1.0000
	Gas	3.0690	1.1025	1.0000	1.1685
IO	Oil		1.7935	1.0000	1.2916
	Gas	2.1250	1.5000	1.2500	1.0000
NF	Oil	8.1778	1.0000	1.3723	7.0405
	Gas	6.4697	1.2466	3.8755	1.0000

The adjustment factor for each category of diameter is computed as shown in Table 5-6. These factors convert the relative probability of failure to the absolute probability of failure for such pipes. The calculated factors of adjustment vary between approximately 20 and 180. The relative probability of failure that can be computed based on the contribution of the basic causes will be combined with the effect of the pipe diameter and installation year. Using Equations 3.8~3.11, the absolute probability of failure with respect to each failure source is calculated. The provided indices can be used for the calculation of the fault tree part of the model. Then, it is required to compute the probability of happening of each after-failure event to calculate the probability of happening of each failure scenario.

Table 5- 6: Diameter-based adjustment factors for all failure sources

Failure source		<=4"	4"-10"	10"-20"	20"-28"	Over 28"
EC	Oil	52.820	35.013	62.825	52.272	
	Gas	117.898	63.874	60.163	60.325	143.380
IC	Oil	114.080	114.059	119.069	112.287	114.082
	Gas	103.808	77.979	22.950	84.664	76.165
MW	Oil	82.161		82.667	82.668	82.667
	Gas	94.462	111.118	74.094	62.968	55.923
MD	Oil	67.481	67.481	67.481	111.649	137.669
	Gas	186.530	100.114	114.958	129.009	252.126
IO	Oil	23.803	21.423	21.423	21.423	
	Gas	46.695				
NF	Oil	120.951	9.584	20.468	24.479	
	Gas	19.315				

Phase 3: Data Analysis of the Event Tree

The process that was explained in the research methodology is applied to develop two indices on the event tree part of the model. The index presents the probability of happening of each hole size including pinhole, puncture, and rupture, in case any of the failure sources happens. It also demonstrates the probability of happening of each ignition type, in case of happening of each type of the hole size. Table 5-7 shows the indices for all failure sources that are developed based on the historical data on oil pipes. As shown, the probability of happening of only a leakage is much higher than the explosion or ignition for all failure sources and hole sizes. Overall, for oil pipes the likelihood of happening of a pinhole is greater than all other hole sizes.

For external corrosion failures, the probability of happening of a puncture-size defect follows that of the pinhole-size one. The likelihood of happening of an ignition or explosion increases by growing the hole size. A similar result can be drawn for internal corrosion failures, with a higher probability of happening of a small hole size. For material and weld defects, the probability of happening of a pinhole is lower than a corrosion defect. Besides, the probability of happening of a rupture is higher than that of a puncture. Overall, around five to seven percent of the ruptures cause an ignition or explosion. For the mechanical damages, the probability of happening of puncture grows significantly while a pinhole is still the most likely hole size to happen. Also, such failures are more likely to cause an explosion or ignition. The probability of happening of a pinhole for incorrect operations is still much higher than a puncture and rupture. However, the punctures are more likely to happen in comparison with ruptures. Also, there is a small higher likelihood of ignition in such failures. Natural forces are different from the other failure sources. The probability of happening of a rupture is higher than a pinhole for such failures. Punctures are the least likely hole sizes to happen in the failures stemming from the natural forces. Table A-5 shows similar indices for gas pipes. Similar conclusions can be drawn from the developed indices for gas pipes. Overall, the probability of happening of an ignition or explosion is higher for gas pipes compared to oil pipes and the likelihood of growing a defect to a puncture or rupture is greater than those assigned to gas pipes.

Table 5- 7: Indices related to probability of after-failure events for oil pipes

Failure source (S)	Hole size (H)	P(H │S)	Ignition type (Ign)	P(Ign │H)
EC	Pinhole	0.800633	Leakage only	0.998814
			Ignition	0.000791
			Explosion	0.000395
	Puncture	0.129747	Leakage only	0.951220
			Ignition	0.024390
			Explosion	0.024390
	Rupture	0.069620	Leakage only	0.863636
			Ignition	0.090909
			Explosion	0.045455
IC	Pinhole	0.844869	Leakage only	0.998870
			Ignition	0.000565
			Explosion	0.000565
	Puncture	0.109785	Leakage only	0.991304
			Ignition	0.004348
			Explosion	0.004348
	Rupture	0.045346	Leakage only	0.831579
			Ignition	0.110526
			Explosion	0.057895
MW	Pinhole	0.722561	Leakage only	0.966245
			Ignition	0.025316
			Explosion	0.008439
	Puncture	0.106707	Leakage only	0.988571
			Ignition	0.005714
			Explosion	0.005714
	Rupture	0.170732	Leakage only	0.875000
			Ignition	0.071429
			Explosion	0.053571
MD	Pinhole	0.540230	Leakage only	0.962234
			Ignition	0.026596
			Explosion	0.011170
	Puncture	0.321839	Leakage only	0.928571
			Ignition	0.044643
			Explosion	0.026786
	Rupture	0.137931	Leakage only	0.910417
			Ignition	0.085417
			Explosion	0.004167
IO	Pinhole	0.676471	Leakage only	0.954348
			Ignition	0.044203
			Explosion	0.001449
	Puncture	0.245098	Leakage only	0.898000
			Ignition	0.100000
			Explosion	0.002000
	Rupture	0.078431	Leakage only	0.743750
			Ignition	0.187500
			Explosion	0.068750
NF	Pinhole	0.424460	Leakage only	0.977966
			Ignition	0.018644
			Explosion	0.003390
	Puncture	0.143885	Leakage only	0.890000
			Ignition	0.055000
			Explosion	0.055000
	Rupture	0.431655	Leakage only	0.948333
			Ignition	0.033333
			Explosion	0.018333

The application of the developed indices to calculate the probability of failure would be through several steps: 1) To find out which category of each basic cause the pipe under study belongs to according to Table 5-2, 2) to locate the category of the basic causes and related distribution functions for EC failures from Table 5-3, for IC and MW failure from Table A-1, MD failures from Table A-2, and IO and NF failures from Table A-3; 3) to calculate the relative probability of failure of the pipe without the effect of the pipe diameter and installation year using Equations 3.8 and 3.9; 4) to locate the PDF related to the contribution of pipe diameter category, installation year and adjustment factor from corresponding tables and compute the absolute probability of failure using Equations 3.10 and 3.11. The probability of happening of each failure scenario can be calculated through the following steps. To locate the likelihood of happening of various hole sizes and ignition, as well as the explosion from Table 5-7, and A-4. Compute the likelihood of after-failure events applying Equations 3.5~3.7.

5.2.2 Sensitivity Analysis

Sensitivity analysis is performed to study and verify the sensitivity of the probability of failure to the basic causes and properties of the pipes using developed indices. For this purpose, in each failure source, all except one of the variables are kept fixed, the value of one variable is changed, and this is repeated for all variables. For example, to conduct the study on external corrosion, a fixed category is assumed for each variable. Then, each variable's category is changed one category each time, and the probability of failure is computed. The calculated values are plotted for each variable as shown in Figure 5-5. The changes of the output are studied versus the changes of the categories of the basic causes and the properties of pipes. For soil resistivity, the pipes buried in the soils with 0 to 967 ohm-cm are the most likely to fail, and the failure probability decreases by increasing the value of this variable. The failure probability grows again when the soil resistivity is higher than 2,900.

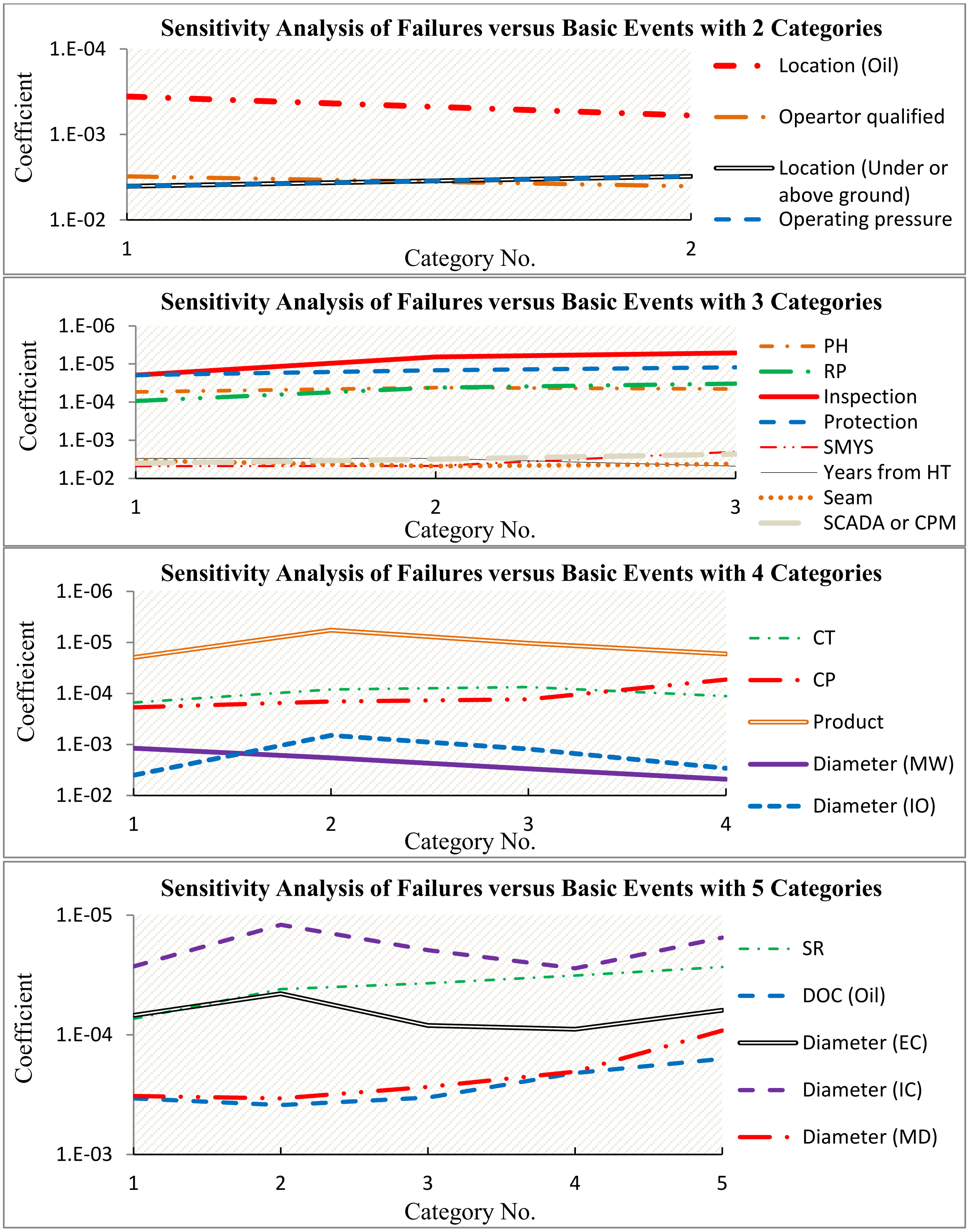


Figure 5- 5: Sensitivity analysis results

The probability of external corrosion failure is not as sensitive to the changes of soil acidity compared to soil resistivity; nevertheless, the values are forecasted to be higher for acidic soils and lower for neutral soils. The amounts for Alcaic soils are lower than those of the acidic ones yet greater than neutral soil types. The estimated probability of failure for soils with lower than 50 m-volt redox potential is the highest while it reduces by increasing the values of redox potential. The value of failure probability with respect to coating types is the lowest when the pipe is coated with Field Applied Epoxy, Fusion Bonded Epoxy, and Extruded Polyethylene; while it is the highest when coated with Coal Tar, Asphalt, and Paint. Similar values are calculated when the pipes are not coated. For Cathodic Protection efficiency, it is observed that the value of failure probability is higher with no/lower protection while it is lower with more efficient protections. The sensitivity of the probability of failure with respect to all causes in all of the failure sources proves the efficiency of the developed model and verifies the soundness of the model.

5.2.3 Validation of the Developed Model

The historical data on of 2014 and the first half of 2015 is collected to validate the developed model. The data includes the failure data and mileage reports. Due to the inexistence of a trackable ID for the pipes, the operators of the pipes that have reported pipe failure during this period are tracked. For each operator, the predicted probability of failure is calculated. Moreover, the actual probability of failure is calculated by dividing the number of failures of each operator by their reported mileage in this period. The predicted amounts are compared with the actual values, and the error measuring methods are used to calculate the accuracy indices. A smaller value of RMSE proves the efficiency of the developed model that is calculated to be 2.44E-5. A closer value to 100% with respect to the average validity percentage (AVP) is considered to prove the prediction respectively. AVP is computed to be around 80.1% in this model that is satisfactory. For further analysis, the forecasted values of probability of failure are plotted against the actual values and as shown in Figure 5-6. The calculated actual and predicted amounts are very close, and the results are satisfactory. However, in the larger values of failure probability there is a larger discrepancy between the actual and forecasted values. Figure 5-7 is also plotted to show the correlation between the actual and predicted values of failure probability. As shown, there is a high correlation between the values with a coefficient of determination of 0.92 that proves the efficiency of the model.

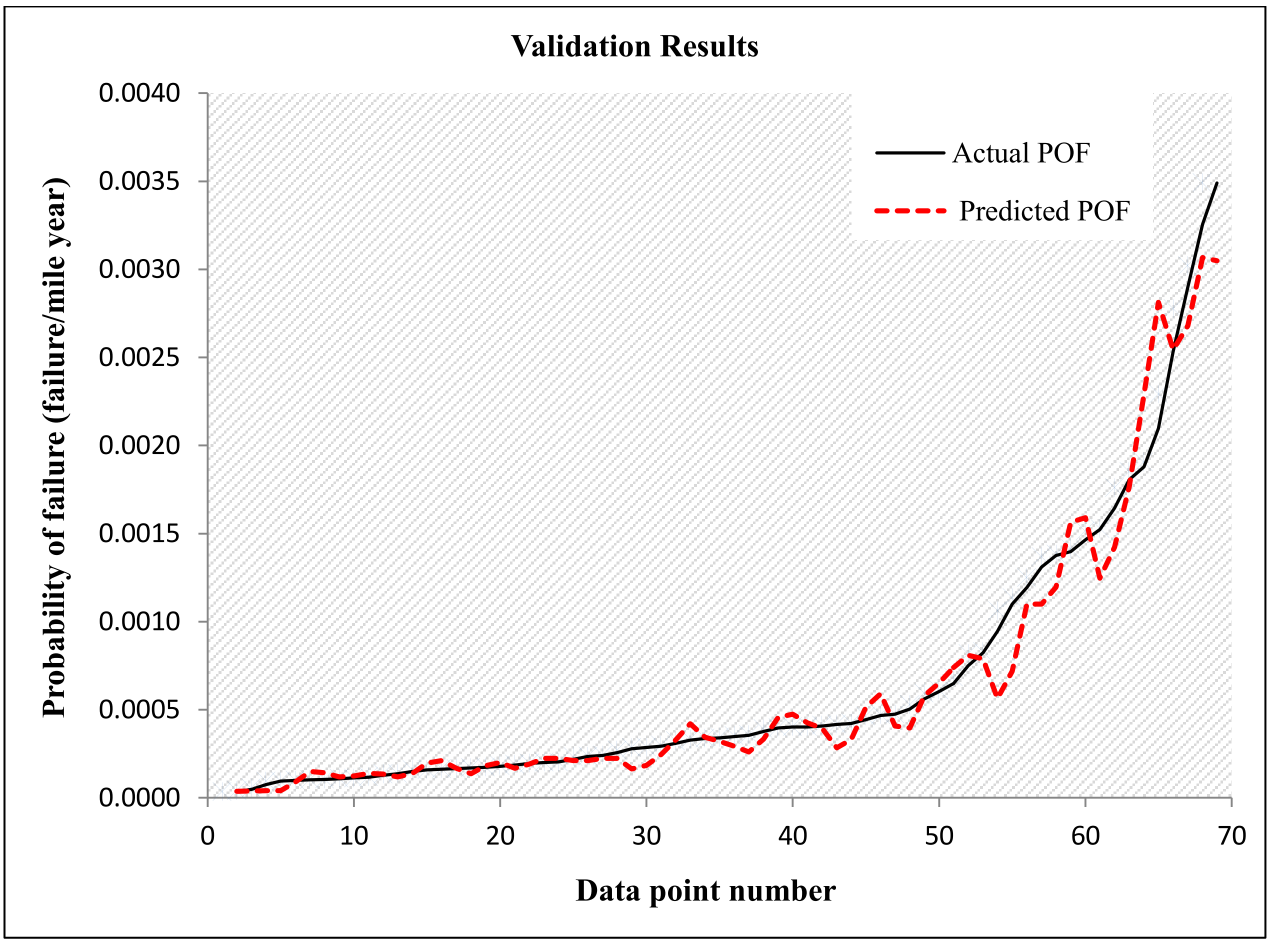


Figure 5- 6: Validation results

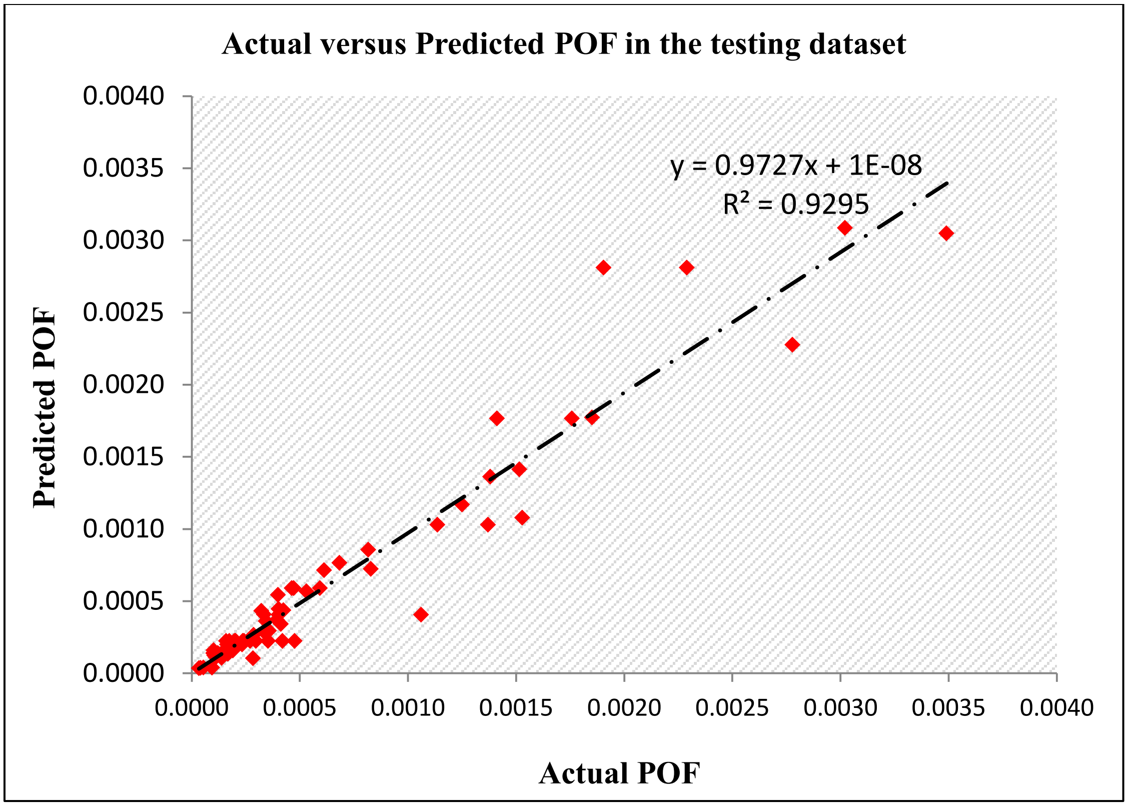


Figure 5- 7: Actual versus Predicted POF in the testing dataset

5.3 Consequences of Failure Prediction Model

In this section, model implementation process and results are explained. The Bow-tie model that was developed in the previous model as shown in Figure 5-1 and 5-2 are used to identify the possible failure scenarios. Financial consequence of oil and gas pipelines includes so many parameters and is very complicated to be estimated. Consequently, the forecast of actual value would not be possible, while the estimation of its level in the scale of one to eleven will not be far from expectation. In this research, the financial damages of the failed pipelines are translated to the levels of the financial consequences as shown in Table 5-8. According to this table, if the consequence of a pipe is in the range of zero to 10,000 US dollars, its consequence level is considered as one. The highest level of the consequence is found for the pipes that have produced over ten million U.S. dollars, which is coded as the eleventh level.

As explained before, several parameters should be determined, such as the training mode, which can be hybrid or back-propagation. The hybrid method of training combines the least squares method with back-propagation. The efficiency of the training is checked against the checking dataset in several data-points called epochs. As mentioned in the literature review, the error of the model trained by Neural Networks and Neuro-Fuzzy systems increases at some points as a result of over-fitting. The system checks the accuracy of the trained network in the checking dataset at each epoch and whenever the error starts increasing, the training process stops. Continuing the training may not help the learning task and generalization capability of the system. A sample entry data that is embedded in the Neuro-fuzzy learning machine is shown in Table 5-9. Location category and failure scenario is computed according to the instructions and the values of SMYS, diameter, operating pressure, and wall thickness of the pipe is inserted as their actual values.

Table 5- 8: Financial consequence levels description

Actual Cost		**Consequence Level**
Min. (unit: 1,000 US $)	**Max.** (unit: 1,000 US$)	
0	10	1
10	25	2
25	50	3
50	100	4
100	250	5
250	500	6
500	1,000	7
1,000	2,500	8
2,500	5,000	9
5,000	10,000	10
10,000	Infinity	11

Table 5- 9: Sample entry data

LC	FS	SMYS	DI	MAOP	WT	Consequence level
1,110	1,110	52,000	26	809	0.28	4
1,110	1,130	45,000	14	1000	0.31	8
2,010	1,110	60,000	12	1440	0.31	5
3,110	1,130	60,000	24	900	0.25	6
1,110	1,330	52,000	16	832	0.22	8
4,110	1,110	42,000	12	780	0.31	3
1,110	1,330	60,000	36	800	0.34	10
1,310	1,110	24,000	8	400	0.19	5
1,110	1,130	46,000	16	1002	0.25	3

Due to the limitation of the number of data-points, a large number of membership functions could not be used for developing the model. Consequently, the number of modifiable parameters was calculated from Equation 3.3 that is explained in the research methodology section, for a combination of four input variables with a trapezoidal or triangular membership function type. There were 650 data-points in the whole database, which should have been larger than the number of modifiable parameters. Consequently, three is the maximum number of the membership functions for each variable. The number of membership functions (MF) in the optimum model can be changed within the range of three plus/minus one MF for the combination of the variables. As a result, if one variable uses four MFs, another variable might use two MFs.

Various combinations of the input variables are tested in the system, and results are recorded. The number of membership functions, as well as their types, is changed in different trials, and the results are recorded as shown in Table 5-10. The triangular and trapezoidal MFs were the only ones in this research that led to acceptable outcomes. In each trial, the error in various datasets and surface view is checked. Surface view checking is a preliminary sensitivity analysis of the produced network.

Table 5- 10: Results of Neuro-fuzzy tested networks

Tested Network	Membership function	LC	FS	SMYS	WT	DI	MAOP	Training	Testing	Checking	Average	Surface View Ok?
		No. of Membership Functions						Error				
1	Trapezoidal	3	3	3	3	NA	3	1.61	1.74	1.80	1.66	Yes
2	Trapezoidal	3	3	5	3	NA	3	1.55	6.08	1.71	2.25	No
3	Trapezoidal	3	3	4	3	NA	3	1.61	1.74	1.72	1.65	Yes
4	Trapezoidal	3	3	3	3	NA	4	1.59	1.78	1.75	1.64	No
5	Triangular	3	3	3	3	NA	3	1.51	1.82	1.90	1.62	Yes
6	Triangular	3	3	4	3	NA	3	1.51	1.82	1.94	1.62	Yes
7	Triangular	3	4	3	3	NA	3	1.46	1.76	2.17	1.61	No
8	Triangular	3	3	3	4	NA	3	1.47	1.83	1.94	1.59	No
9	Triangular	3	3	3	3	NA	4	1.50	1.81	1.87	1.60	Yes
10	Triangular	2	3	3	3	NA	3	1.53	1.82	1.73	1.60	Yes
11	Trapezoidal	3	3	3	3	NA	NA	1.69	1.75	1.74	1.71	No
12	Trapezoidal	3	3	3	4	NA	NA	1.69	1.73	1.74	1.70	Yes
13	Trapezoidal	4	3	3	3	NA	NA	1.69	1.73	1.75	1.71	No
14	Trapezoidal	3	4	3	3	NA	NA	1.67	1.83	1.76	1.71	No
15	Trapezoidal	3	3	4	3	NA	NA	1.69	1.75	1.80	1.72	No
16	Trapezoidal	2	3	3	4	NA	NA	1.70	1.80	1.74	1.72	Yes
17	Triangular	3	3	3	3	NA	NA	1.62	1.75	6.70	2.40	Yes
18	Triangular	3	3	3	4	NA	NA	1.62	1.75	6.80	2.42	Yes
19	Triangular	3	3	4	3	NA	NA	1.61	1.74	1.80	1.66	No
20	Triangular	3	4	3	3	NA	NA	1.60	1.86	1.75	1.66	No
21	Triangular	4	3	3	3	NA	NA	1.62	1.81	6.90	2.44	No
22	Trapezoidal	3	3	3	NA	3	NA	1.55	1.58	2.01	1.62	Yes
23	Trapezoidal	3	3	4	NA	3	NA	1.52	1.60	2.04	1.61	Yes
24	Trapezoidal	3	4	3	NA	3	NA	1.54	1.63	3.60	1.86	No
25	Trapezoidal	4	3	3	NA	3	NA	1.55	1.61	1.98	1.62	Yes
26	**Trapezoidal**	**2**	**3**	**4**	**NA**	**3**	**NA**	**1.52**	**1.54**	**2.01**	**1.60**	**Yes**
27	Triangular	3	3	3	NA	3	NA	1.56	2.00	2.20	1.72	No
28	Triangular	3	3	4	NA	3	NA	1.51	1.63	1.96	1.60	No
29	Triangular	2	3	4	NA	3	NA	1.56	1.62	1.90	1.62	No
30	Triangular	3	3	3	NA	4	NA	1.52	4.00	4.10	2.28	No
31	Triangular	3	3	3	NA	4	NA	1.72	1.70	1.80	1.73	No
32	Trapezoidal	3	3	3	3	3	NA	1.64	1.97	1.71	1.70	No
33	Trapezoidal	3	3	4	3	3	NA	1.63	1.97	1.71	1.69	Yes
34	Trapezoidal	3	3	3	3	4	NA	1.61	1.79	1.68	1.65	No
35	Triangular	3	3	3	3	3	NA	1.53	1.86	1.93	1.64	Yes
36	Triangular	3	3	4	3	3	NA	1.53	1.87	1.93	1.64	Yes
37	Triangular	3	3	3	3	4	NA	1.53	1.86	1.89	1.63	No
38	Triangular	3	3	3	4	3	NA	1.46	2.01	2.08	1.64	Yes
39	Triangular	2	3	4	3	3	NA	1.58	1.82	1.76	1.64	Yes
40	Triangular	3	4	3	3	3	NA	1.49	2.10	1.64	1.60	Yes

The models that result in negative outcomes or outcomes that are not in the range of one to eleven that is the range of outcomes in this model, the surface view of that network is deemed not acceptable. Also, if the change of one or more of the variables does not affect the changes in the outcome of the project, the surface view is again deemed not acceptable. The performance of each network is compared with the others to select the best combination and optimize the variable selection. More than 200 various networks are tested and the ones that resulted in legitimate outcomes are reported. Finally, the neuro-fuzzy model with the lowest error is selected, which is numbered 26. The selected network produces the least average error, and its surface view is also acceptable. The model considers the location category, failure scenario, SMYS, and diameter of the pipe to forecast the failure consequence level of the pipes. The error of each network that is produced in this research is calculated by comparing the estimated outputs with the actual data. Mean square error (MSE) is computed using Equation 3.18. MSE is used to measure the mean squares of errors in each dataset. Comparing the MSE values leads to the identification of the models with the smallest error. The error is measured by embedding the testing dataset in the produced model. The architecture of the final model is presented in Figure 5-8. The model includes four inputs, one output, and the final model includes 72 fuzzy if-then rules. The output will be in the range of one to eleven.

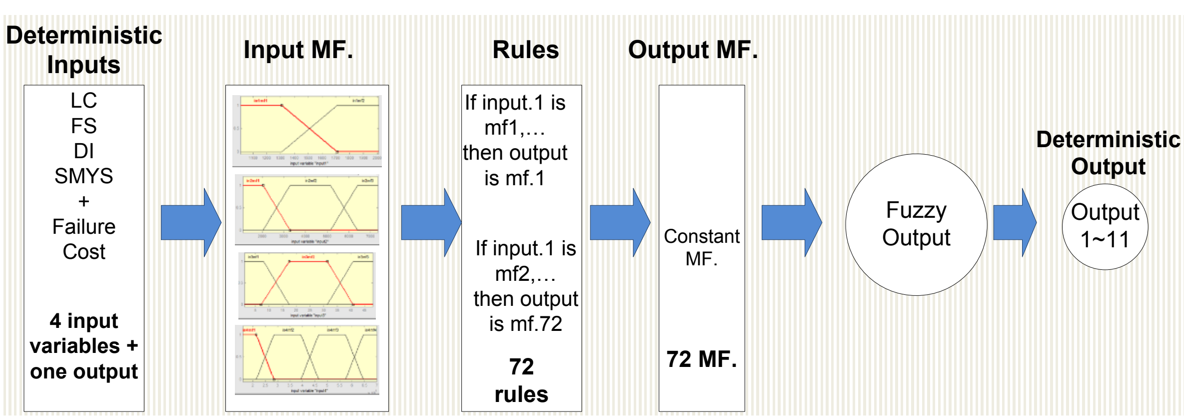


Figure 5- 8: Structure of the Model

The selected model uses two, three, four and three membership functions for the location category, failure scenario, SMYS and diameter of the pipe variables as shown in Figure 5-9. Location class is determined by two trapezoidal membership functions, which mainly indicate the onshore and offshore pipes. Three membership functions are allocated to the failure scenarios. Pipe diameter is presented with three membership functions entitled: small, medium to large, and very large. Finally, the SMYS of the pipes are fuzzified with four membership functions showing the strength of the pipes. The four membership functions are titled: very weak material, weak material, medium material and strong material. The location is clustered into low-consequence and high consequence locations. The failure scenario is also categorized into Time dependent failure sources; Time independent failure sources; and Stable failure sources.

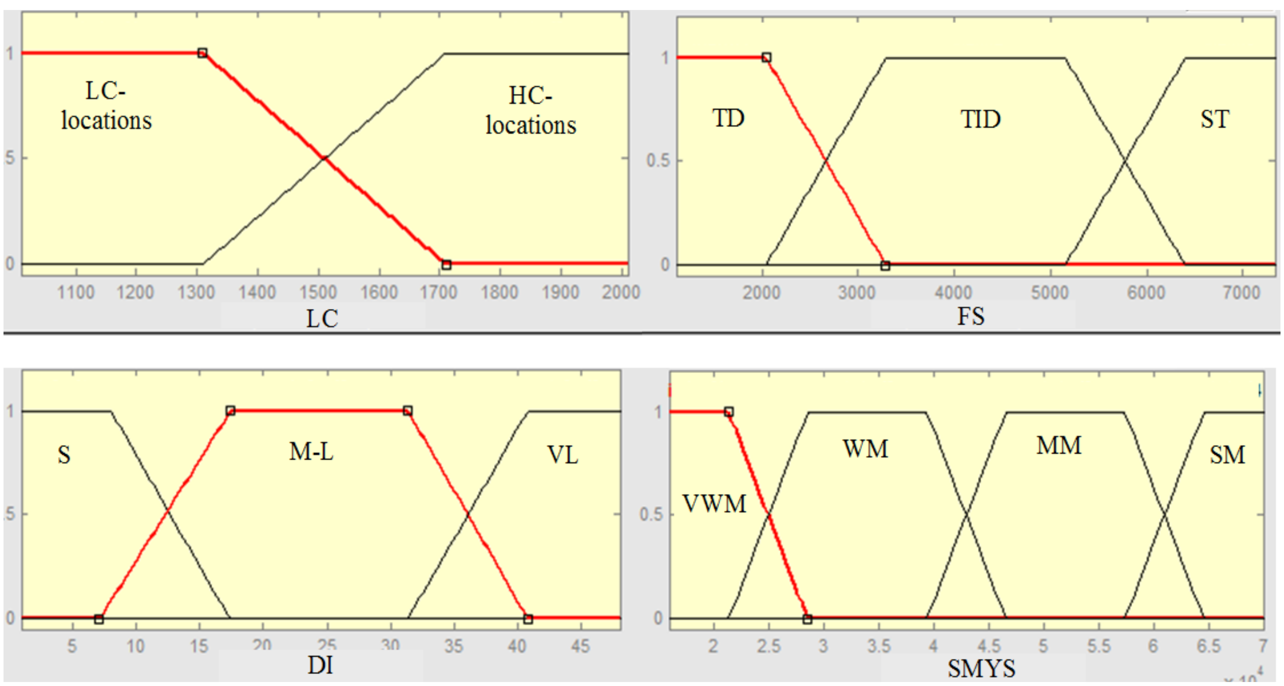


Figure 5- 9: Membership function generated for input variables

LC- locations: Low consequence locations; HC-locations: High consequence locations
TD: Time-dependent failure sources; TID: Time-independent failure sources; ST: Stable failure sources
S: Small pipes; M-L: Medium to large pipes; VL: Very large pipes
VWM: Very weak material; WM: Weak material; MM: Medium material; SM: Strong material

A random selection of the generated outputs versus the input variables is presented in Table 5-11. There is a low difference between the actual and predicted values especially in lower financial consequences.

Table 5- 11: Sample of predicted data

No.	Location Category	ET class	DI	SMYS	Actual Cost Level	Predicted Cost Level
1	1,110	2,110	30	60,000	7	6.0
2	1,110	4,130	4	42,000	3	4.5
3	1,110	4,110	2	35,000	4	4.7
4	2,010	2,320	16	52,000	7	5.4
5	1,110	4,110	4	42,000	4	4.5
6	2,010	2,110	10	46,000	5	4.8
7	1,310	4,110	10	49,000	5	4.5
8	1,210	1,110	13	52,000	7	4.9
9	2,010	2,110	12	52,000	4	4.9
10	2,010	4,130	10	42,000	9	7.0
11	1,110	3,110	26	52,000	5	5.4
12	2,010	2,110	2	35,000	5	5.5
13	1,110	1,130	4	24,000	4	3.5
14	1,310	6,130	10	35,000	6	4.1
15	1,110	4,110	8	24,000	3	3.4

Three-dimensional surface views present the sensitivity of the output variable based on the changes of two selected input variables according to the final model as shown in Figure 5-10. These surfaces help in understanding the changes of the output versus the input variables. As shown, the offshore pipes result in higher consequences of failure, while the onshore pipes produce a smaller level of the consequence of failure. It is also obvious that higher location classes and high consequence areas result in larger consequences. Input 2 is related to the failure scenario, and the graph proves that time-dependent failures result in lower consequence levels. Time independent failures such as Material and weld defects, as well as the mechanical damages, produce larger consequences. Stable failure sources, such as the damages as a result of natural forces, have caused more significant consequences than the mechanical damages. The fourth graph investigates the changes of the consequence of failure with respect to the SMYS of the pipes. According to this figure, the smallest SMYS values resulted in the highest consequences, while it drops dramatically when the SMYS reaches to around 30,000. The failure consequences fluctuate around 5.5 to 6 when the SMYS values are between 30,000 to 60,000. It increases significantly when the SMYS of the pipes is increased to 70,000. Totally, graphs prove the higher importance of SMYS in the estimation of the consequence of failure.

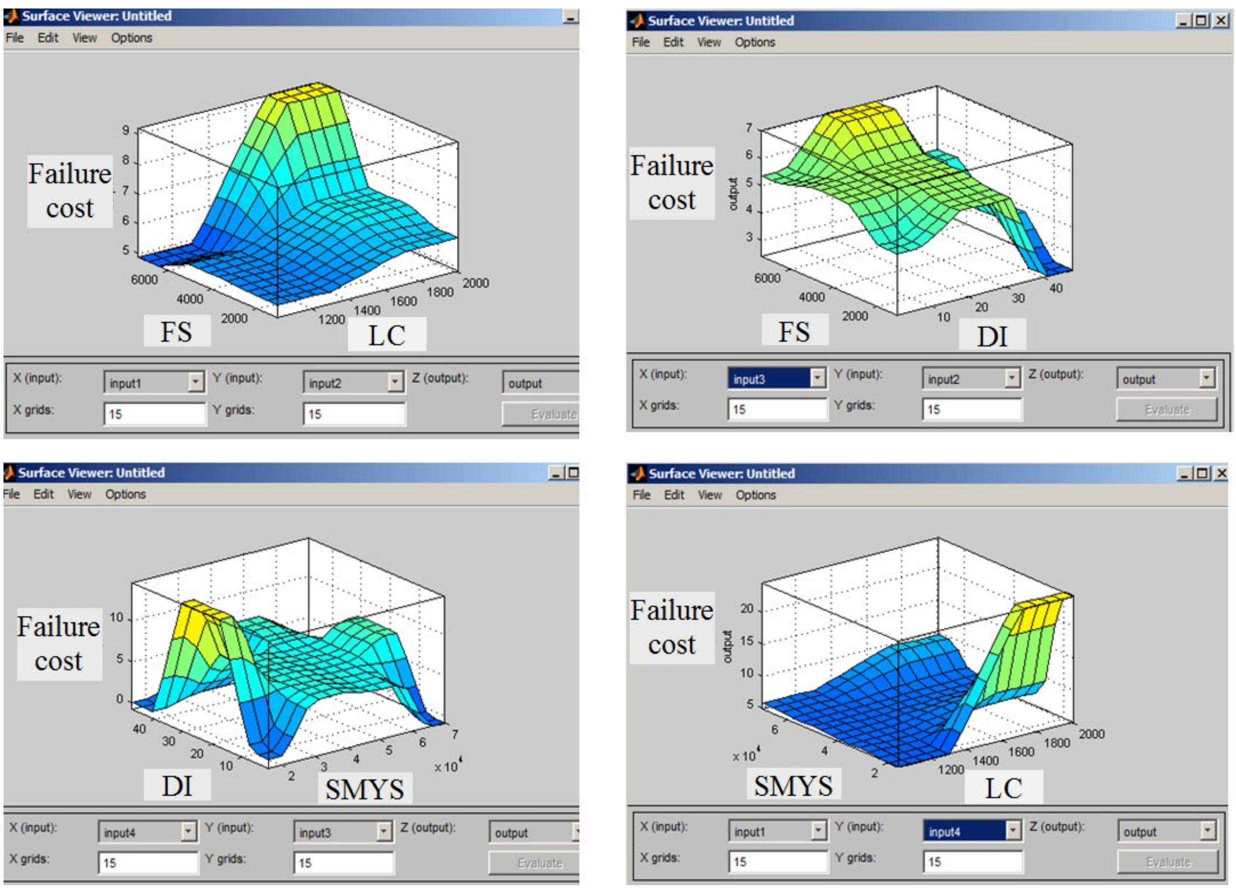


Figure 5- 10: Three dimensional sensitivity surfaces

5.3.1 Consequences of Failure Model Validation

The dataset was divided into training and testing dataset. The error in the testing dataset is measured to validate the produced model. The error is measured by comparing the estimated results of the model against the actual data using Equations 3.19~3.23. The final model is tested by comparing the predicted and actual outputs to validate the produced model. RMSE, MAE, AIP, AVP and the Median Symmetric Absolute Percentage Error (i.e. MdsAPE) of the model are computed as shown in Table 5-12. The closer value of RMSE and MAE to zero proves the higher efficiency of the models. RMSE and MAE for the model in this research are calculated equal to 1.503 and 1.250 respectively that shows the effectiveness of the model is acceptable. The average validity of the model is estimated as 78 percent that is satisfactory. Finally, the MdsAPE index is calculated approximately 80 percent that proves the model is capable of predicting the consequence of failure with a high validity.

Table 5- 12: Validation results of the final model

Measure of error method	**RMSE**	**MAE**	**AIP**	**AVP**	**MdsAPE**
Calculated index	1.5032	1.2504	21.8588	78.1411	79.7752

5.4 Integrated Fuzzy Risk Index

In this model, the level of risk of failure is assessed with respect to each failure source that was identified in the Bow-tie model. The calculated amounts of the probability of failure and the corresponding consequences of failure are used to evaluate the risk index. A fuzzy inference system is defined in this model that assesses the risk of failure of such pipes. The membership functions that define the level of risk for the calculated logarithmic grade of the probability of failure are then assigned, the thresholds of which are extracted from the existing guidelines. Similarly, the membership functions that fuzzify the calculated consequences of failure are defined in a fuzzy expert system. Figure 5-11 shows the defined membership functions (MF) for the inputs and output of the system. Part "a" of the figure shows the MFs related to the probability of failure and “b” demonstrates the membership functions related to the consequences of failure, while part “c” of the figure shows the Membership functions assigned to the output of the model. The rules of the fuzzy inference system are developed based on the human expertise and literature review. The rules are defined to map the inputs to the output of the system. This fuzzy inference system applies the Mamdani fuzzy model. Once aggregated the membership functions of the inputs and output according to the fuzzy rules, a fuzzy set is assigned to the risk index. This fuzzy set is defuzzified using the centroid defuzzification method.

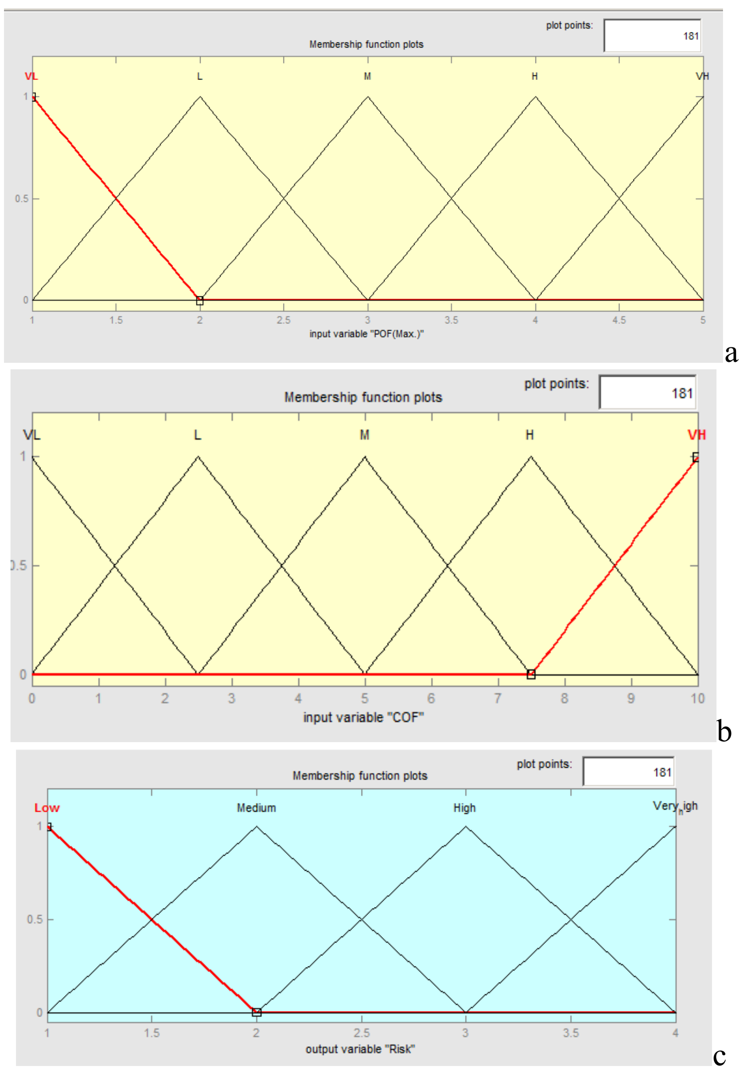


Figure 5- 11: Risk index model fuzzy rules

Figure 5-12 shows the risk index surface that is the demonstration of the relationship between the inputs and output of the fuzzy inference system. As shown, a higher risk index is assigned when the consequence of failure is higher while increasing the probability of failure with a low consequence of failure does not result in a high-risk level. Once the risk level is assessed for the pipe with respect to each failure source, the calculated risk scores can be used separately to present the level of risk with respect to each source. Also, they can be averaged or maximized to show the total risk of the pipe.

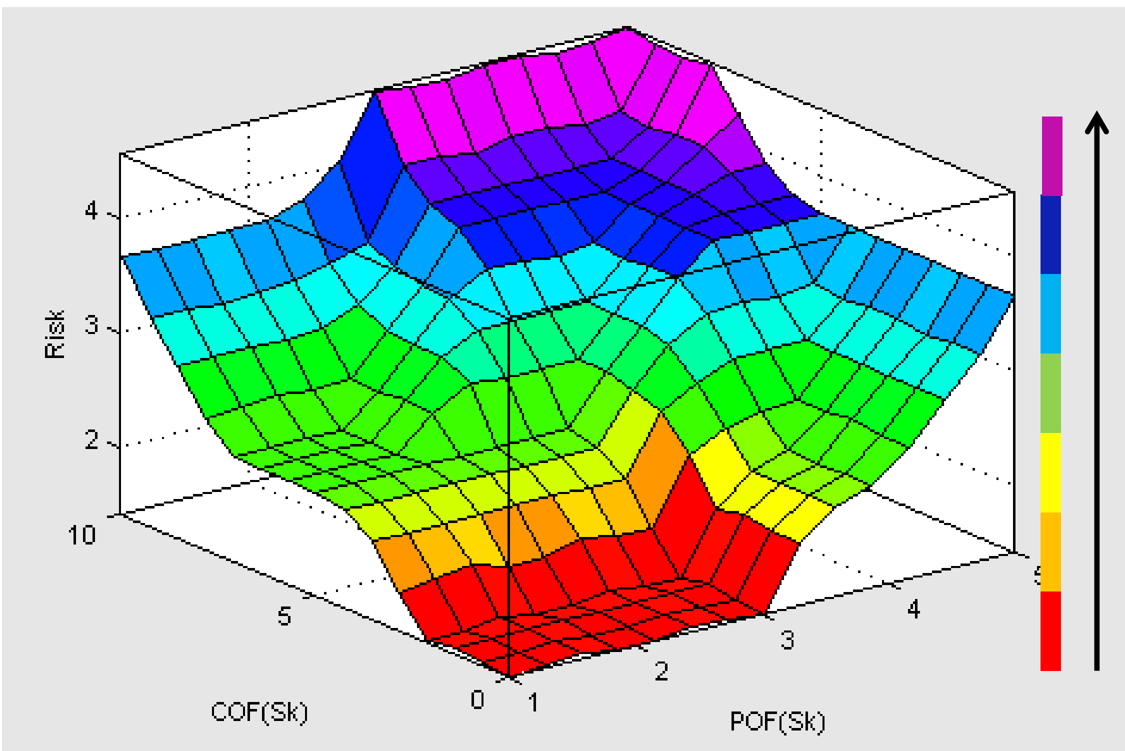


Figure 5- 12: Risk Index surface demonstration

5.5 Inspection Planning

Inspection planning is performed after that the risk of failure is assessed using the models developed in the previous sections. This model has two main phases: 1) select the tools and determine the frequency and 2) rank the scenarios of inspection and propose the optimum plan.

For this purpose, a fuzzy inspection tool selection model is developed. The triangular MFs that were used in the fuzzy integrated risk index model to assess the probability of failure and consequence of failure are applied here to fuzzify the inputs. The outputs of the model are the frequency of inspection and selection of inspection tools. The probability of failure will be compared with the available risk scale to determine the running frequency. The inspection tool selection will be based on the consequences of failure.

The comparison will be performed for all of the major failure sources that existed in the Bow-tie model. A table is developed in this model, which suggests the suitable inspection tools with their frequency ranges and cost of operating. Table 5-13 presents a proposed categorization of existing inspection tools. These inspection techniques can be divided into three main categories. The first category of inline inspection tools (ILI) includes those techniques that are used to perform an inline inspection such as MFL tools and Transverse flux and UT[2] with different resolution levels. The other group is composed of direct assessment techniques that inspect the pipelines from the external surfaces. In this method, various places around the pipes are excavated to be inspected visually using tools from the exterior surface of the pipe. This method is categorized in terms of its cost based on the distances between digging points. There is another main type of inspection technique, namely hydrostatic testing, that is mainly applied at the beginning of the life of a pipeline, which is necessary for all pipes. This method inspects the newly constructed pipelines against the potential near critical flaws that can exist in the pipeline. It is not common to apply this technique frequently.

[2] This inspection tool is not applicable for gas pipelines but only oil pipelines.

Table 5- 13: Inspection methods applied for external corrosion failures

Type	Inspection tool	Frequency range	Ave. Cost of Running
ILI	MFL Standard Resolution	7-12 years	2,300
	MFL High Resolution		3,400
	Transverse Flux		NA
	UT (Compression wave)		2,300
	UT (Shear wave)		4,700
DA	ECDA (Dig every 8 Kilometer of pipe)	-	2,200
	ECDA (Dig every 3 Kilometer of pipe)		6,700
HD	Hydrostatic Testing	Mostly used for the newly constructed pipeline	11,300-34,000

Another table is developed to demonstrate the frequency of operating the inspection techniques versus the failure probability level. A table is developed in this section as shown in Table 5-14, which shows the frequency of running of the identified inspection tools for external corrosion versus various failure probability levels. The table suggests inspecting the pipes that are more prone to failure with a higher frequency.

Table 5- 14: Frequency range of Inline inspection application for oil and gas pipelines with respect to their level of failure probability

PoF Level		Mid-Point of Frequency MF (year)
1	Very low	9
2	Low	8
3	Medium	7
4	High	6
5	Very high	5

As mentioned in chapter 3, the primary selection of inspection technique is based on the failure consequence level that is computed with respect to the consequence model developed in the previous section. For this purpose, a table is provided for each failure source that determines the appropriate type of inspection tool with respect to the failure consequence level. Table 5-15 shows the proposed inspection tools selection versus the failure consequence levels. It suggests the application of direct assessment in longer digging distances and low-resolution inspection tools for those pipes with low and very low consequences of failure. It also proposes to apply direct assessment in smaller digging distances and high-resolution tools for the pipes with the high and very high consequence of failure. As seen in this table, the decisions regarding the inspection tool selection such as considering an inspection tool as a high resolution or low resolution is fuzzy. Similarly, the decision about distance for digging in the direct assessment method is also fuzzy. As a result, in this study a fuzzy expert system for the selection of the inspection tools and determining their frequency of running using these tables is offered.

Table 5- 15: Inspection tool selection versus failure consequence level

Consequence of failure		**Inspection tool selection**
1~4	Low and Very Low	• Direct assessment in long digging distances • Low-resolution Inline inspection
3~7	Low and Medium	• Direct assessment in medium digging distances • Standard resolution Inline inspection
7~10	High and Very High	• Direct assessment in small digging distances • High-resolution Inline inspection

The fuzzy membership functions assigned to the input and output variables are shown in Figure 5-13. Triangular membership functions are used in this model. The fuzzy rules that map the inputs to output variables are defined based on pre-developed tables. Figure 5-14 shows the surface demonstrating the relationship between inputs and outputs. As shown, the frequency of running the inspection tool increases when the POF grade grows. Similarly, a higher resolution tool is suggested when the financial consequence of the risk of failure increases.

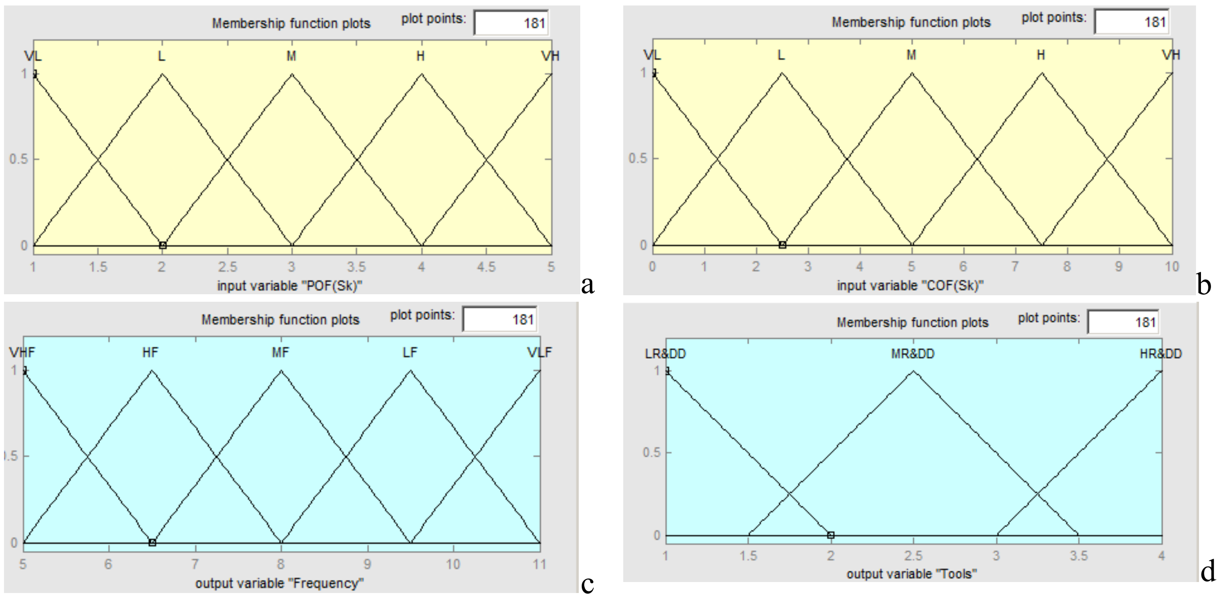


Figure 5- 13: Membership functions of Fuzzy Inspection Tool Selection Model

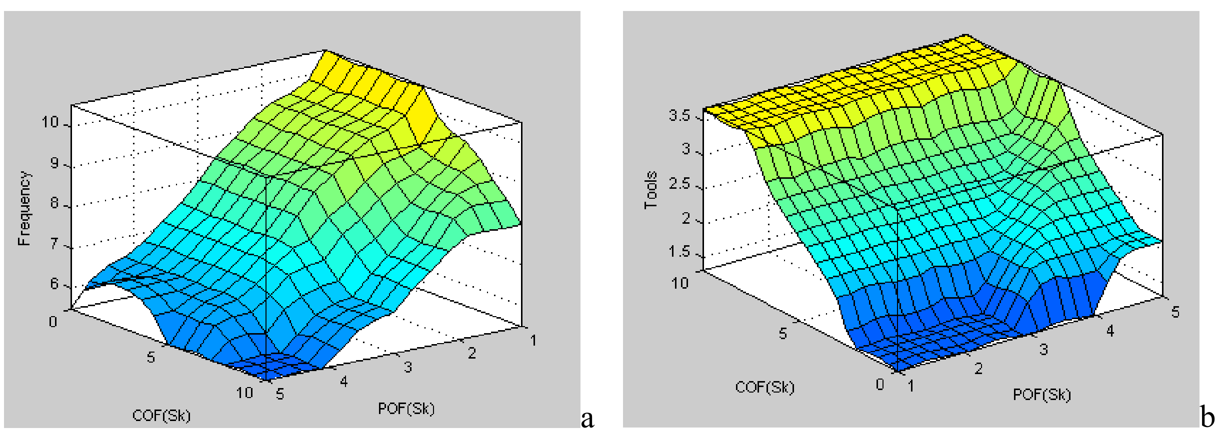


Figure 5- 14: Surfaces demonstration of the Fuzzy Inspection Tool Selection Model

After selecting the inspection techniques and the frequency of inspection through the inspection frequency index, the life cycle analysis of various scenarios of inspection is implemented. Different combinations of the selected inspection techniques with the corresponding frequency of application are used. The cumulative risk profile of the failed pipes is developed applying non-linear regression and obtaining the historical data in the US ($PHMSA_a$ 2014). Figure 5-15 presents the cumulative risk growth profile versus the age of failure. As it is clear, the risk of failure increases during the service life of the pipelines with a third-degree equation. The R-squared coefficient of the fitted model is 0.99 that proves the efficiency of the model.

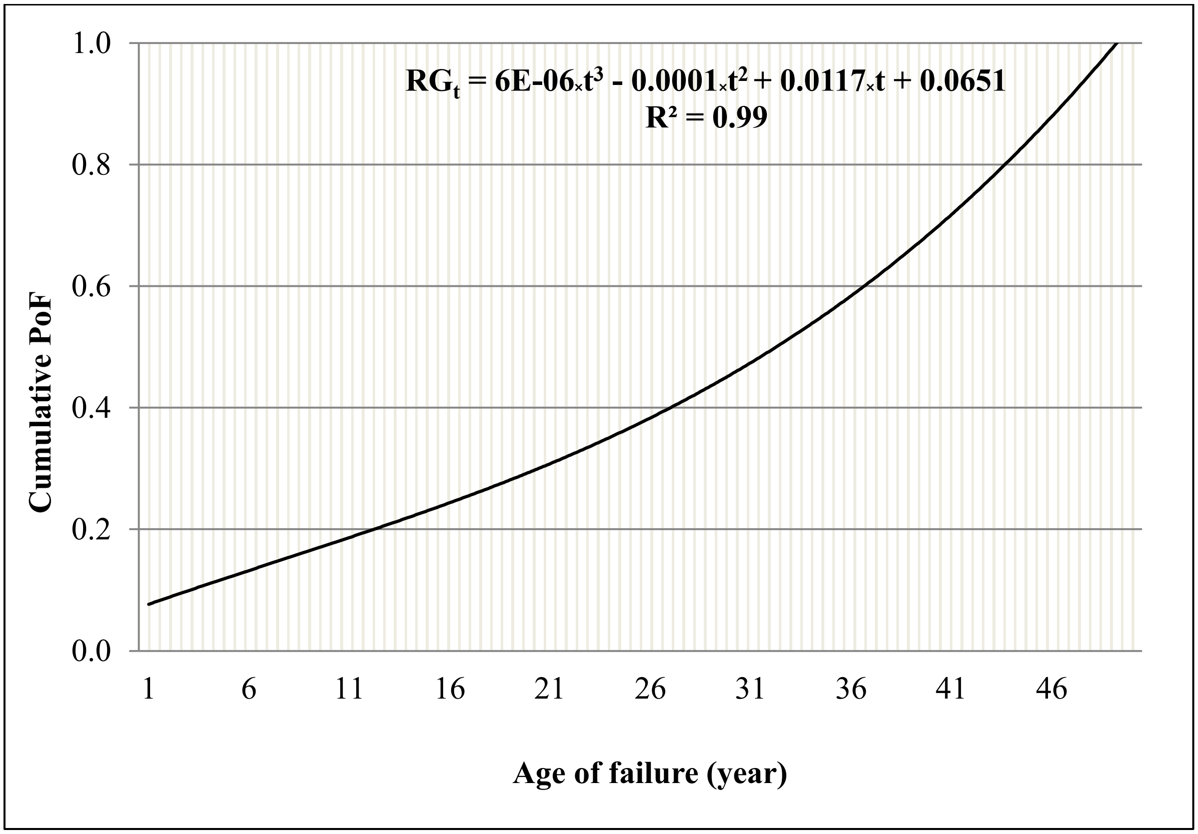


Figure 5- 15: Cumulative risk growth profile

Figure 5-16 shows the membership functions that are defined to assess the capability of inspection tools. As seen, the membership functions are triangular, and the scale of assessment is an 11-grade granular fuzzy scale similar to that of Sadiq et al. (2004). After the calculation of risk reduction index, the risk profile after-inspection is developed for each scenario. Consider an example of a pipeline that is supposed to be inspected every ten years with an inspection tool that is calculated to reduce the risk of failure by 25% after the inspection. The risk profile of this scenario is presented in Figure 5-17. The risk of the pipeline is increased every year according to the cumulative risk profile. Once the inspection is performed, it is assumed that the risk is decreased by 25%. Then it continues to increase until the next inspection. This process is repeated for the whole life of the pipeline. In this example, it is assumed that the average life of such pipelines is equal to 50 years. The maximum risk of the pipeline, which happens in the last year of the service life is determined through this profile.

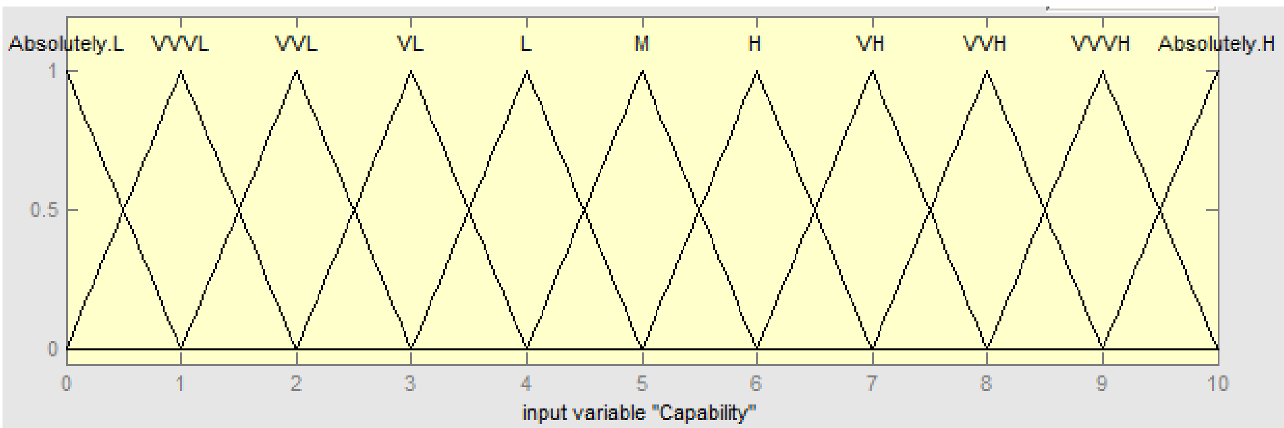


Figure 5- 16: Fuzzy membership functions of the inspection tools' detection capability

Inspection cash flow of the pipeline is calculated after developing this profile embedding the cost of operating the inspection tools. After that, the equivalent economic value of each scenario is calculated. Economic equivalent values of the scenarios are computed using the Equations 3-22 to 3-24. The probability distribution functions of the inspection cost are assumed triangular due to the limited rehabilitation cost data. The equivalent economic value of each scenario is calculated applying the Monte Carlo simulation in @Risk 6 software. Figure 5-18 presents the results of the Monte Carlo simulation for the EUAC calculation of the example case study. The average EUAC is computed as 8,284 US$. Then the Risk-Cost index of each scenario is computed applying Equation 3-25.

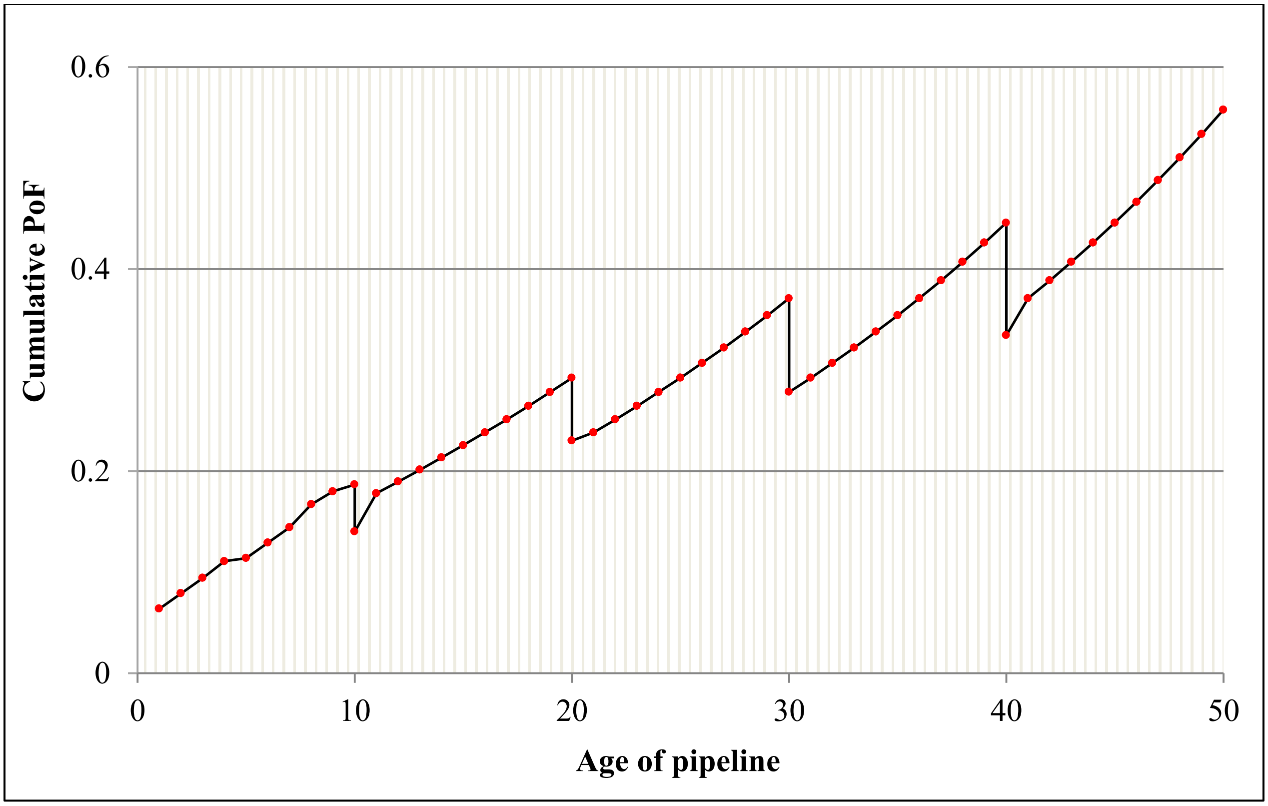


Figure 5- 17: Cumulative after inspection risk profile of an example pipeline

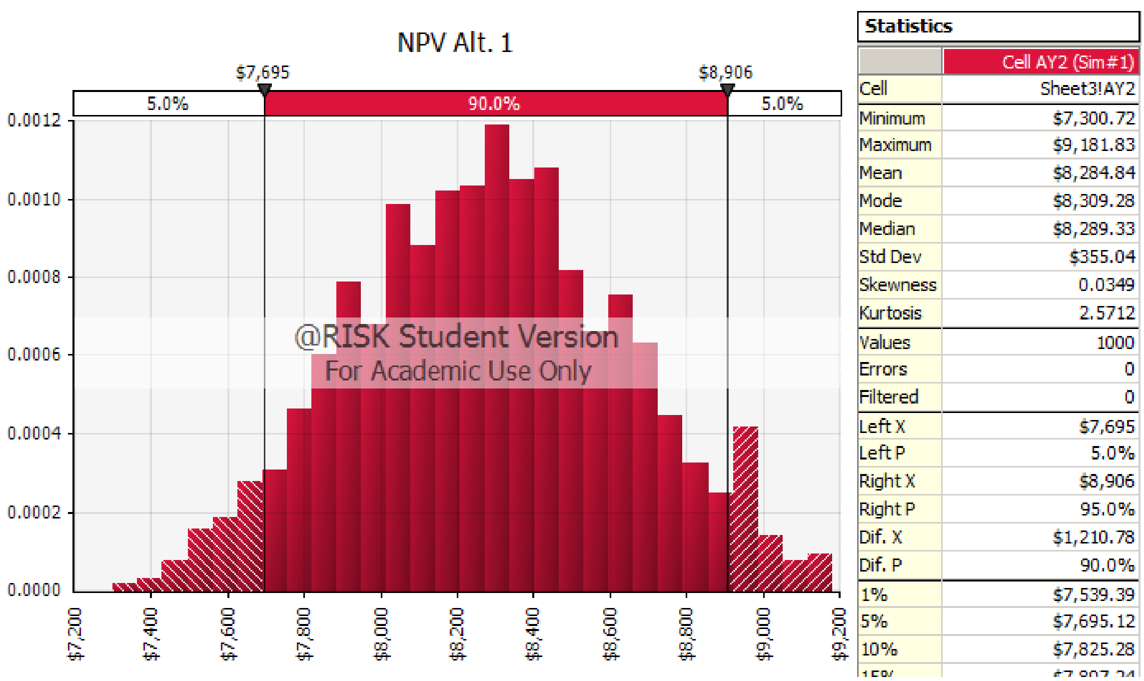


Figure 5- 18: EUAC Result of Monte Carlo simulation

For the example scenario, the Risk-Cost index is calculated to be 4,639. This process is repeated for each scenario, and the result is compared. The best scenario is the scenario with lower Risk-Cost index. Application of the Monte-Carlo simulation is due to the uncertainty that exists in the cost elements and interest rate.

5.6 Rehabilitation Planning Model

The size of defects affects the maintenance decision process of oil and gas pipelines, especially in the rehabilitation of underground and offshore pipelines. As mentioned before in the methodology section, a defect size scale is developed for each maintenance operation type (i.e., recoat, repair, and replacement) based on its nature. Table 5-16 lists the sizes of the maintenance operation types used herein. Seven defect sizes are used to predict the cost of operations required to perform on such pipes.

Table 5- 16: Defects Size Scale for Various Rehabilitation Techniques (meters)

Size No.	Recoating	Repair	Replacement
S1	1.0	0.1	1.5
S2	2.0	0.2	2.0
S3	4.0	0.4	4.0
S4	5.0	0.8	5.0
S5	6.0	1.5	6.0
S6	8.0	2.0	8.0
S7	10.0	4.0	10.0

The overall pipeline condition changes from excellent (i.e., a score of “10”) to extremely poor (i.e., score of “0”). The condition increment of a recoated section is assumed equal to the 50% of the difference between the current and the maximum condition of a pipeline. The relative condition increment for repair and replacement is equal to 70% and 100% of the difference between the current and the maximum conditions, respectively. The estimated condition increments are then multiplied by the size of the maintenance operation and divided by the segment's length, which is assumed herein equal to ten meters.

Table 5-17 summarizes the condition increase for every size of each maintenance operation in a segment of ten-meters based on current overall conditions. For example, let us consider the condition increment of the recoat operation "S1", which consists of recoating one meter in a ten-meter pipeline section. Let us also assume that the current condition of the pipeline at the time of recoating is equal to eight. Hence, the difference between the maximum pipeline condition and the current condition is two (i.e., "10 – 8"). Therefore, the condition increment would be 0.10 (i.e. 0.50 × 2 × 0.10). In other words, if one meter of a ten-meter pipeline section is recoated then the condition increment would be equal to "0.1". As a result, the condition of the pipeline section after recoating will be equal to 8.10.

Table 5- 17: Condition Increments for Different Types of Rehabilitation

Size of Defect	Operation Type					
	Recoat Primary Condition =8	Repair Primary Condition =7	Replace Primary Condition =5	Recoat Primary Condition =7	Repair Primary Condition =6	Replace Primary Condition =4
S1	0.10	0.02	0.75	0.15	0.03	0.63
S2	0.20	0.04	1.00	0.30	0.06	0.84
S3	0.40	0.08	2.00	0.60	0.11	1.68
S4	0.50	0.17	2.50	0.75	0.22	2.10
S5	0.60	0.32	3.00	0.90	0.42	2.52
S6	0.80	0.42	4.00	1.20	0.56	3.36
S7	1.00	0.84	5.00	1.50	1.12	4.20

Deterioration profile is developed based on the risk growth profile. There is a reverse relationship between the deterioration of the pipes and their risk growth. Equation 5.1 is developed to forecast the condition of the pipes during their service life. The produced conditions from this equations show some limitations that are addressed in Equation 5.2 by some modifications, which changes the starting and ending condition of the profile. These limitations are: 1) the condition of a newly constructed pipe is calculated to be 9.35 and 2) the condition of the pipe end of its useful life would be less than zero. The modifications are applied to the factor that is multiplied by the risk growth index and constant value to fix these two problems. Figure 5-19 shows the developed deterioration profile. The developed deterioration profile is drawn based on Equation 5.2. However, the developed deterioration profile is the before-intervention profile of the pipes based on an average behavior.

$$C_t = 10 - 10 \times RG_t = 10 - 10 \times (6E\text{-}6 \times t^3 - 0.0001 \times t^2 + 0.0117 \times t + 0.0651) \tag{5.1}$$

$$\boldsymbol{C_t = -5E - 5 \times t^3 + 0.0009 \times t^2 - 0.1031 \times t + 10} \tag{5.2}$$

Where, C_t is the condition of the pipe at age « t », RG_t is the risk growth index at age « t », t is the age of the pipe.

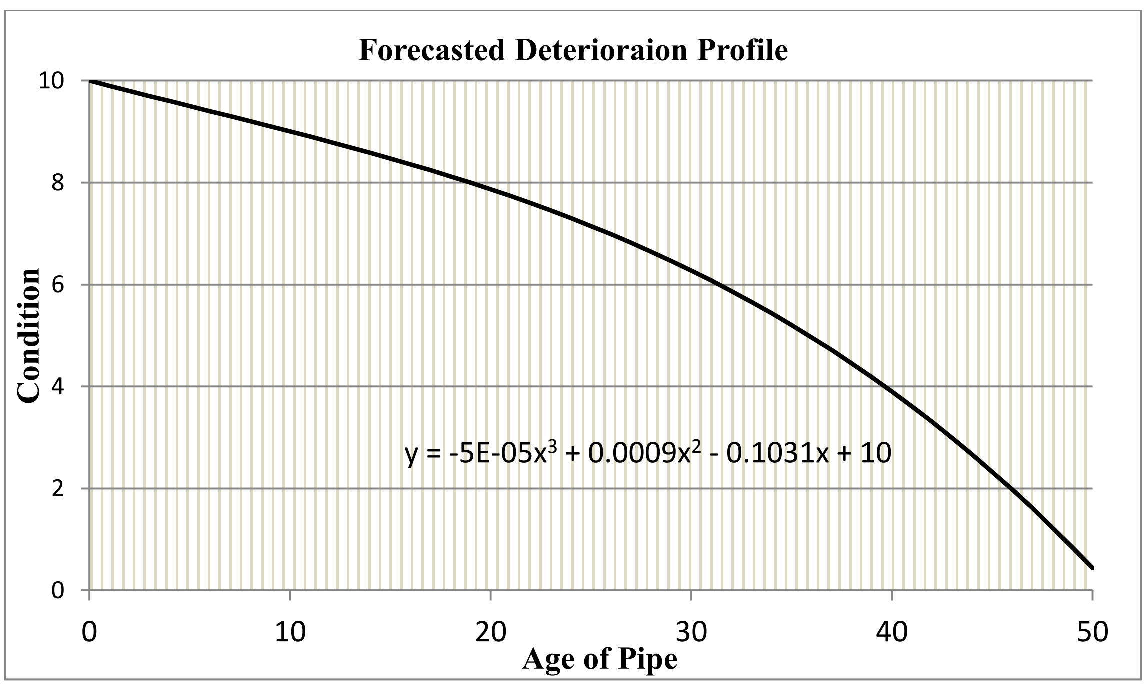


Figure 5- 19: Risk-based deterioration profile

Once the deterioration of the pipe can be predicted before rehabilitation, there is a need for the development of the after rehabilitation deterioration profile. Figure 5-20 shows a conceptual profile that is used to analyze the scenarios of rehabilitation in this research. Any time that a rehabilitation action is performed, the condition is supposed to be increased. Also, the thresholds of the condition are used to decide about the actions that are required for the maintenance of the pipe. All defect sizes are repeated in ten-meter segments of the pipeline. A 10-centimeter size defect is repeated on all segments of the pipeline section under analysis. In a one-kilometre section, a ten-centimetre size defect is assumed to occur in each segment. The condition increment is proportional to the size of the maintenance action on the segment. As a result, the condition increment of small maintenance sizes is lower compared to those of larger maintenance sizes.

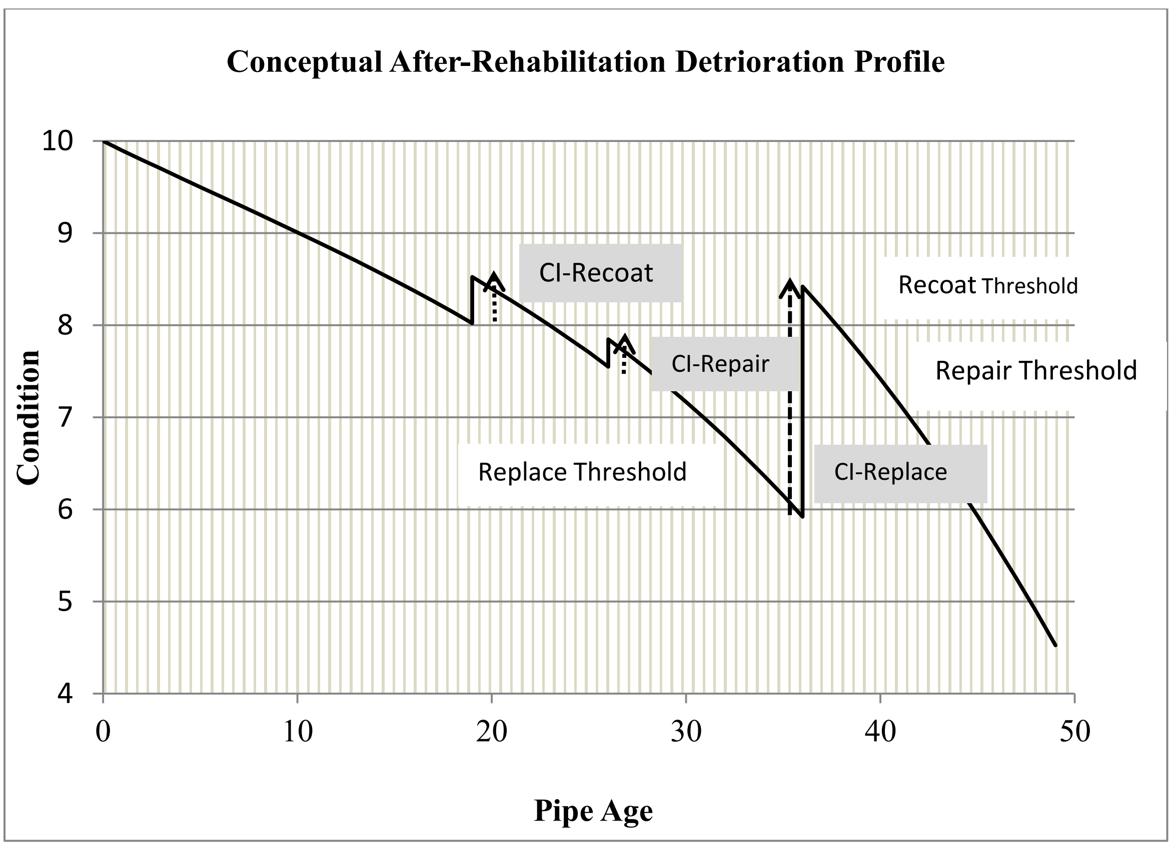


Figure 5- 20: Conceptual Deterioration Profile With and Without Interventions

5.6.1 Overall Scenarios

As mentioned in the Methodology section, conservative and regular plans were implemented for the maintenance of pipelines. Table 5-18 summarized the pipeline condition thresholds and their corresponding maintenance operation types in both plans. It is worth noting that higher pipeline condition thresholds are assigned for the conservative plans. For example, it shows that a recoating action must take place if the pipeline condition is less than or equal to 8 in the conservative plan. On the other hand, the recoating action can occur if the pipeline condition is less than or equal to 7 in the regular plan.

Table 5- 18: Pipeline Condition Thresholds for Rehabilitation Techniques

Rehabilitation Technique	Conservative Plan	Regular Plan
Recoating	8	7
Repair	7	6
Replacement	6	5

Several scenario groups are developed based on these thresholds using various types of operations as shown in Table 5-19. The first three groups (i.e., 1, 2, and 3) are based on the conservative plan while the second three groups (i.e., 4, 5, and 6) are based on the regular plan. Group 1 scenarios include the combination of remedial actions, repair, and replacement under conservative thresholds. The conservative plan specifies the use of recoating, repair, and replacement when the pipeline condition falls below 8, 7, and 6, respectively. In other words, the rules for Group 1 indicate that a one-time recoating is needed when the condition falls below 8. Repair is needed when the condition falls below seven, and it is repeated every year. When the condition drops below five, a replacement is required. In some of the scenarios, there is no need for replacement as the repair increases the condition more than the deterioration rate. As a result, the condition never falls under six. The inspection is included in all of the scenarios since it is required according to the existing recommendations. Group 2 scenarios, which do not include remedial actions, contain repair and replacement with conservative thresholds. Accordingly, the rehabilitation starts with repair at a condition of seven while replacement begins when the condition falls below five. Group 3 refers to the alternatives with the repair as the major action. Finally, scenario groups 4-6 that are similar to their counterparts (i.e., Groups 1-3), are implemented under the regular plans (i.e., with lower condition thresholds). The conservative plans are proposed to be implemented for high and very high-risk pipes while the regular plans of rehabilitation are suggested for medium and lower risk pipes.

Table 5- 19: Overall Scenario Types

No.	Combinations of Rehabilitation Types	No. of Scenarios	Plan Type	Abbreviation of the Scenarios ("n" shows the size of the repair or replacement and changes from one to seven)
1	Inline Inspection+ Recoating +Repair +Replacement	14	Conservative Plan	An (sleeve are used to repair) Bn (Clamps are used to repair)
2	Inline Inspection+ Repair +Replacement	14	Conservative Plan	Cn (sleeve are used to repair) Dn (Clamps are used to repair)
3	Inline Inspection+ Recoating+ Repair+ Replacement	14	Regular Plan	Fn (sleeve are used to repair) Gn (Clamps are used to repair)
4	Inline Inspection+ Repair+ Replacement	14	Regular Plan	Hn (sleeve are used to repair) In (Clamps are used to repair)

5.5.2 Economic Parameters

The scenario cash flow is determined using a model that is developed using Microsoft Excel (Microsoft 2010). It was computed using the cost data previously described in the Data

Collection chapter. The equivalent economic value of each scenario is computed using the Net Present Value (NPV). Monte Carlo simulation is used to address the uncertainties in the cost of operations and the interest rates. Equations 5.21~5.23 are used to calculate the probabilistic NPV values. The costs of the maintenance operations are used in constant 2013 dollars (i.e., without considering the effect of inflation) and are discounted with the forecasted interest rates.

5.7 Model Implementation to a Case Study

In this section, the developed models are applied to a case study of a 24-inch pipeline in North America. Table 5-20 shows the data regarding the pipe that is used to analyze the risk of failure and maintenance planning of the pipe. The pipe is composed of two diameter size parts 24” and 30”. It is planned to be constructed with High-Strength material. It will be coated with Field Applied Epoxy (FBE). The pipe will be laid underground, and the depth of cover will be four feet. It is a high-pressure pipe, which spans over 323 miles and transfers crude oil. A highly accurate leak detection system will be installed on the pipeline.

The models developed in the previous sections are applied to calculate the probability of failure. First, the categories related to each variable in the Bow-tie model are identified. Then, related PDF is located for each category with respect to each failure source. Finally, the developed equations are used to compute the probability of failure for each failure source of the pipes. Monte Carlo simulation is applied to calculate the mean value for the probability of failure with respect to each failure source, and determining attributed distribution function. Monte-Carlo simulation is applied to fit the calculated data with the best distribution function. Figure 5-21 shows the result of the calculated probabilities of failure with respect to each failure source. The mean value of the POF with respect to external corrosion is computed to be equal to 2.9E-5. The overall POF of the pipe that is the summation of the POF with respect to all sources is computed equal to 4.9E-4 failures/mile.year. Considering the whole length of the pipe, the POF comes up to around 0.16 failures per year.

Table 5- 20: Primary data of case study

Variable	Value
Location	Texas
Diameter	24inch and 30 inch
Material	High Strength
Coating type	FBE
Depth of Cover	4 feet
MAOP	1,440 psig
Location	Belowground
Length	323 miles
SMYS	70,000 and 80,000
Product transported	Crude oil
Leak detection system	Highly accurate: Capable of detecting a 5% leak in 90 min; and a 53% leak in 5 min
Pipe wall thickness	0.343 inches, and 0.375 inches

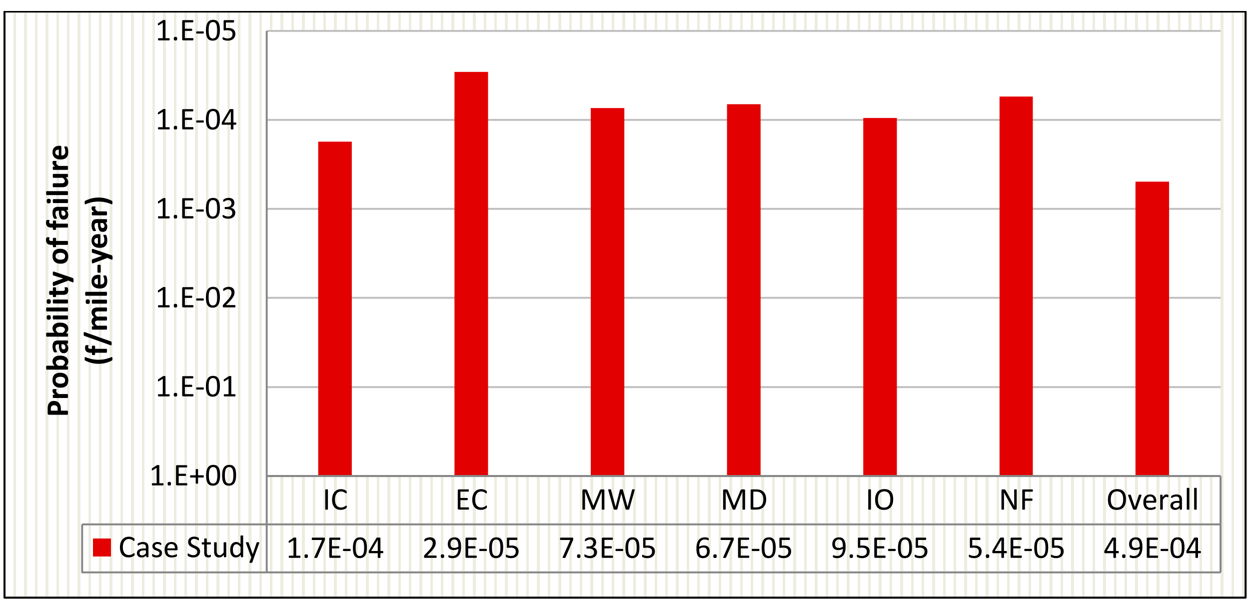


Figure 5- 21: Calculated mean values of POF with respect to all

For the consequences of failure, the developed neuro-fuzzy model is used to forecast the consequence values. For the location of the pipe, two different class locations and existence of HPA and non-HPA is considered. Then the failure consequences are computed for both of the states. Figure 5-22 shows the calculated amounts for the consequences of failures of the pipe. The estimated values for a higher class location and high populated area are ten that is a Very High consequence. While the external corrosion and internal corrosion for a high-class location is considered to be very high, the consequences of failure for material and weld damages and mechanical damages are estimated to be at medium level, around five. The consequences are forecasted to be higher for class location 1 for material and weld defects, mechanical damages, and incorrect operations. That could be because of the accessibility limitations of the operators and the lack of inspection. A potential failure due to the external and internal corrosion in a low class location produces lower consequences. A failure stemming from natural forces in a low class location is expected to result in the lowest consequence level. The calculated consequences of failure levels are used in the integrated fuzzy risk index evaluation model to assess the risk of failure of pipe with respect to all failure sources.

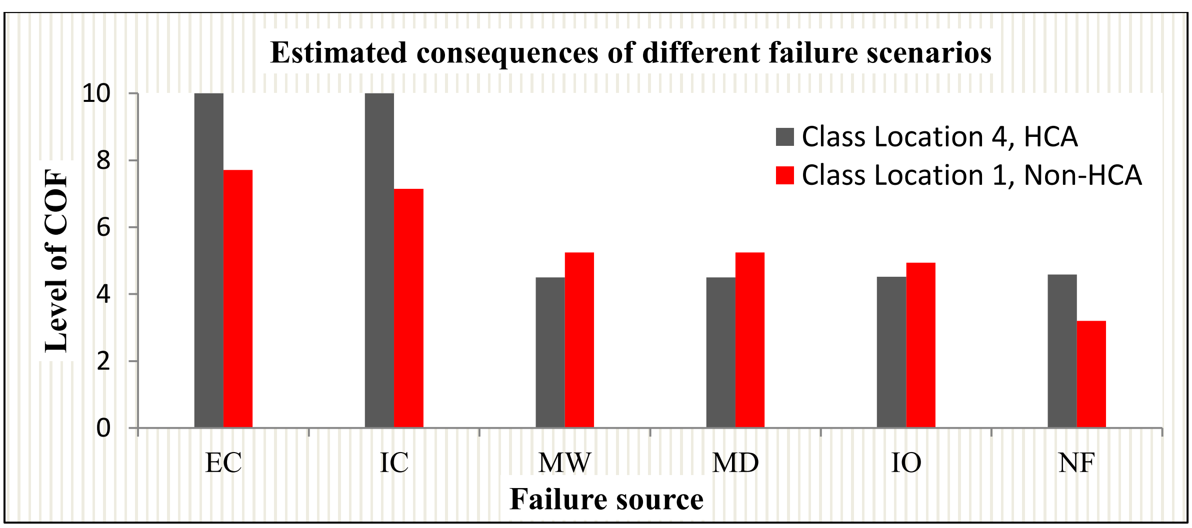


Figure 5- 22: Estimated consequences of failure for all failure sources

After the computation of the POF and COF for each failure source, the risk index is calculated with respect to the failure sources using the Integrated Fuzzy Risk Model. The scores of POF and COF are inserted to the MATLAB FIS and the risk indices are calculated. Table 5-21 shows the risk parameters and risk indices for the case study with respect to all of the failure sources. As shown, the maximum risk index for the pipe belongs to internal corrosion followed by external corrosion. Minimum risk index belongs to the failures with natural force damages.

Table 5- 21: Risk parameters and Risk indices of the case study

Source	POF Overall	POF Level	COF1	COF2	Risk Score1	Risk Score2
IC	1.75E-04	4.24	7.71	10	3.71	4.54
EC	2.89E-05	3.46	7.15	10	3.38	4.50
MW	7.33E-05	3.86	5.25	4.5	3.43	3.32
MD	6.66E-05	3.82	5.25	4.5	3.37	3.31
IO	9.54E-05	3.98	4.94	4.52	3.62	3.35
NF	5.45E-05	3.74	3.2	4.59	2.71	3.24

Once the risk indices are calculated, the result is used to select the inspection tools and their frequency of running. The calculations are performed for all failure sources as shown in Table 5-22. The frequency of running the inspection tools for all sources hover around 6 and 7. The inspection tools are selected with respect to the highest COF or internal corrosion to be more conservative,. As a result, in this case, all of the selected inline inspection tools are high resolution. Data on inline inspection tools are gathered from ROSEN (2015). Rosen is a provider of inspection operations to the operators of oil and gas companies in North America. Table 5-23 shows the collected data on four selected inspection tools. The selected tools use MFL and UT technologies. Expert opinion is used to obtain data on the detection capability of each inspection tool with respect to the sources of failure.

Table 5- 22: Frequency determination and Inspection tool selection for case study

Source	POF Level	COF1	COF2	Frequency	Inspection tool
IC	4.24	7.71	10.00	5.51	3.66
EC	3.46	7.15	10.00	6.18	3.64
MW	3.86	5.25	4.50	6.76	2.57
MD	3.82	5.25	4.50	6.82	2.57
IO	3.98	4.94	4.52	6.54	2.49
NF	3.74	3.20	4.59	6.95	2.38

Table 5- 23: Detection capability level for the selected inspection tools

Inspection Tool / Failure source	ROCOMBO MFL-A/XT	ROCD UT-C	ROGEO XT	ROCORR MFL-A
EC	5	6	7	4
IC	5	6	7	4
MW	6	2	6	3
MD	6	2	6	3

The risk reduction index, as well as accuracy percentage index, is computed for each tool as shown in Table 5-24. These values are then used to develop the risk growth profile of the pipe using each inspection tool every six years. The maximum risk is computed for each profile as obtained at the end of the service life. The highest risk reduction index belongs to ROGEO XT inspection tool. Figure 5-23 shows the risk growth profile for one of the selected inspection tools in which the maximum risk is computed to be 0.58 that happens at the end of the life cycle. After developing the risk growth profile and computing the maximum risk for each scenario, the Equivalent Uniform Annual Cost (EUAC) is calculated for each scenario applying Monte Carlo simulation.

Table 5- 24: Calculated indices for each inspection tool

Indices \ Inspection Tools	ROCOMBO MFL-A/XT	ROCD UT-C	ROGEO XT	ROCORR MFL-A
DC	7.5	6.5	8.5	5.5
Ac	0.65	0.58	0.47	0.61
ACp	0.90	0.91	0.93	0.90
RRi	0.67	0.59	0.79	0.50

The risk cost index is computed as shown in Table 5-25. As shown, the ROGEO XT inspection tool has the lowest risk-cost index, although it has a higher life cycle cost. Consequently, this inspection is ranked first in the preference of the selected inspection tools.

Table 5- 25: Maximum risk, EUAC and Risk-Cost indices of the inspection scenarios

Indices \ Inspection Tool	ROCOMBO MFL-A/XT	ROCD UT-C	ROGEO XT	ROCORR MFL-A
Max. Risk	0.58	0.73	0.31	0.86
EUAC	1,203	1,133	1,593	1,062
RISK-COST	698	827	489	913

The developed models on rehabilitation planning are implemented on the 24” part of the pipeline. The selection of the 24” pipeline is due to the availability of the rehabilitation cost data. To identify the required yearly rehabilitation actions, the overall condition before intervention is computed every year for the whole service life of the pipeline. The calculated amounts represent the risk-based deterioration profile of the pipeline before intervention operations. Then, the calculated condition is checked against the condition thresholds in each scenario’s group to forecast the required maintenance work over the service life of the pipeline.

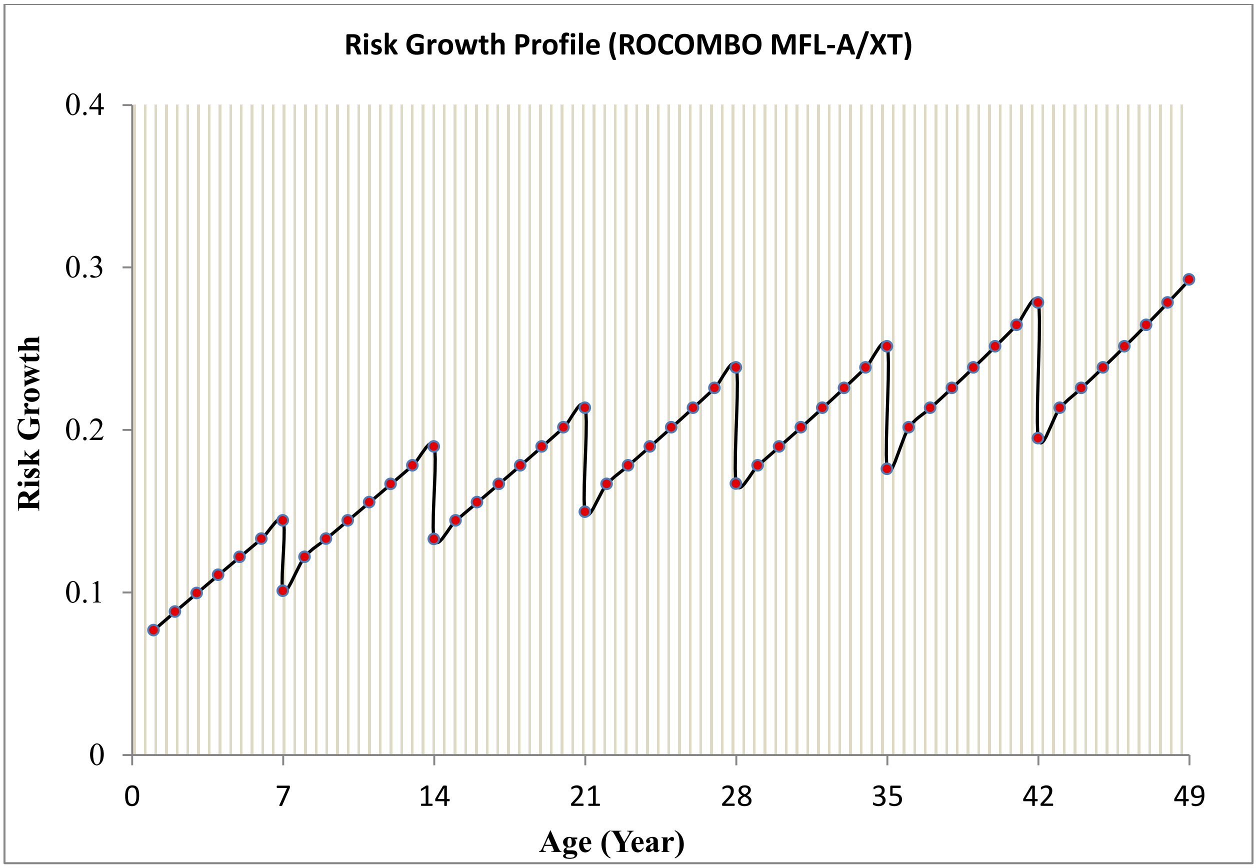


Figure 5- 23: Risk growth Profile for ROCOMBO MFL-A/XT

If any action is necessary, the condition after-intervention is computed according to the increment tables that are calculated proportionally to the size of the rehabilitation work as previously explained. The deterioration profiles of the scenarios are then determined. Finally, the required actions are planned, and related cash flows are calculated by summing up the estimated costs of the planned maintenance works. In each scenario group, the seven sizes of defects are used to develop several possible scenarios. Due to the high-risk indices, only conservative rehabilitation plans are selected for this case study. As a result, 21 scenarios are built based on the conservative plans. The scenarios' cash flows are calculated based on the estimated costs of each maintenance operation type for each size. Sample deterioration profiles of Group C of scenarios with size one, four, and seven are shown in Figure 5-24. It is clear that the condition of the pipelines never falls below six for Group C of scenarios.

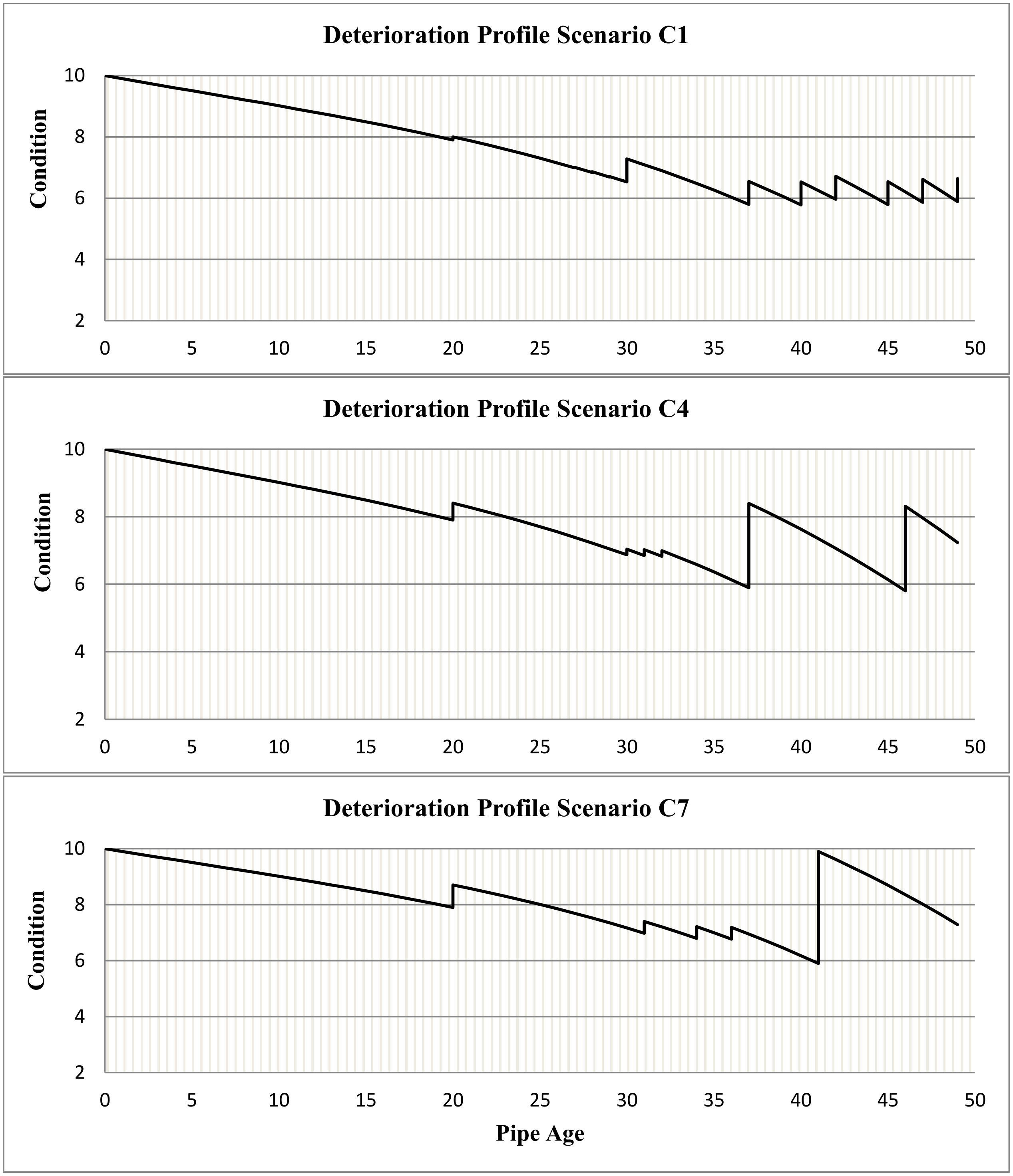


Figure 5- 24: Sample Deterioration Profiles

For clarification, let us consider an example from the Group 1 scenario. This group includes inline inspection, recoating, repair, and replacement. The condition thresholds that determine the required maintenance actions were obtained from Table 5-24. The table shows that recoating, repair and replacement are needed when the condition falls below 8, 7, and 5, respectively. The condition of the pipeline before interventions during a 50-year service life is computed with the pre-mentioned assumptions. It is clear that the recoating would be the first action to be performed on this type of scenarios. Let us consider "S1" that refers to the smallest sizes of the maintenance actions. The first required action according to the thresholds and condition of the pipeline is identified as recoating in year twenty when the condition starts to fall below 8. Consequently, it is decided to recoat the pipeline with "S1" type in year fourteen. The condition of the pipeline is calculated after this intervention using Table 5-23. As a result, the condition of the pipeline is increased by 0.1. The deterioration continued until the condition falls below 7 at year 23. As a result, repair starts in year 23.

The condition after repair is calculated to be 7.02. Considering the deterioration rate and the repair thresholds, this operation is required for this scenario every year starting from year 23. The condition is then calculated after each repair for the following years. Finally, a replacement is required at age 38 because the condition falls below 5. Repair continues between years 38 and 45. In year 45, the replacement is again required because the condition of the pipeline falls below 5. However, the condition does not increase above the threshold of repair. Consequently, repair continues until the end of the service life of the pipeline (i.e., 50 years). Different scenarios of repair and replacement are generated to be used in the life cycle cost analysis. After the development of the maintenance scenarios, the probability distributions of the rehabilitation action costs are defined to calculate the probabilistic cash flow of each alternative. Table 4-2 shows the estimated minimum, average, and maximum costs for the different maintenance operation types and sizes. In each scenario, the probability distribution functions of the maintenance operation cost and interest rate were defined.

The required functions for the calculation of the NPV are then built. Consequently, the model is used to simulate each scenario for 1,000 iterations, and the obtained results are recorded. The @Risk 6 application (PALISADE 2013) is used for the Monte Carlo simulation. The software calculates the NPV amounts for the specified iterations. Then, it fits the best distribution function to the calculated amounts and estimates the mean, minimum, and maximum of the distribution function. After running the simulation for all of the scenarios, they are sorted in ascending order with respect to their NPV values. Table 5-26 summarizes the simulation-based net present value calculated amounts of all scenarios. As shown in the table, the lower values are mostly generated by the scenarios that combine various operation types including recoating, repair, and replacement.

Plan C3 that proposes the combination of recoat, repair and replacement with an "S3" size is ranked first. Figure 5-25 summarizes the mean values of each scenario's NPV. There is a significant difference between the highest and the lowest scenarios' NPV. Figure 5-26 shows the amounts of NPV for each scenario including the most likely, minimum and maximum NPV values. The medium size rehabilitations produce lower cost during the service life of the pipes. This finding supports the idea of maintaining several defects of the pipeline at the same time, however not leaving it to grow and become vast. It is tried to develop the model as flexible and general as possible so the users can change the input data and adjust it based on their asset's properties.

Table 5- 26: Scenarios Sorted Based on Simulation-Based NPV (US $)

No.	Title	Rehabilitation Types	Size	Minimum	Maximum	Most Likely
1	C3	Recoat+Repair+Replace	S3	1,140,439.82	2,004,766.73	1,743,275.42
2	C6	Recoat+Repair+Replace	S6	1,187,726.54	2,070,699.01	1,800,607.84
3	C2	Recoat+Repair+Replace	S2	1,143,664.40	2,072,874.04	1,802,499.17
4	C4	Recoat+Repair+Replace	S4	1,216,413.97	2,158,030.22	1,876,548.02
5	C1	Recoat+Repair+Replace	S1	1,215,241.39	2,220,380.43	1,930,765.59
6	C5	Recoat+Repair+Replace	S5	1,267,745.43	2,263,181.87	1,967,984.23
7	B2	Repair+Replace	S2	1,460,293.32	2,721,771.46	2,366,757.80
8	B1	Repair+Replace	S1	1,454,896.15	2,729,629.82	2,373,591.15
9	C7	Recoat+Repair+Replace	S7	1,581,911.37	2,814,484.00	2,447,377.39
10	B7	Repair+Replace	S7	1,520,628.43	2,927,407.04	2,545,571.34
11	B6	Repair+Replace	S6	1,591,622.43	3,065,704.12	2,665,829.67
12	A5	Recoat+Repair+Replace	S5	1,708,717.64	3,114,144.70	2,707,951.91
13	A7	Recoat+Repair+Replace	S7	1,722,404.02	3,127,558.06	2,719,615.71
14	A4	Recoat+Repair+Replace	S4	1,735,152.72	3,172,982.90	2,759,115.57
15	A6	Recoat+Repair+Replace	S6	1,796,620.76	3,238,856.74	2,816,397.16
16	A2	Recoat+Repair+Replace	S2	1,916,426.42	3,283,492.51	2,855,210.88
17	A1	Recoat+Repair+Replace	S1	1,938,594.49	3,316,532.47	2,883,941.28
18	B5	Repair+Replace	S5	1,726,976.52	3,348,156.45	2,911,440.39
19	A3	Recoat+Repair+Replace	S3	1,930,719.07	3,573,037.51	3,106,989.14
20	B4	Repair+Replace	S4	1,898,800.63	3,664,624.85	3,186,630.30
21	B3	Repair+Replace	S3	1,968,215.68	3,765,274.77	3,274,151.98

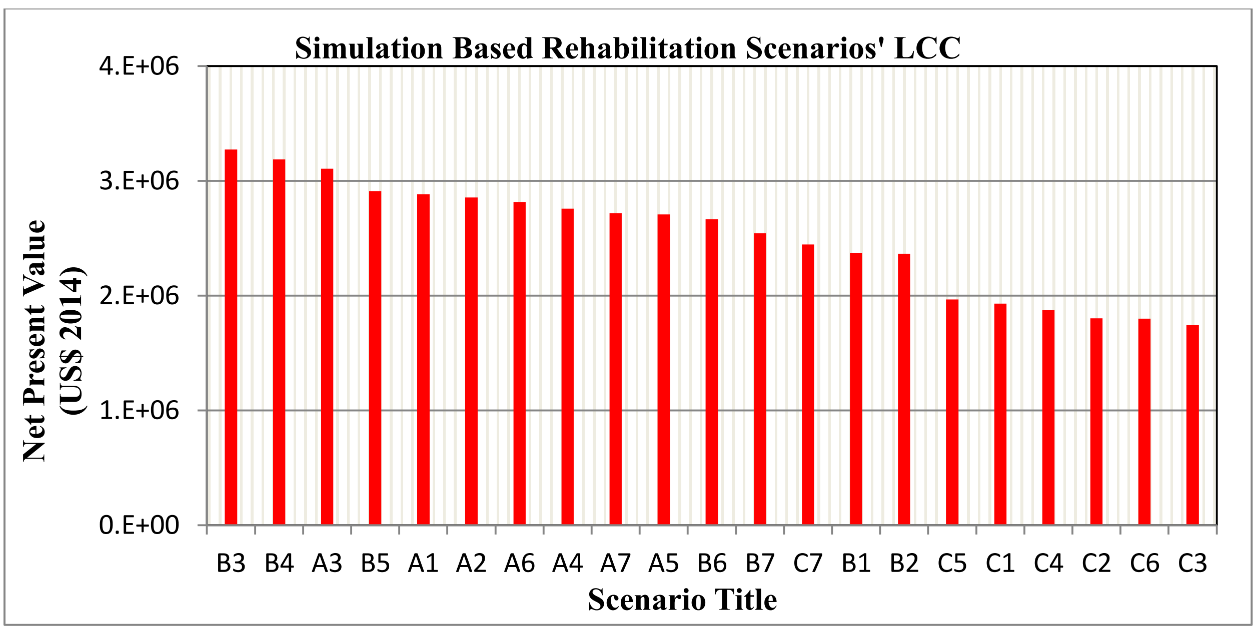


Figure 5- 25: Simulation-Based EUAC Amounts (Sorted based on NPV, Most Likely)

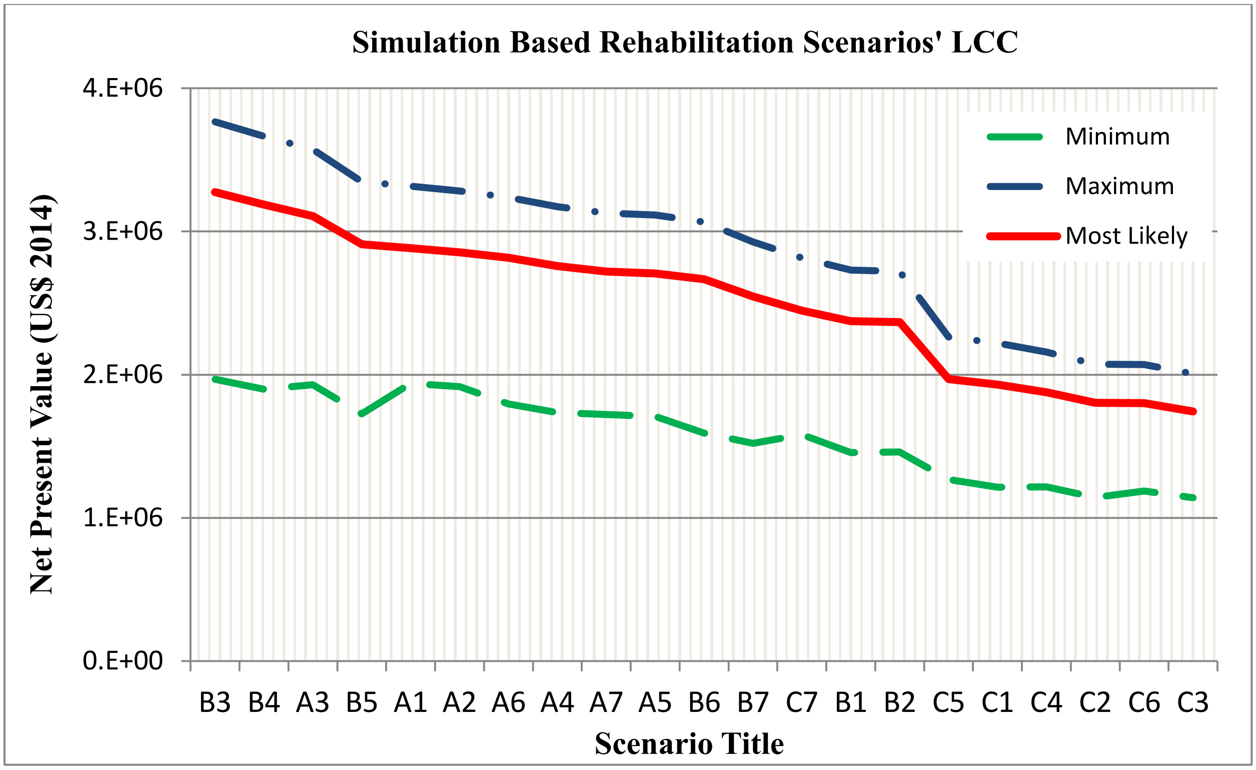


Figure 5- 26: Simulation- Based NPV Amounts

The scenario with the lowest LCC is titled C3 that uses a combination of recoat, repair, and replacement and is inspected every seven years. This scenario is intended to be rehabilitated with S3 sizes of rehabilitation types. Its NPV is calculated to be around 1.7 million USD (2013 constant dollars). In this scenario, the pipe is recoated at year 20 when the condition is below 8. Then, it is not maintained until the condition falls below 7 while the repair of the pipe starts. Three repair actions are perfumed until the pipe condition reaches below 6. At that time, part of the pipe is replaced with an S3 size of replacement. Regular maintenance operations are repeated in the whole life cycle of the pipe. The maintenance scenario of C3 is proposed as the optimum rehabilitation plan of the pipe, and the actions that are required to be performed are listed in Table 5-27. As shown, the regular maintenance will be performed every year, while the repair with Sleeves is planned to be performed at years 20, 27, 30, and 31. After that, the replacement is proposed to be performed instead of repair, which will happen at years 35 and 43. Inspection with a high-resolution tool is planned to be run every 6 years, which happens at years 6, 12, 18, 24, 30, 36, 42, and 48. Direct assessment of the pipe is planned to be performed between the Inline inspections with medium distances of digging. While the suggested plan is the ideal rehabilitation plan, there will be a need to inspect the pipe regularly and perform the emergency repair actions if necessary.

Table 5- 27: Case Study Maintenance Plan

Year	Actions to be performed		Year	Actions to be performed	
1	Regular Maintenance		26	Regular Maintenance	
2	Regular Maintenance		27	Regular Maintenance	**DA (Medium), Repair S3**
3	Regular Maintenance	**DA (Medium)**	28	Regular Maintenance	
4	Regular Maintenance		29	Regular Maintenance	
5	Regular Maintenance		30	Regular Maintenance	**ILI (ROGEO XT), Repair S3**
6	Regular Maintenance	**ILI (ROGEO XT)**	31	Regular Maintenance	**Repair S3**
7	Regular Maintenance		32	Regular Maintenance	
8	Regular Maintenance		33	Regular Maintenance	**DA (Medium)**
9	Regular Maintenance	**DA (Medium)**	34	Regular Maintenance	
10	Regular Maintenance		35	Regular Maintenance	**Replace S3**
11	Regular Maintenance		36	Regular Maintenance	**ILI (ROGEO XT)**
12	Regular Maintenance	**ILI (ROGEO XT)**	37	Regular Maintenance	
13	Regular Maintenance		38	Regular Maintenance	
14	Regular Maintenance		39	Regular Maintenance	**DA (Medium)**
15	Regular Maintenance	**DA (Medium)**	40	Regular Maintenance	
16	Regular Maintenance		41	Regular Maintenance	
17	Regular Maintenance		42	Regular Maintenance	**ILI (ROGEO XT)**
18	Regular Maintenance	**ILI (ROGEO XT)**	43	Regular Maintenance	**Replace S3**
19	Regular Maintenance		44	Regular Maintenance	
20	Regular Maintenance	**DA (Medium), Recoat S3**	45	Regular Maintenance	**DA (Medium)**
21	Regular Maintenance		46	Regular Maintenance	
22	Regular Maintenance		47	Regular Maintenance	
23	Regular Maintenance		48	Regular Maintenance	**ILI (ROGEO XT)**
24	Regular Maintenance	**ILI (ROGEO XT)**	49	Regular Maintenance	
25	Regular Maintenance		50	Regular Maintenance	

5.8 Automation of the developed model

The developed risk assessment and maintenance planning model is semi-automated. The first part of the model that belongs to the probability of failure is automated in Excel 2010. All of the required probability distribution functions and required equations for each failure source are defined in the semi-automated program. Figure 5-27 demonstrates a sample excel sheet that is developed to automate the computation of the POF with respect to internal corrosion of a sample pipe. To use the model, it is only required to select the category of each variable according to the properties the pipe and the probability of failure will be computed. The @Risk software is used to apply the Monte Carlo simulation, and the shown result is the mean value estimated to be the POF of the pipe.

	A	C	D	E	F	G	H
1	Varaiable	Category					Case study
2	Product type	Crude oil	HVL	Non-HVL	Natural Gas		1
3		0.046857	0.00118297	0.0068725	0.029671726		
4	Inspection	No-inspection	Inspection less than 5 years	Inspection less than 2 years			3
5		0.077725	0.0028279	0.002651			
6	Protection	No Protection	Inhibitor only	Dewatering claeaning or lining			3
7		0.148437	0.060849	0.036972			
8	DI-Oil	4" or Less	over 4" thru 10"	over 10" thru 20"	over 20" thru 28"	over 28"	4
9		0.00018736	0.00008411	0.00013712	0.00019476	0.00010745	
23	Ins-Year	Before 1950	1950-1970	1970-1990	1990-2013		4
25		1.860332282	1	1.754702057	1.826661028		
35	Adj.Factor	4" or Less	over 4" thru 10"	over 10" thru 20"	over 20" thru 28"	over 28"	4
36		114.0795743	114.0586804	119.0686985	112.2866642	114.082228	
37	Calculation	POF (Internal Corrosion)					2.04E-04
38							
39							

Figure 5- 27: Sample Excel sheet calculation for Internal Corrosion Failures

Once the calculation for the probability of failure is performed, it is required to compute the consequences of failure. The fuzzy inference system for this model is defined in MATLAB R2010b. Figure 5-28 shows a sample calculation sheet as demonstrated in MATLAB. It only needs the values of four inputs to calculate the consequence of failure. The four variables include the event tree class, location category, and diameter and Specified minimum yield strength of the pipe. The value for the location category, diameter, and SMYS might be fixed if it does not change the length of the pipe. However, for the event tree there will be more than one value. All of the possible scenarios of failure including the failure source, the hole size and ignition possibility can be analyzed, and related COF can be calculated.

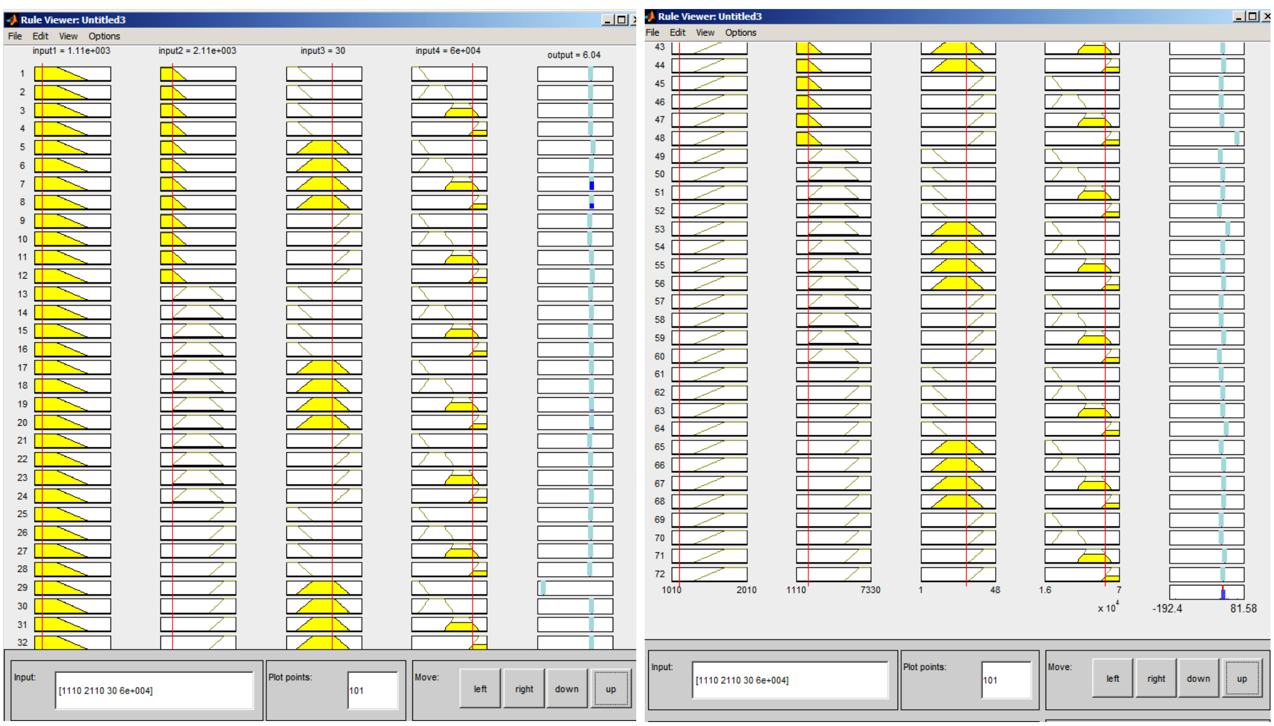


Figure 5- 28: Sample COF calculation sheet

The risk index can be computed based on the estimated probability of failure and consequence of failure. Once the absolute probability of failure is calculated, and the grade of the related probability of failure is computed, the risk index is forecasted. A fuzzy inference system (FIS) is defined in MATLAB based on the developed model in the previous sections as shown in Figure 5-29. For the defined FIS, all of the membership functions of the inputs, output, and the fuzzy rules are defined, and the FIS is developed. The FIS only needs the grade of the probability of failure and consequence of failure to calculate the risk index. The index can be computed with respect to each failure source. The overall risk index can be the maximum of the computed values. In the sample shown in the figure, the probability of failure and the consequence of failure values are inserted as 3.86 and 4.15 and the risk index is calculated 3.32.

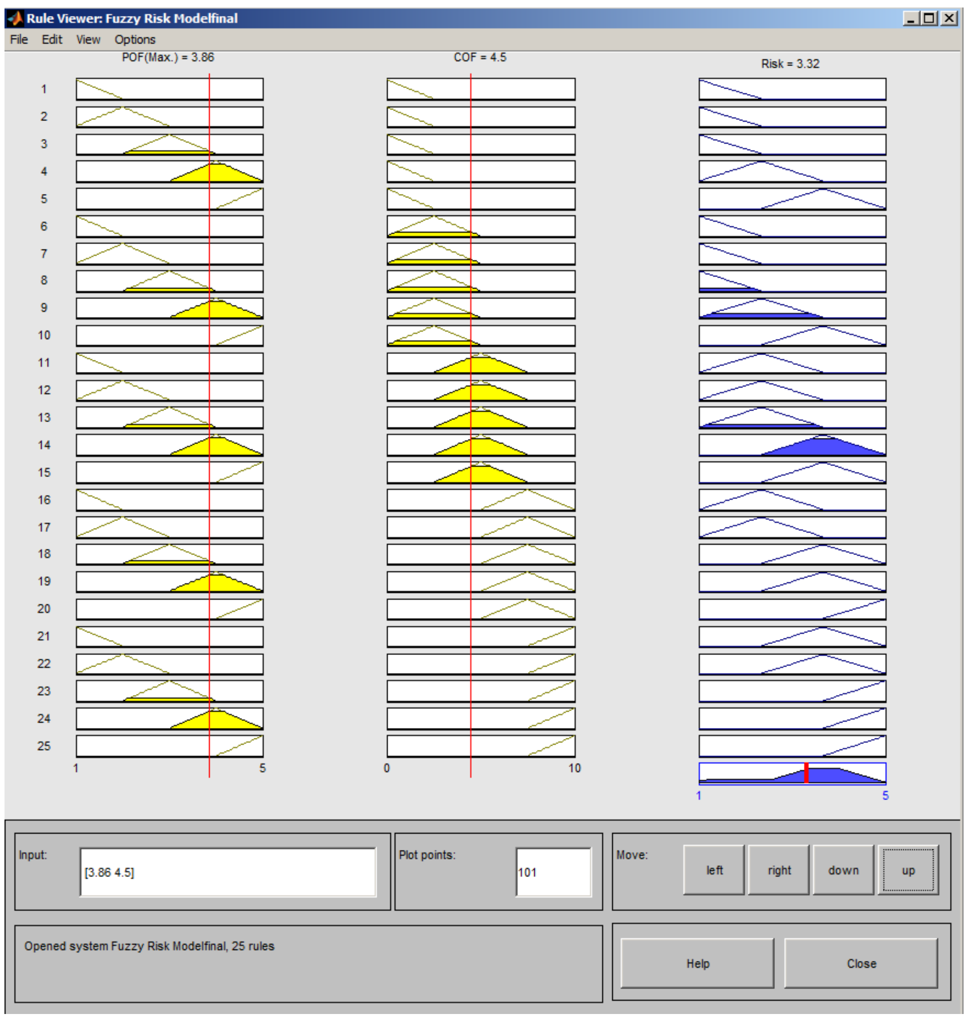


Figure 5- 29: Sample risk score calculation of the case study

Another FIS is developed for the fuzzy inspection tool selection model. A sample calculation sheet as demonstrated in MATLAB as shown in Figure 5-30. In this model, it is required to insert the value for the probability of failure and consequence of failure. The frequency of running the inspection tools and the tools resolution and cost level can be selected based on the tool selection variable.

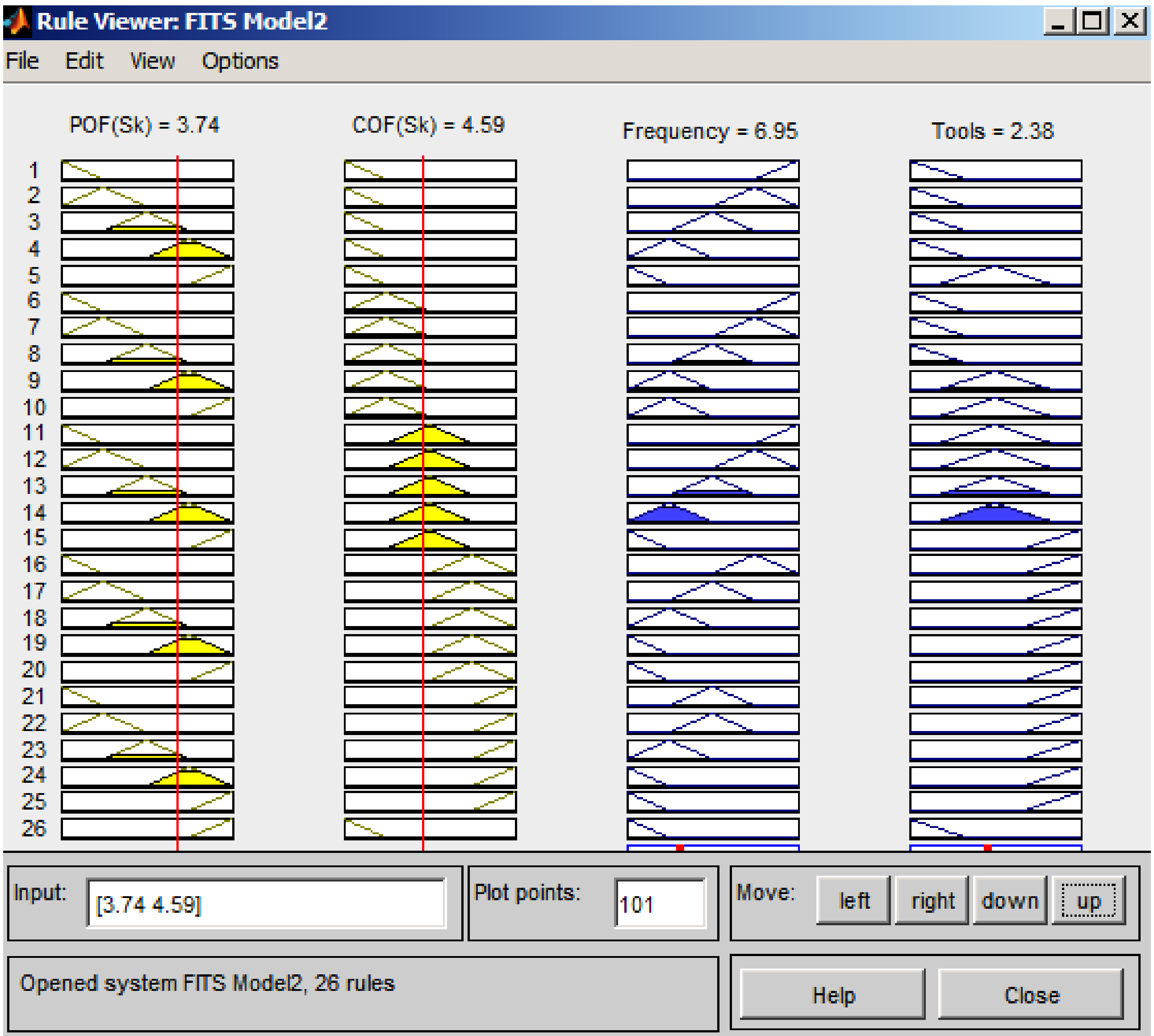


Figure 5- 30: Fuzzy inspection tool selection model demonstration

Figure 5-31 shows a sample calculation sheet in Excel 2010 software that computes the life cycle cost of rehabilitation scenarios. Once the action to be performed and the years in which the rehabilitation actions should be executed are determined, the calculations of the net present value (NPV) of the defined scenario can be completed. The developed model estimates the minimum, maximum, and most likely amounts of the NPV during the service life of the pipe. The deterioration profile determines the times of performing the rehabilitation techniques. Figure 5-32 shows a sample demonstration of the deterioration profile development and determination of the years of rehabilitation actions. The condition of the pipe before and after rehabilitation is computed, and the condition increment is determined based on the rules developed in the model. The condition increment is defined based on the type of the rehabilitation technique and its size.

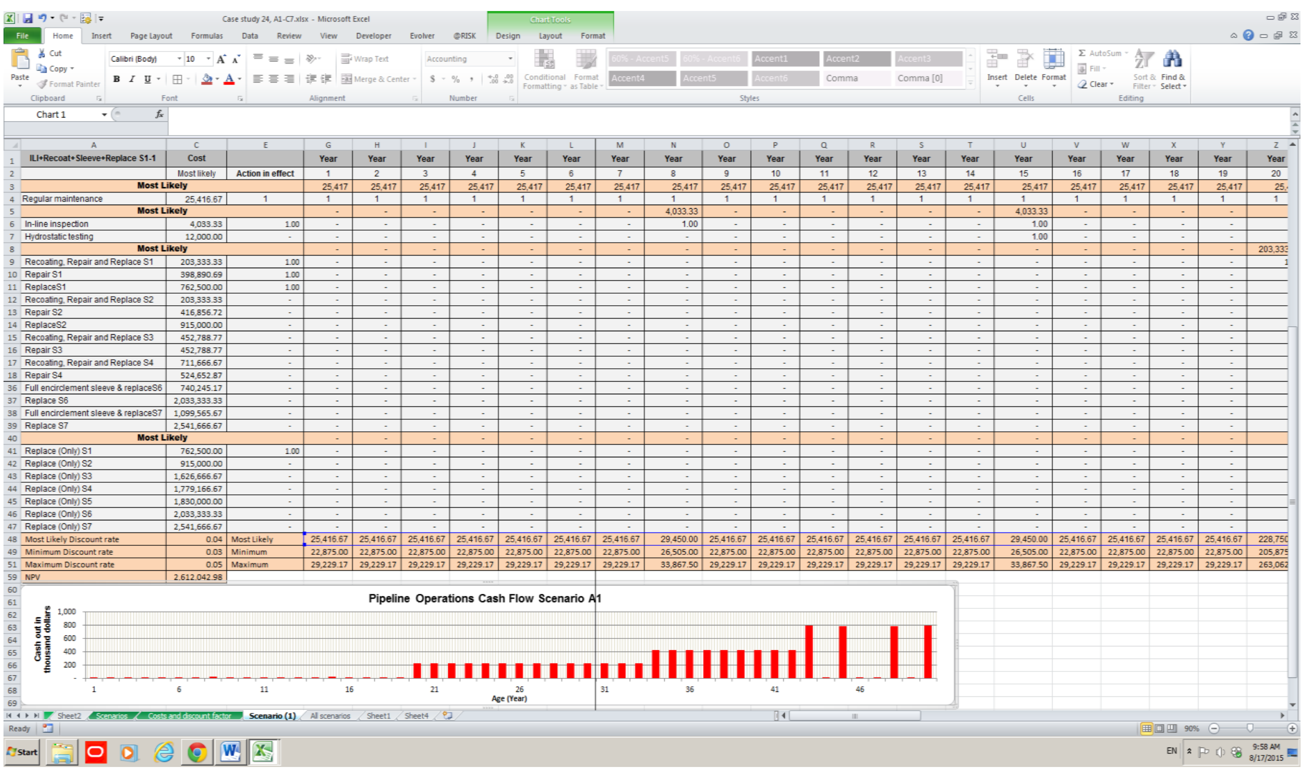
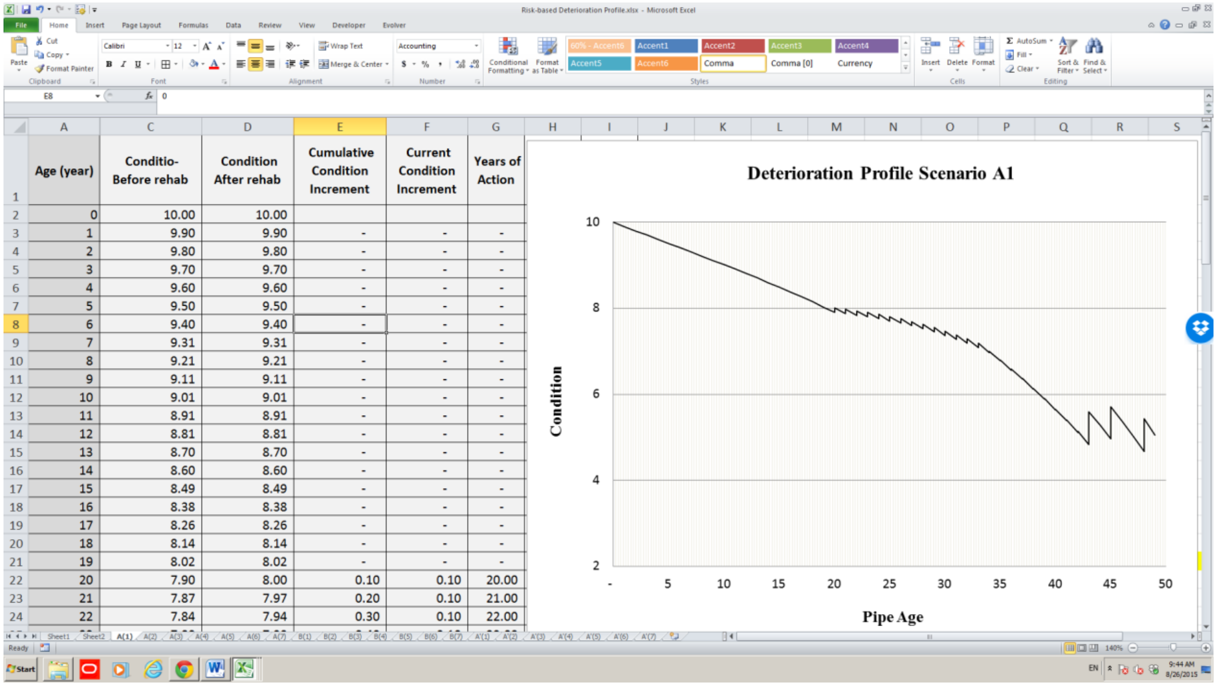


Figure 5- 31: Sample calculation sheet for life cycle cost analysis of rehabilitation scenarios



Age (year)	Conditio-Before rehab	Condition After rehab	Cumulative Condition Increment	Current Condition Increment	Years of Action
0	10.00	10.00			
1	9.90	9.90	-	-	-
2	9.80	9.80	-	-	-
3	9.70	9.70	-	-	-
4	9.60	9.60	-	-	-
5	9.50	9.50	-	-	-
6	9.40	9.40	-	-	-
7	9.31	9.31	-	-	-
8	9.21	9.21	-	-	-
9	9.11	9.11	-	-	-
10	9.01	9.01	-	-	-
11	8.91	8.91	-	-	-
12	8.81	8.81	-	-	-
13	8.70	8.70	-	-	-
14	8.60	8.60	-	-	-
15	8.49	8.49	-	-	-
16	8.38	8.38	-	-	-
17	8.26	8.26	-	-	-
18	8.14	8.14	-	-	-
19	8.02	8.02	-	-	-
20	7.90	8.00	0.10	0.10	20.00
21	7.87	7.97	0.20	0.10	21.00
22	7.84	7.94	0.30	0.10	22.00

Figure 5- 32: Deterioration profile development based on the rehabilitation action

CHAPTER 6: CONCLUSIONS AND RECOMMENDATIONS

6.1 Summary and Conclusions

The aging infrastructure and the considerable number of failures of oil and gas pipelines, as well as the significant consequences of their failures, have been a motivation for many researchers to study pipeline failure. A comprehensive study of these research efforts revealed the lack of a comprehensive objective model of failure assessment of oil and gas pipes. Some studies focused on corrosion or third-party failures and could not assess the probability of other failure sources. Most studies that consider multiple or even all failure sources are either subjective or they develop physical models that are very expensive to implement. The subjective models are usually qualitative and rely on expert opinion that is difficult if not impossible to obtain due to the location of most pipelines, which are buried underground. Apart from the expenses that can be imposed on the operators, the shortage of inspection data on unpiggable pipelines and in the early stages of pipeline operation has been a limitation. The existing maintenance planning models either do not use failure or risk assessment models to plan for pipeline life cycles, or they are not structured.

The lack of effective models motivates this research to develop a comprehensive risk-based maintenance planning model for the life cycle of pipelines. The model developed in this research provides an overall image throughout the service life of pipelines. This model is able to predict the probability and the level of financial consequences of pipeline failures. Failure probability is calculated through a Bow-tie-based quantitative prediction model. The model predicts the probability of failure for six main sources of oil and gas pipeline failure using the probability theory. The comparison of the actual and predicted probability of failure in a sample of more than one year period throughout the US proves the model's efficiency and its accuracy with an average validity percentage of over 80%.

A Neuro-Fuzzy consequence of failure prediction model is developed to forecast the financial consequences of possible failure scenarios. The model uses the location category, failure scenario, pipe diameter and the Specified Minimum Yield Strength data to forecast the failure consequences. The average validity percentage of the model is computed as being approximately 78%, proving the accuracy of the model. An integrated fuzzy risk assessment model is developed that evaluates the risk of failure of pipes considering the calculated probability and consequences of failure.

Using the results of the risk assessment model, a risk-based inspection planning model is developed to produce pipe inspection plans. A fuzzy expert system selects the appropriate inspection tools and determines the frequency of running these tools. Various inspection scenarios are developed. The maximum risk of failure is calculated through a regression-based deterioration profile considering the effect of inspection tools in reducing the risk of failure. The life cycle of the pipelines for each scenario is computed applying Monte-Carlo simulation. An index is introduced, the Risk-Cost index, which is the multiplication of the maximum risk by the LCC. The risk-cost index is used to rank the inspection scenarios. The rehabilitation planning model applies a risk–based deterioration profile that is used to predict the required rehabilitation actions. The combinations of the pre-defined maintenance operation types and possible defects' sizes are applied to develop rehabilitation scenarios over a pipelines' service life. Monte Carlo simulation is applied to analyze the life cycle cost of the scenarios due to the uncertainties of the economic factors and the maintenance operation costs.

The results of the sensitivity analysis show that soils with a low resistivity, acidic environment, and low redox potential have a higher contribution to the corrosivity of the soil around pipes. The results also proved that pipes with coal tar, asphalt, or paint coatings are more likely to fail as a result of an external corrosion failure. For internal corrosion failures, the product type effect is major, while inspection efficiency has a considerable impact on such failures. Mechanical damages are affected mainly by the pipes' depth of cover. Most of the failure sources are affected significantly by the diameter of the pipes and their installation date.

The results proved the importance of the location category and the specified minimum yield strength of the pipes on the level of financial consequences. This research can be used by the oil and gas pipeline operators to predict the risk of failure of such pipes. The results are specific to the location and environment of the pipelines, as well as their geometric properties and installation year. The computed values can quantitatively forecast the probability of pipe failure and the level of monetary consequences.

Risk evaluation is a crucial aid in the decision-making process of infrastructure systems. This model also helps in planning the inspection and maintenance of the pipes as mandated by Canadian and American regulators of the petroleum industry, while the required tools were not existed. In addition, this model will be useful in assisting the operators of such facilities in the maintenance and inspection planning. The model can rank the selected tools based on their risk growth and life cycle cost. The maintenance planning model can also plan for the maintenance of pipeliness based on their predicted deterioration and can propose the least expensive maintenance alternative for a pipeline's service life.

This research develops a novel framework for the development of risk assessment models completely based on the historical failure data. The methodology is applied on the infrastructure of oil and gas pipelines. However, it can be expanded to be used in other infrastructure types. The main value of such models is that they reduce the cost of failure prediction with or without inspection data. These models can produce indices of the probability assessment and consequences of failure that can be used to assess the failure risk of different infrastructure types and to plan accordingly for the life cycle of such infrastructures.

6.2 Research Contributions

The main contributions of this research include the following:

- A framework to develop risk assessment models for different infrastructure types using historical data;
- A probabilistic Bow-tie-based model to predict the probability of failure in oil and gas pipelines;
- A consequences of failure model to forecast the financial consequences of failure, using a Neuro-Fuzzy technique;
- An integrated fuzzy risk assessment model to evaluate the risk level of a pipeline;
- A fuzzy expert system for selecting the most appropriate inspection tools and to determine the frequency at which to run those tools;

- An inspection planning model to develop various inspection scenarios versus a pipeline's risk growth and to rank them based on their Risk-cost indices; and
- A rehabilitation planning model to develop different intervention scenarios and rank them based on the LCC.

6.3 Research Limitations

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

1) The probability of failure prediction model does not consider the interdependency of basic events.
2) The event-tree does not consider the effect of safety barriers that can reduce the probability of ignition or explosion.
3) The consequence of failure prediction model is only capable of forecasting the overall financial consequences of potential failures.
4) The inspection planning model only proposes a fixed scale for selecting the inspection tools based on the failure consequences.
5) The developed automated tool still requires the user to enter the times of rehabilitation and replacement for each scenario type, based on the calculation of the deterioration profile.
6) In the absence of required data on the identified variables, the model could only be developed for onshore pipes.

6.4 Future Work and Recommendations

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 Bayesian network to consider the variables that were not available through the historical data and develop a network of the identified basic events. The development of the probability of failure assessment model was limited to the availability of historical data, while in the Bayesian network expert opinion can be fused with other variables' contribution to pipe failure.
- Consider the requirements of offshore pipelines for maintenance planning, such as the extra cost of renting an offshore vessel and the estimated time required for each rehabilitation activity.
- Collect more data in order to consider the interdependency of the failure sources among each other, especially the effect of thinning the wall thickness on time-independent failure sources. The enhancement can help in extending the model to consider the effect of corrosion on other failure probabilities.
- Develop a consequence of failure prediction model on non-financial types of consequences, for example the amount of product released to the environment based on a failure scenario. The prediction of the environmental effects of pipe failure needs more data, including the discharge rate, the hole size, and the estimation of the time the leakage might happen.
- Consider the possible defect types in developing rehabilitation scenarios. This model might be able to predict the types of defects that can cause the failure of a pipeline and thus make it possible to plan for the maintenance accordingly.
- Develop a dynamic age of failure prediction model and consider it in the rehabilitation planning model. Considering the actual metal loss can help in

estimating the age at failure, which in turn can estimate the short-term requirements of rehabilitation.

6.4.2 Extension Areas

- Although inspection data is expensive, it is required to inspect pipelines every few years after a pipeline's start of operation. Consequently, it is recommended to extend the application of this model to infuse the extracted historical data on pipeline failures with data gathered from the inline inspection tools.
- The developed model applies the historical data on the failures of oil and gas pipelines in the US. While this database is very comprehensive, and many operators worldwide use this database to forecast the failure probability of their pipes, there is a need to compare the forecasted rates with those of other countries. This might lead to some adjustment factors for various locations to consider the differences in their regulations and construction conditions.
- The developed model could be extended if enough data can be collected to map the forecasted amounts of failure probability with the actual condition of the pipes under evaluation. This extension will lead to a dynamic model that can forecast the probability of failure at different stages of operation based on the availability of inspection data.

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Appendix (A): Developed indices to calculate the POF of pipes

Table A-1 shows the parameters of the selected functions for internal corrosion and material and weld damages. As shown, for internal corrosion the index is not separated for oil and gas pipes, however, the product type can be among the four pre-defined categories. First category belongs to crude oil, and the fourth category determines the gas pipes. While the probability of failure with respect to internal corrosion for oil pipes is the highest, the contribution of gas pipes to such failures is around half in terms of the mean values of the defined PDFs. Also, it is clear from comparing the mean values that the pipes with frequent inspections have been at least 3 times less prone to internal corrosion failures.

Then, Table A-2 shows the parameters of the selected functions for mechanical damages for oil and gas pipes. The mean contribution of depth of cover to mechanical damage sources of failure increases when the depth of cover decreases. In lower location classes where there is a less density of the building and as a result the operators' control over the pipeline decreases, the probability of failure with mechanical damages increases. The existence of a computer-based inspection system decreases the probability of a mechanical damage failure for gas pipes. Being located in a highly populated are decreases the probability of happening of a mechanical damage. Notifying the One-call system decreases the POF considerably with respect to mechanical failures. Being marked accurately is the other factors of mitigating the risk of failures with respect to the mechanical damages.

Table A- 1: Contribution of basic causes to IC and MW failures

Basic causes			1	2	3	4
Internal Corrosion	Product type	Function	Lognorm	Normal	Lognorm	LogLogistic
		parameter #1	0.02093	0.00118	0.00863	-0.03172
		parameter #2	0.02341	0.00098	0.00657	0.06011
		parameter #3	0.02593		-0.00175	8.83810
	Inline Inspection	Function	Lognorm	Logistic	Logistic	NA
		parameter #1	0.02821	0.00283	0.00265	-
		parameter #2	0.02799	0.00154	0.00148	-
		parameter #3	0.04951	-	-	-
	Internal protection	Function	Eponen	Eponen	Normal	NA
		parameter #1	0.01673	0.01320	0.03697	-
		parameter #2	-0.13171	-0.04765	0.01470	-
		parameter #3	-			-
Material & weld defects (Gas)	Seam types	Function	Normal	Lognorm	Normal	NA
		parameter #1	0.01058	0.02611	0.05159	-
		parameter #2	0.00704	0.02087	0.02405	-
		parameter #3	-	-0.00483	-	-
	SMYS	Function	ExtValue	ExtValueMin	Logistic	NA
		parameter #1	0.02183	0.04849	0.01152	-
		parameter #2	0.01291	0.01222	0.00350	-
		parameter #3	-	-	-	-
	Inspection	Function	Logistic	ExtValueMin	Logistic	NA
		parameter #1	0.00558	0.00566	0.07343	-
		parameter #2	0.00472	0.00559	0.01360	-
		parameter #3	-	-	-	-
Material & weld defects (Oil)	Seam types	Function	Lognorm	LogLogistic	LogLogistic	NA
		parameter #1	0.02089	-0.00832	-0.02418	-
		parameter #2	0.01509	0.04333	0.05027	-
		parameter #3	-0.00569	3.58460	8.14210	-
	SMYS	Function	ExtValue	LogLogistic	Normal	NA
		parameter #1	0.03421	0.00797	0.00309	-
		parameter #2	0.01382	0.02533	0.00587	-
		parameter #3	-	2.72760	-	-
	Inspection	Function	ExtValueMin	Exponen	Logistic	NA
		parameter #1	0.04793	0.04255	0.15336	-
		parameter #2	0.01768	-0.00532	0.04918	-
		parameter #3	-	-	-	-

Table A- 2: Contribution of the identified basic causes to the MD failures

Basic causes			1	2	3	4	5
Mechanical damages (Gas)	Depth of cover	Function	Normal	Lognorm	Normal	Logistic	NA
		parameter #1	0.03451	0.01957	0.02148	0.00404	-
		parameter #2	0.01112	0.01458	0.00978	0.00215	-
		parameter #3	-	-0.00352	-	-	-
	Location class	Function	Lognrom	Normal	NA	NA	NA
		parameter #1	0.05723	0.01837	-	-	-
		parameter #2	0.03230	0.00845	-	-	-
		parameter #3	0.00819	-	-	-	-
	Computer-based inspection	Function	Normal	Normal	NA	NA	NA
		parameter #1	0.09524	0.15476	-	-	-
		parameter #2	0.04647	0.03259	-	-	-
		parameter #3	-	-	-	-	-
	Highly populated area	Function	Normal	Loglogistic	NA	NA	NA
		parameter #1	0.00926	-0.04628	-	-	-
		parameter #2	0.00345	0.11790	-	-	-
		parameter #3	-	8.36350	-	-	-
	One call	Function	Normal	Loglogistic	NA	NA	NA
		parameter #1	0.01580	-0.27835	-	-	-
		parameter #2	0.00645	0.34480	-	-	-
		parameter #3	-	23.92600	-	-	-
	Accurately marked	Function	Normal	Weibul	NA	NA	NA
		parameter #1	0.02842	4.52720	-	-	-
		parameter #2	0.01419	0.07413	-	-	-
		parameter #3	-	-0.01262	-	-	-
Mechanical damages (Oil)	Depth of cover	Function	Normal	Normal	Normal	Logistic	Logistic
		parameter #1	0.02189	0.03241	0.02104	0.00505	0.0022234
		parameter #2	0.01418	0.01282	0.01029	0.00255	0.002207
		parameter #3	-	-	-	-	-
	Location	Function	Exponen	Loglogistic	NA	NA	NA
		parameter #1	0.01557	0.01872	-	-	-
		parameter #2	-0.00130	0.04390	-	-	-
		parameter #3	-	4.59370	-	-	-
	Highly populated area	Function	Laplace	Lognorm	Loglogistic	NA	NA
		parameter #1	0.02250	0.01602	0.00669	-	-
		parameter #2	0.01768	0.00401	0.03546	-	-
		parameter #3	-	-0.00518	3.69830	-	-

Table A-3 continues the demonstration of the parameters of the functions for incorrect operations and natural forces. The existence of an efficient SCADA or CPM decreases the POF with respect to incorrect operations, while the unqualified operators can grow the probability of such failures. Also, the aboveground parts of pipes are more vulnerable to the incorrect operation failures.

Table A- 3: Contribution of the identified basic causes to IO and NF

Basic causes			1	2	3	4
Incorrect Operation	CMS efficiency	Function	Normal	Normal	Normal	NA
		parameter #1	0.16766	0.06448	0.02021	-
		parameter #2	0.03598	0.01848	0.00375	-
		parameter #3	-	-	-	-
	Qualification of Operator	Function	Exponen	Uniform	NA	NA
		parameter #1	0.01054	0.10843	-	-
		parameter #2	0.05211	0.25301	-	-
		parameter #3	-	-	-	-
	Operating pressure	Function	Laplace	Normal	NA	NA
		parameter #1	0.18519	0.06482	-	-
		parameter #2	0.05587	0.02371	-	-
		parameter #3	-	-	-	-
	Location of Pipe	Function	Laplace	Normal	NA	NA
		parameter #1	0.18519	0.06482	-	-
		parameter #2	0.05587	0.02371	-	-
		parameter #3	-	-	-	-
Natural Forces	Washout	Function	Logistic	Extvalue	Lognorm	NA
		parameter #1	0.01131	0.01166	0.05161	-
		parameter #2	0.00846	0.01598	0.06824	-
		parameter #3	-	-	-0.00374	-
	Extreme Temperature	Function	ExtvalueMin	Extvalue	Lognorm	Logistic
		parameter #1	0.02015	0.01582	0.05238	0.0068216
		parameter #2	0.01246	0.01455	0.02540	0.00918
		parameter #3	-	-	-0.02212	-
	Wind	Function	ExtvalueMin	Logistic	Extvalue	NA
		parameter #1	0.03004	0.01412	0.01668	-
		parameter #2	0.03203	0.02453	0.03206	-
		parameter #3	-	-	-	-

For natural force damages, an extreme cold temperature during winter, a high precipitation, and wind-speed are the main drivers of such failures. Table A-4 presents the contribution of the pipe diameter categories with respect to the mechanical damage, incorrect operation, and natural force failures. Large oil pipes are more likely to fail compared to their small counterparts. However, it is the opposite for gas pipes. For the incorrect operation failures of oil pipes, the probability of happening of a failure is higher for small pipes, while it is less likely for the pipes of above 10" to fail from such sources. For gas pipes, there is not enough observation to make a difference between various categories of diameter; consequently only one probability distribution function is calculated to compute the absolute POF with respect to such failures. For natural force damages, there is a significant difference between the contribution of the smallest diameter category of oil pipes and the larger pipes. The former is the most likely to fail from such failure sources. For those gas pipes that failed due to the natural force damages, there is not enough data on the diameter of the pipes. As a result, only one probability distribution function is introduced as the contribution of these pipes to calculate the absolute probability of failure.

Table A-5 presents the indices to compute the after-failure events for gas pipes. Overall, the probability of a leakage is higher than larger hole sizes. However, this is not the case for incorrect operations, where it is less likely that a hole does not grow into a puncture or rupture. The probability of happening of ignition and explosion is higher than those of the oil pipes as was expected. The probability of growing a hole to a rupture is the highest for external corrosion while it stands second for the natural force damages.

The probability of ignition or explosion of such pipes in case of happening of a larger defect is overall higher than that of a smaller defect. The highest probability of occurrence of an ignition or explosion is related to the incorrect operations. The ignition or explosion is also more likely to happen in the case of a rupture due to the material and weld defects.

Table A- 4: Contribution of the pipe diameter categories to MD, IO and NF failure sources

Basic causes			<=4"	4"-10"	10"-20"	20"-28"	Over 28"
Mechanical Damage	Oil	Function	Normal	Normal	Gamma	Logistic	Logistic
		parameter #1	0.00008569	0.00008978	0.00003659	0.00003253	0.00001192
		parameter #2	0.00010044	0.00003203	-0.00002403	0.00004662	0.00002383
		parameter #3	-	-	-	-	-
	Gas	Function	Exponen	Normal	Normal	Normal	Logistic
		parameter #1	0.00011862	0.00007637	0.00008559	0.00003285	0.00001165
		parameter #2	0.00002838	0.00002659	0.00003248	0.00002080	0.00000790
		parameter #3	-	-	-	-	-
Incorrect Operation	Oil	Function	-	Logistic	Logistic	Logistic	-
		parameter #1	-	0.00052941	0.00020767	0.00025724	-
		parameter #2	-	0.00048980	0.00009503	0.00015701	-
		parameter #3		-	-	-	
	Gas	Function	Extvalue				
		parameter #1	0.00001039				
		parameter #2	0.00000491				
		parameter #3	-				
Natural Forces	Oil	Function	Logistic	Normal	Normal	Logistic	-
		parameter #1	0.00052941	0.00011497	0.00021210	0.00025724	-
		parameter #2	0.00048980	0.00007349	0.00016840	0.00015701	-
		parameter #3	-	-	-	-	-
	Gas	Function	Lognorm				
		parameter #1	0.00005441				
		parameter #2	0.00002931				
		parameter #3	-0.00001529				

Table A- 5: Indices related to probability of after-failure events for gas pipes

Failure source (S)	Hole size (H)	P(H│S)	Ignition type (Ign)	P(Ign│H)
EC	Pinhole	0.553846	Leakage only	0.983333
			Ignition	0.001389
			Explosion	0.015278
	Puncture	0.007692	Leakage only	0.800000
			Ignition	0.100000
			Explosion	0.100000
	Rupture	0.438462	Leakage only	0.578947
			Ignition	0.228070
			Explosion	0.192982
IC	Pinhole	0.691589	Leakage only	0.878378
			Ignition	0.054054
			Explosion	0.067568
	Puncture	0.065421	Leakage only	0.585714
			Ignition	0.400000
			Explosion	0.014286
	Rupture	0.242991	Leakage only	0.461538
			Ignition	0.307692
			Explosion	0.230769
MW	Pinhole	0.548182	Leakage only	0.986316
			Ignition	0.011579
			Explosion	0.002105
	Puncture	0.209463	Leakage only	0.936639
			Ignition	0.005510
			Explosion	0.057851
	Rupture	0.242354	Leakage only	0.666667
			Ignition	0.142857
			Explosion	0.190476
MD	Pinhole	0.358779	Leakage only	0.934043
			Ignition	0.054255
			Explosion	0.011702
	Puncture	0.358779	Leakage only	0.881915
			Ignition	0.085106
			Explosion	0.032979
	Rupture	0.282443	Leakage only	0.877027
			Ignition	0.081081
			Explosion	0.041892
IO	Pinhole	0.200000	Leakage only	0.633333
			Ignition	0.183333
			Explosion	0.183333
	Puncture	0.733333	Leakage only	0.586364
			Ignition	0.227273
			Explosion	0.186364
	Rupture	0.066667	Leakage only	0.800000
			Ignition	0.100000
			Explosion	0.100000
NF	Pinhole	0.112583	Leakage only	0.864706
			Ignition	0.123529
			Explosion	0.011765
	Puncture	0.516556	Leakage only	0.946154
			Ignition	0.051282
			Explosion	0.002564
	Rupture	0.370861	Leakage only	0.892857
			Ignition	0.053571
			Explosion	0.053571

Appendix (B): Sample probability distribution functions for POF model

Table B- 1: Distribution functions associated with soil corrosion

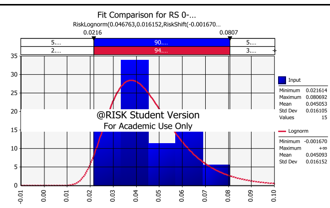
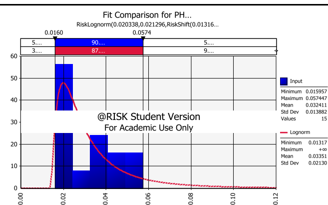
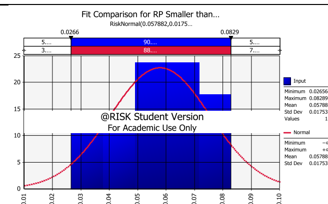
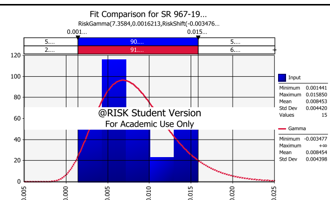
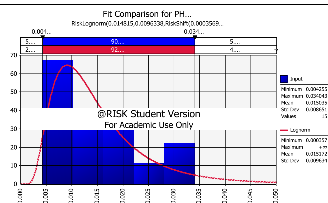
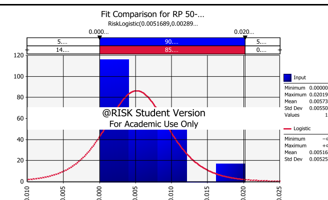
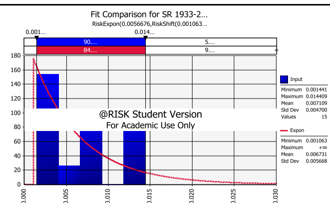
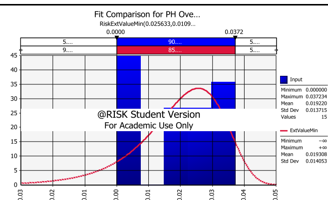
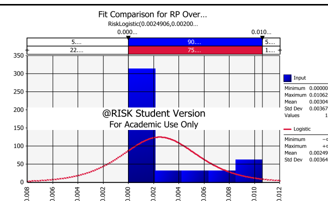
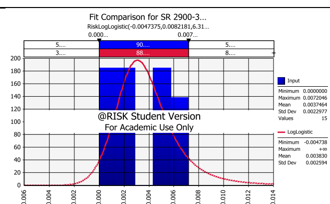
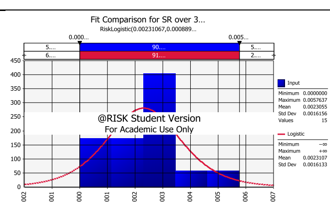
i	SR_i	PH_i	RP_i
1			
2			
3			
4		**NA**	**NA**
5		**NA**	**NA**

Table B- 2: Distribution functions associated with diameter categories of Gas Onshore Pipes

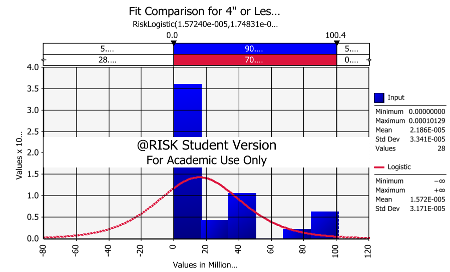
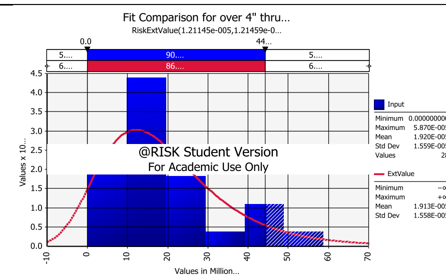
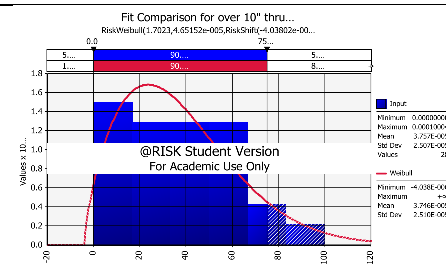
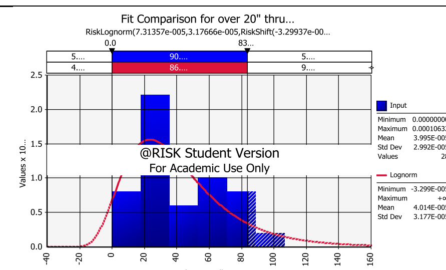
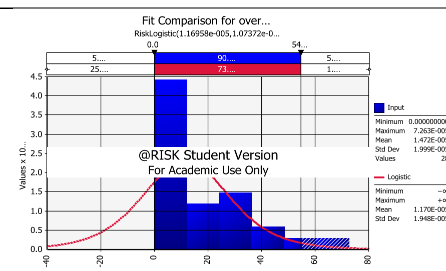
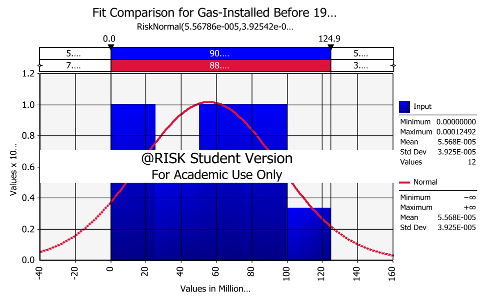
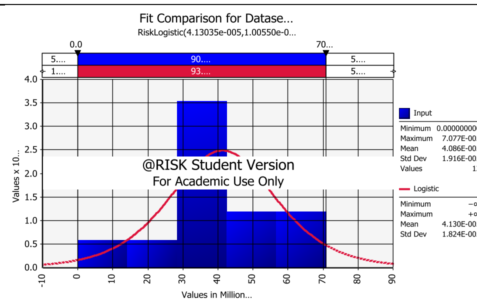
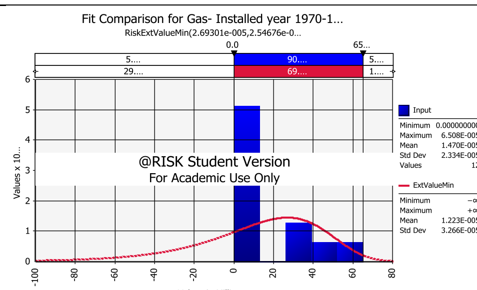
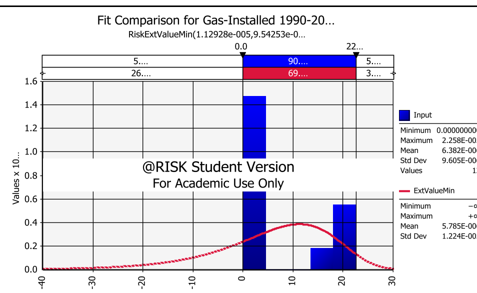
Category	Diameter range (inch)	POF (failures/ mile. year)
D_1	4" or Less	
D_2	Over 4" thru 10"	
D_3	Over 10" thru 20"	
D_4	Over 20" thru 28"	
D_5	Over 28"	

Table B- 3: Distribution functions associated with installation year categories of gas onshore pipes

<table>
<tr><th>Category</th><th>Installation year range (Year)</th><th>PoF
(failures/ mile. year)</th></tr>
<tr><td>IY_1</td><td>1900-1950</td><td></td></tr>
<tr><td>IY_2</td><td>1950-1970</td><td></td></tr>
<tr><td>IY_3</td><td>1970-1990</td><td></td></tr>
<tr><td>IY_4</td><td>1990-2013</td><td></td></tr>
</table>

Appendix (C): Fields of historical data

of gas transmission and gathering pipes' failures (2010-2015)

Table C- 1: Data fields on Gas transmission and Gathering Pipes (2010-2015)

Field Name Description
Data as of date
Identify if record meets the significant criteria or not: If there was fatality, injury, or total property damage is $50K or more in 1984 dollars, then SIGNIFICANT='YES', else SIGNIFICANT='NO'.
Identify if record meets the SERIOUS criteria or not: If there was fatality or injury then SERIOUS = 'YES' else SERIOUS = 'NO'.
PHMSA DOT assigned unique identifier for report
PHMSA DOT assigned unique identifier for report submission
Date when Original Report submitted
Report Type (Original, Supplemental, Final)
Operator's OPS-issued Operator Identification number
Operator Name
Operator Address - Street
Operator Address - City
Operator Address - State
Operator Address - Zip
Local time (24-hr clock) and date of the Incident
Year incident occurred, derived from incident date
Incident Location Latitude
Incident Location Longitude
National Response Center Report Number
National Response Center time and date of initial telephonic report
Incident resulted from (Unintentional release of gas, or intentional release of gas, or reasons other than release of gas)
Type of Gas released (Natural, Propane, Synthetic, Hydrogen, or Other gas)
Other Commodity Name
Estimated volume of gas released unintentionally in Thousand Cubic Feet (MCF)
Estimated volume of intentional and controlled release/blowdown in Thousand Cubic Feet (MCF)
Estimated volume of accompanying liquid released in Barrels
Fatalities (Yes, No)
Number of Fatalities of Operator Employees
Number of Fatalities of Contractor Employees working for the Operator
Number of Fatalities of Non-Operator emergency responders
Number of Fatalities of Workers working on the right-of-way, but not associated with this Operator
Number of Fatalities of General Public
Total number of Fatalities
Injuries (Yes, No)

Number of Injuries of Operator Employees
Number of Injuries of Contractor Employees working for the Operator
Number of Injuries of Non-Operator emergency responders
Number of Injuries of Workers working on the right-of-way, but not associated with this Operator
Number of Injuries of General Public
Total number of Injuries
The pipeline/facility shutdown due to the Incident (Yes, No, Null)
if PART A.14 is "No" - The pipeline/facility shutdown due to the Incident - Explain No shutdown
The pipeline/facility shutdown due to the Incident - Local time and date of shutdown
The pipeline/facility shutdown due to the Incident - Local time pipeline/facility restarted
Elapsed Time Until Area Was Made Safe / Hours
The pipeline/facility shutdown due to the Incident - Still shut down (Yes, Null)
Commodity ignite (Yes, No)
Commodity explode (Yes, No)
Number of general public evacuated
Time sequence - Local time operator identified Incident
Time sequence - Local time operator resources arrived on site
Origin of Incident Onshore or Offshore
Onshore - State
Onshore - Zip Code
Onshore - City
Onshore - County or Parish
Onshore - Operator-designated location
Onshore - Operator-designated location name
Onshore - Pipeline/facility name
Onshore - Segment Name
Onshore - Federal land (Yes, No, Null)
Onshore - Location of Incident
Onshore - Area of Incident
Onshore - Area of Incident Sub-type
Onshore - Describe Other Area of Incident
Onshore Underground - Depth-of-Cover (in)
Onshore - Incident occurred in a crossing (Yes, No, Null)
Onshore - Bridge Crossing (Yes, Null)
Onshore - Bridge Type
Onshore - Railroad Crossing (Yes, Null)
Onshore - Railroad Type
Onshore - Road Crossing (Yes, Null)
Onshore - Road Type
Onshore - Water Crossing (Yes, Null)
Onshore - Water Type
Onshore - Name of body of water, if commonly known
Onshore - Approx. water depth (ft) at the point of the Incident

Onshore - Water Crossing Sub-type
Offshore - Approximate water depth (ft.)
Offshore - Origin of Incident (State, Outer Continental Shelf=OCS)
Offshore State waters - State
Offshore State waters - Area
Offshore State waters - Block/Tract
Offshore State waters - Nearest County/Parish
Offshore OCS - Area
Offshore OCS - Block
Offshore - Area of Incident
Pipeline/facility Interstate or Intrastate
Part of system involved in Incident
Item involved in Incident
Part of Pipe (Pipe Body, Pipe Seam)
Nominal diameter of Pipe (in)
Wall thickness (in)
SMYS (Specified Minimum Yield Strength) of pipe (psi)
Pipe specification
Type of Pipe Seam
Type of Pipe Seam - Pipe Seam Other Details
Type of Pipe Seam - Pipe manufacturer
Year of manufacture of Pipe
Pipeline coating type at point of Incident
Pipeline coating - Other pipeline coating type
Weld Sub-type
Other Weld Sub-type Details
Type of Valve
Type of Valve - Type of Mainline Valve
Type of Valve - Other Mainline Valve Details
Type of Valve - Mainline valve manufacturer
Type of Valve - Year of manufacture of Mainline valve
Other Item Involved Details
Year item installed that involved in Incident
Material involved in Incident
Material involved - Other Material than Carbon Steel Details
Type of Incident involved
Mechanical Puncture - Approx. size - Axial (in.)
Mechanical Puncture - Approx. size - Circumferential (in.)
Leak Type
Leak Type Other Details
Rupture Orientation (Circumferential, Longitudinal, Other)
Rupture Orientation Other Details
Rupture - Approx. size (in.) (length circumferentially or axially)

Rupture - Approx. size (in.) (widest opening)
Type of Incident Other Details
Type of class location for incident
Incident occurred in High Consequence Area (HCA) (Yes, No)
Specific method used to identify the High Consequence Area (HCA)
What is the PIR (Potential Impact Radius) for the location of this Incident - Approx. size (feet)
Were any structures outside the PIR impacted or otherwise damaged by heat/fire resulting from the Incident (Yes, No)
Were any structures outside the PIR impacted or otherwise damaged NOT by heat/fire resulting from the Incident (Yes, No)
Were any of the fatalities or injuries reported for persons located outside the PIR (Yes, No)
Estimated Property Damage - Estimated cost of public and non-Operator private property damage paid/reimbursed by the Operator
Converted Property Damage to Current Year dollars
Cost of Gas Released - Estimated cost of gas released during intentional and controlled blowdown
Converted Property Damage to Current Year dollars
Cost of Gas Released - Estimated cost of gas released unintentionally
Converted Property Damage to Current Year dollars
Estimated Property Damage - Estimated cost of Operator's property damage & repairs
Converted Property Damage to Current Year dollars
Estimated Property Damage - Estimated cost of Operator's emergency response
Converted Property Damage to Current Year dollars
Estimated Property Damage - Estimated other costs
Converted Property Damage to Current Year dollars
Estimated Property Damage - Estimated other costs details
Total of all costs (Sum of EST_COST_OPER_PAID,EST_COST_GAS_RELEASED,EST_COST_INTENT_REL,EST_COST_PROP_DAMAGE,EST_COST_EMERGENC,EST_COST_OTHER)
Converted Property Damage to Current Year dollars
Estimated pressure at the point and time of the Incident (psig)
Maximum Operating Pressure (MOP) at the point and time of the Incident (psig)
Maximum Operating Pressure (MOP) established by 49 CFR section
Maximum Operating Pressure (MOP) established by 49 CFR section other details
Describe the pressure on the system or facility relating to the Incident (exceed MOP or not)
System or facility relating to the Incident operating under an established pressure restriction with pressure limits below those normally allowed by the MOP (Yes, No, Null)
Pressure exceed established pressure restriction (Yes, No, Null)
Mandated by (PHMSA, State, Not mandated)
Part of system is "Onshore Pipeline, Including Valve Sites" or "Offshore Pipeline, Including Riser and Riser Bend" (Yes, No)
Type of upstream valve used to initially isolate release source
Type of downstream valve used to initially isolate release source
Length of segment initially isolated between valves (ft)
Pipeline configured to accommodate internal inspection tools (Yes, No, Null)
Physical features which limit tool accommodation - Changes in line pipe diameter (Yes, Null)

Physical features which limit tool accommodation - Presence of unsuitable mainline valves (Yes, Null)

Physical features which limit tool accommodation - Tight or mitered pipe bends (Yes, Null)

Physical features which limit tool accommodation - Other passage restrictions (Yes, Null)

Physical features which limit tool accommodation - Extra thick pipe wall (Yes, Null)

Physical features which limit tool accommodation - Other (Yes, Null)

Physical features which limit tool accommodation - Other physical features Details

Operational factors which significantly complicate the execution of an internal inspection tool run (Yes, No, Null)

Operational factors complicate execution - Excessive debris or scale (Yes, Null)

Operational factors complicate execution - Low operating pressure(s) (Yes, Null)

Operational factors complicate execution - Low flow or absence of flow (Yes, Null)

Operational factors complicate execution - Incompatible commodity (Yes, Null)

Operational factors complicate execution - Other Complications (Yes, Null)

Operational factors complicate execution - Other Operational factors Details

Function of pipeline system

Supervisory Control and Data Acquisition (SCADA)-based system in place on the pipeline or facility involved in the Incident (Yes, No, Null)

SCADA operating at the time of the Incident (Yes, No, Null)

SCADA fully functional at the time of the Incident (Yes, No, Null)

SCADA -based information (such as alarm (s), event(s), and/or volume or pack calculations) assist with the detection of the Incident (Yes, No, Null)

SCADA -based information (such as alarm (s), event(s), and/or volume or pack calculations) assist with the confirmation of the Incident (Yes, No, Null)

How Incident was identified for the Operator

How Incident was identified for the Operator - Other Details

Specify Type of Operator

Investigation initiated into whether or not the controller(s) or control room issues were the cause of or a contributing factor to the Incident (Yes, No, Not necessary)

Operator did not find that an investigation of the controller(s) actions or control room issues was necessary due to

Investigation reviewed schedule rotations, continuous hours of service and other factors associated with fatigue (Yes, Null)

Investigation did NOT reviewed schedule rotations, continuous hours of service and other factors associated with fatigue (Yes, Null)

Details of Investigation did NOT reviewed schedule rotations, continuous hours of service and other factors associated with fatigue

Investigation initiated - No control room issues (Yes, Null)

Investigation initiated - No controller issues (Yes, Null)

Investigation initiated - Incorrect controller action or controller error (Yes, Null)

Investigation initiated - That fatigue may have affected the controller(s) involved or impacted the involved controller(s) response (Yes, Null)

Investigation initiated - Incorrect procedures (Yes, Null)

Investigation initiated - Incorrect control room equipment operation (Yes, Null)

Investigation initiated - Maintenance activities that affected control room operations, procedures, and/or controller response (Yes, Null)

Investigation initiated - Other areas (Yes, Null)

Investigation initiated - Other areas Details

Operator employees tested under the post-Incident drug and alcohol testing requirements of DOT's Drug & Alcohol Testing regulations (Yes, No)

Number of employees tested

Number of employees failed

Operator contractor employees tested under the post-Incident drug and alcohol testing requirements of DOT's Drug & Alcohol Testing regulations (Yes, No)

Number of contractors tested

Number of contractors failed

Apparent Cause of the Incident

Detailed Cause of the Incident

Cause by PHMSA for 20 year incident trending

SubCause by PHMSA for 20 year incident trending

Corrosion Failure Sub-Cause (Internal, External)

External Corrosion - Visual Examination

External Corrosion - Other Visual Examination Details

External Corrosion Type - Galvanic

External Corrosion Type - Atmosphere

External Corrosion Type - Stray Current

External Corrosion Type - Microbiological

External Corrosion Type - Selective Seam

External Corrosion Type - Other

External Corrosion Type - Other Details

External Corrosion Type Based on - Field Examination

External Corrosion Type Based on - Metallurgical Analysis

External Corrosion Type Based on - Other Analysis

External Corrosion Type Based on - Other Analysis Details

External Corrosion - Failed item buried under the ground (Yes, No, Null)

Under Cathodic Protection (Yes, No, Null)

Year Cathodic Protection Started

Shielding, tenting, or disbonding of coating evident at the point of Incident (Yes, No, Null)

Cathodic Survey Type

Cathodic Protection Annual Survey

Close Interval Survey

Other Cathodic Protection Survey

Cathodic Protection Annual Survey Year

Close Interval Survey Year

Other Cathodic Protection Survey Year

Failed item externally coated or painted

External Corrosion - Observable damage to the coating or paint in the vicinity of the corrosion

Internal Corrosion - Visual Examination Results

Internal Corrosion - Other Visual Examination Results Details

Internal Corrosion Cause - Corrosive Commodity

Internal Corrosion Cause - Water Acid

Internal Corrosion Cause - Microbiological

Internal Corrosion Cause - Erosion

Internal Corrosion Cause - Other

Internal Corrosion Cause - Other Details

Internal Corrosion Cause Based on - Field Examination

Internal Corrosion Cause Based on - Metallurgical Analysis

Internal Corrosion Cause Based on - Other Analysis

Internal Corrosion Cause Based on - Other Analysis Details

Internal Corrosion Location - Low point in pipe

Internal Corrosion Location - Elbow

Internal Corrosion Location - Drop out

Internal Corrosion Location - Other

Internal Corrosion Location - Other Details

Internal Corrosion - Commodity treated with corrosion inhibitors or biocides (Yes, No, Null)

Internal Corrosion - Interior coated or lined with protective coating (Yes, No, Null)

Internal Corrosion - Cleaning/dewatering pigs (or other operations) routinely utilized (Yes, No, Not applicable)

Internal Corrosion - Corrosion coupons routinely utilized (Yes, No, Not applicable)

Internal Corrosion - One or more internal inspection tool collected data at incident (Yes, No)

Corrosion Pipe/Weld - Magnetic Flux Leakage Tool (Yes, Null)

Corrosion Pipe/Weld - Magnetic Flux Leakage Tool Year

Corrosion Pipe/Weld - Ultrasonic (Yes, Null)

Corrosion Pipe/Weld - Ultrasonic Year

Corrosion Pipe/Weld - Geometry (Yes, Null)

Corrosion Pipe/Weld - Geometry Year

Corrosion Pipe/Weld - Caliper (Yes, Null)

Corrosion Pipe/Weld - Caliper Year

Corrosion Pipe/Weld - Crack (Yes, Null)

Corrosion Pipe/Weld - Crack Year

Corrosion Pipe/Weld - Hard Spot (Yes, Null)

Corrosion Pipe/Weld - Hard Spot Year

Corrosion Pipe/Weld - Combination Tool (Yes, Null)

Corrosion Pipe/Weld - Combination Tool Year

Corrosion Pipe/Weld - Transverse Field/Triaxial (Yes, Null)

Corrosion Pipe/Weld - Transverse Field/Triaxial Year

Corrosion Pipe/Weld - Other Internal Inspection Tool (Yes, Null)

Corrosion Pipe/Weld - Other Internal Inspection Tool Details

Corrosion Pipe/Weld - Other Internal Inspection Tool Year

Corrosion - One or more Hydrotest or other pressure test conducted since original construction (Yes, No, Null)

Corrosion Pipe/Weld - Pressure test conducted year

Corrosion Pipe/Weld - Test pressure (psig)

Corrosion - One or more Direct Assessment inspection(s) conducted (Yes, No, Null)

Corrosion Pipe/Weld - Year Direct Assessment dig

Corrosion Pipe/Weld - Year Direct Assessment no dig

Corrosion - One or more Non-destructive examination been conducted since January 1, 2002 (Yes, No, Null)

Corrosion Pipe/Weld Non-destructive examination Type - Radiography (Yes, Null)

Corrosion Pipe/Weld Non-destructive examination - Radiography Year

Corrosion Pipe/Weld Non-destructive examination Type - Guided Wave Ultrasonic (Yes, Null)

Corrosion Pipe/Weld Non-destructive examination - Guided Wave Ultrasonic Year

Corrosion Pipe/Weld Non-destructive examination Type - Handheld Ultrasonic Tool (Yes, Null)

Corrosion Pipe/Weld Non-destructive examination - Handheld Ultrasonic Tool Year

Corrosion Pipe/Weld Non-destructive examination Type - Wet Magnetic Particle Test (Yes, Null)

Corrosion Pipe/Weld Non-destructive examination - Wet Magnetic Particle Year

Corrosion Pipe/Weld Non-destructive examination Type - Dry Magnetic Particle Test (Yes, Null)

Corrosion Pipe/Weld Non-destructive examination - Dry Magnetic Particle Year

Corrosion Pipe/Weld Non-destructive examination Type - Other (Yes, Null)

Corrosion Pipe/Weld Non-destructive examination - Other Year

Corrosion Pipe/Weld Non-destructive examination - Other Type Details

Natural Force Damage Sub-Cause

Natural Force Damage - Sub-type of Earth Movement, NOT due to Heavy Rains/Floods

Natural Force Damage - Sub-type of Heavy Rains/Floods

Natural Force Damage - Sub-type of Lightning

Natural Force Damage - Sub-type of Temperature

Natural Force Damage - Other Natural Force Damage or Sub-type Details

Natural Force Damage - Natural forces causing incident generated in conjunction with an extreme weather event (Yes, No, Null)

Extreme weather - Hurricane (Yes, Null)

Extreme weather - Tropical Storm (Yes, Null)

Extreme weather - Tornado (Yes, Null)

Extreme weather - Other type (Yes, Null)

Extreme weather - Other type Details

Excavation Damage Sub-Cause

Excavation Damage Previous Damage due to Excavation Activity - One or more Internal Inspection tool collected data (Yes, No, Null)

Internal Inspection Tool - Magnetic Flux Leakage Tool (Yes, Null)

Internal Inspection Tool - Magnetic Flux Leakage Tool Year

Internal Inspection Tool - Ultrasonic (Yes, Null)

Internal Inspection Tool - Ultrasonic Year

Internal Inspection Tool - Geometry (Yes, Null)

Internal Inspection Tool - Geometry Year

Internal Inspection Tool - Caliper (Yes, Null)

Internal Inspection Tool - Caliper Year

Internal Inspection Tool - Crack (Yes, Null)

Internal Inspection Tool - Crack Year

Internal Inspection Tool - Hard Spot (Yes, Null)

Internal Inspection Tool - Hard Spot Year
Internal Inspection Tool - Combination Tool (Yes, Null)
Internal Inspection Tool - Combination Tool Year
Internal Inspection Tool - Transverse Field/Triaxial (Yes, Null)
Internal Inspection Tool - Transverse Field/Triaxial Year
Internal Inspection Tool - Other Internal Inspection Tool (Yes, Null)
Internal Inspection Tool - Other Internal Inspection Tool Year
Internal Inspection Tool - Other Internal Inspection Tool Details
Excavation Damage Previous Damage due to Excavation Activity - Internal inspection was completed before damage was sustained (Yes, No, Null)
Excavation Damage Previous Damage due to Excavation Activity - One or more Hydrotest or other pressure test conducted since original construction (Yes, No, Null)
Pressure test conducted year
Test pressure (psig)
Excavation Damage Previous Damage due to Excavation Activity - Type of Direct Assessment
Direct Assessment and Investigative dig conducted - Year
Direct Assessment conducted but point of Incident was not identified as dig site - Year
Excavation Damage Previous Damage due to Excavation Activity - One or more Non-destructive examination been conducted since January 1, 2002 (Yes, No, Null)
Non-destructive examination Type - Radiography (Yes, Null)
Non-destructive examination Type - Radiography Year
Non-destructive examination Type - Guided Wave Ultrasonic (Yes, Null)
Non-destructive examination Type - Guided Wave Ultrasonic Year
Non-destructive examination Type - Handheld Ultrasonic Tool (Yes, Null)
Non-destructive examination Type - Handheld Ultrasonic Tool Year
Non-destructive examination Type - Wet Magnetic Particle Test (Yes, Null)
Non-destructive examination Type - Wet Magnetic Particle Year
Non-destructive examination Type - Dry Magnetic Particle Test (Yes, Null)
Non-destructive examination Type - Dry Magnetic Particle Year
Non-destructive examination Type - Other (Yes, Null)
Non-destructive examination Type - Other Year
Non-destructive examination Type - Other Type Details
Excavation Damage Third Party - Operator got prior notification of the excavation activity (Yes, No, Null)
Notification received from One-Call System (Yes, Null)
Notification received from Excavator (Yes, Null)
Notification received from Contractor (Yes, Null)
Notification received from Landowner (Yes, Null)
Excavation Damage CGA-DIRT Program questions - Do you want PHMSA to upload CGA-DIRT Program questions to CGA-DIRT.com (Yes, No, Null)
Excavation Damage CGA-DIRT Program questions Right-of-Way (RoW) - Public (Yes, Null)
Excavation Damage CGA-DIRT Program questions Right-of-Way (RoW) - Public Sub-type
Excavation Damage CGA-DIRT Program questions Right-of-Way (RoW) - Private (Yes, Null)
Excavation Damage CGA-DIRT Program questions Right-of-Way (RoW) - Private Sub-type
Excavation Damage CGA-DIRT Program questions Right-of-Way (RoW) - Pipeline Property/Easement (Yes, Null)

Excavation Damage CGA-DIRT Program questions Right-of-Way (RoW) - Power/Transmission Line (Yes, Null)

Excavation Damage CGA-DIRT Program questions Right-of-Way (RoW) - Railroad (Yes, Null)

Excavation Damage CGA-DIRT Program questions Right-of-Way (RoW) - Dedicated Public Utility Easement (Yes, Null)

Excavation Damage CGA-DIRT Program questions Right-of-Way (RoW) - Federal Land (Yes, Null)

Excavation Damage CGA-DIRT Program questions Right-of-Way (RoW) - Data not collected (Yes, Null)

Excavation Damage CGA-DIRT Program questions Right-of-Way (RoW) - Unknown/Other Row (Yes, Null)

Excavation Damage CGA-DIRT Program questions - Type of Excavator

Excavation Damage CGA-DIRT Program questions - Type of Excavation Equipment

Excavation Damage CGA-DIRT Program questions - Type of Work Performed

Excavation Damage CGA-DIRT Program questions - One-Call Center notified (Yes, No, Null)

Ticket Number of One-Call Center

State where more than a single One-Call Center exists, list name of One-Call Center notified

Excavation Damage CGA-DIRT Program questions - Type of Locator

Excavation Damage CGA-DIRT Program questions - Facilities marks visible

Excavation Damage CGA-DIRT Program questions - Facilities marked correctly

Excavation Damage CGA-DIRT Program questions - Damage cause interruption in service

Duration of the interruption in service (hrs)

Excavation Damage CGA-DIRT Program questions - Root cause

Excavation Damage CGA-DIRT Program questions - One-Call Notification Practices Not Sufficient Sub-type

Excavation Damage CGA-DIRT Program questions - Locating Practices Not Sufficient Sub-type

Excavation Damage CGA-DIRT Program questions - Excavation Practices Not Sufficient Sub-type

Excavation Damage CGA-DIRT Program questions - Other Root Cause Details

Other Outside Force Damage Sub-Cause

Other Outside Force Damage - Vehicle Sub-type

Other Outside Force Damage Extreme weather - Hurricane (Yes, Null)

Other Outside Force Damage Extreme weather - Tropical Storm (Yes, Null)

Other Outside Force Damage Extreme weather - Tornado (Yes, Null)

Other Outside Force Damage Extreme weather - Heavy Rains/Flood (Yes, Null)

Other Outside Force Damage Extreme weather - Other type (Yes, Null)

Other Outside Force Damage Extreme weather - Other type Details

Other Outside Force Damage Previous Damage due to Excavation Activity Pipe/Weld - One or more Internal Inspection tool collected data (Yes, No, Null)

Internal Inspection Tool - Magnetic Flux Leakage Tool (Yes, Null)

Internal Inspection Tool - Magnetic Flux Leakage Tool Year

Internal Inspection Tool - Ultrasonic (Yes, Null)

Internal Inspection Tool - Ultrasonic Year

Internal Inspection Tool - Geometry (Yes, Null)

Internal Inspection Tool - Geometry Year

Internal Inspection Tool - Caliper (Yes, Null)

Internal Inspection Tool - Caliper Year

Internal Inspection Tool - Crack (Yes, Null)

Internal Inspection Tool - Crack Year

Internal Inspection Tool - Hard Spot (Yes, Null)
Internal Inspection Tool - Hard Spot Year
Internal Inspection Tool - Combination Tool (Yes, Null)
Internal Inspection Tool - Combination Tool Year
Internal Inspection Tool - Transverse Field/Triaxial (Yes, Null)
Internal Inspection Tool - Transverse Field/Triaxial Year
Internal Inspection Tool - Other Internal Inspection Tool (Yes, Null)
Internal Inspection Tool - Other Internal Inspection Tool Year
Internal Inspection Tool - Other Internal Inspection Tool Details
Other Outside Force Damage Previous Damage due to Excavation Activity Pipe/Weld - Internal inspection was completed before damage was sustained (Yes, No, Null)
One or more Hydrotest or other pressure test conducted since original construction (Yes, No, Null)
Pressure test conducted year
Test pressure (psig)
Other Outside Force Damage Previous Damage due to Excavation Activity Pipe/Weld - Type of Direct Assessment
Direct Assessment and Investigative dig conducted - Year
Direct Assessment conducted but point of Incident was not identified as dig site - Year
One or more Non-destructive examination been conducted since January 1, 2002 (Yes, No, Null)
Non-destructive Examination - Radiography (Yes, Null)
Non-destructive Examination - Radiography Year
Non-destructive Examination - Guided Wave Ultrasonic (Yes, Null)
Non-destructive Examination - Guided Wave Ultrasonic Year
Non-destructive Examination - Handheld Ultrasonic Tool (Yes, Null)
Non-destructive Examination - Handheld Ultrasonic Tool Year
Non-destructive Examination - Wet Magnetic Particle Test (Yes, Null)
Non-destructive Examination - Wet Magnetic Particle Year
Non-destructive Examination - Dry Magnetic Particle Test (Yes, Null)
Non-destructive Examination - Dry Magnetic Particle Year
Non-destructive Examination - Other Internal Inspection Tool (Yes, Null)
Non-destructive Examination - Other Internal Inspection Tool Year
Non-destructive Examination - Other Internal Inspection Tool details
Other Outside Force Damage - Intentional Damage Sub-type
Other Outside Force Damage - Intentional Damage Other Details
Other Outside Force Damage - Other Details
Material Failure of Pipe or Weld Sub-Cause
Material Failure of Pipe or Weld sub-cause Based on - Field Examination (Yes, Null)
Material Failure of Pipe or Weld sub-cause Based on - Metallurgical Analysis (Yes, Null)
Material Failure of Pipe or Weld sub-cause Based on - Other Analysis (Yes, Null)
Material Failure of Pipe or Weld sub-cause Based on - Other Analysis Details
Material Failure of Pipe or Weld - Sub-cause is Tentative or Suspected; Still Under Investigation (Yes, Null)
Construction/Installation/Fabrication related - Contributing factors
Construction/Installation/Fabrication related - Contributing factors related to Fatigue/Vibration

Construction/Installation/Fabrication related - Contributing factors related to Fatigue/Vibration Other Details

Construction/Installation/Fabrication related - Contributing factors related to Mechanical Stress

Construction/Installation/Fabrication related - Contributing factors related to Other factors

Construction/Installation/Fabrication related - Contributing factors related to Other factors Details

Original Manufacturing related (NOT girth weld or other welds formed in the field) - Contributing factors

Original Manufacturing related (NOT girth weld or other welds formed in the field) - Contributing factors related to Fatigue/Vibration

Original Manufacturing related (NOT girth weld or other welds formed in the field) - Contributing factors related to Fatigue/Vibration Other Details

Original Manufacturing related (NOT girth weld or other welds formed in the field) - Contributing factors related to Mechanical Stress

Original Manufacturing related (NOT girth weld or other welds formed in the field) - Contributing factors related to Other factors

Original Manufacturing related (NOT girth weld or other welds formed in the field) - Contributing factors related to Other factors Details

Material Failure of Pipe or Weld related to Environmental Cracking - Stress Sub-type

Material Failure of Pipe or Weld related to Environmental Cracking - Stress Sub-type Other Details

Material Failure of Pipe or Weld Additional factor - Dent

Material Failure of Pipe or Weld Additional factor - Gouge

Material Failure of Pipe or Weld Additional factor - Pipe Bend

Material Failure of Pipe or Weld Additional factor - Arc Burn

Material Failure of Pipe or Weld Additional factor - Crack

Material Failure of Pipe or Weld Additional factor - Lack of Fusion

Material Failure of Pipe or Weld Additional factor - Lamination

Material Failure of Pipe or Weld Additional factor - Buckle

Material Failure of Pipe or Weld Additional factor - Wrinkle

Material Failure of Pipe or Weld Additional factor - Misalignment

Material Failure of Pipe or Weld Additional factor - Burnt Steel

Material Failure of Pipe or Weld Additional factor - Other

Material Failure of Pipe or Weld Additional factor - Other details

Material Failure of Pipe or Weld - One or more Internal Inspection tool collected data (Yes, No, Null)

Internal Inspection Tool - Magnetic Flux Leakage Tool (Yes, Null)

Internal Inspection Tool - Magnetic Flux Leakage Tool Year

Internal Inspection Tool - Ultrasonic (Yes, Null)

Internal Inspection Tool - Ultrasonic Year

Internal Inspection Tool - Geometry (Yes, Null)

Internal Inspection Tool - Geometry Year

Internal Inspection Tool - Caliper (Yes, Null)

Internal Inspection Tool - Caliper Year

Internal Inspection Tool - Crack (Yes, Null)

Internal Inspection Tool - Crack Year

Internal Inspection Tool - Hard Spot (Yes, Null)

Internal Inspection Tool - Hard Spot Year

Internal Inspection Tool - Combination Tool (Yes, Null)

Internal Inspection Tool - Combination Tool Year
Internal Inspection Tool - Transverse Field/Triaxial (Yes, Null)
Internal Inspection Tool - Transverse Field/Triaxial Year
Internal Inspection Tool - Other Internal Inspection Tool (Yes, Null)
Internal Inspection Tool - Other Internal Inspection Tool Year
Internal Inspection Tool - Other Internal Inspection Tool Details
Material Failure of Pipe or Weld - Hydrotest or other pressure test conducted (Yes, No, Null)
Pressure test conducted year
Test pressure (psig)
Material Failure of Pipe or Weld - Type of Direct Assessment Inspection
Year Direct Assessment dig
Year Direct Assessment no dig
Material Failure of Pipe or Weld - Non-destructive examination (Yes, No, Null)
Material Failure of Pipe or Weld - Radiography (Yes, Null)
Material Failure of Pipe or Weld - Radiography Year
Material Failure of Pipe or Weld - Guided Wave Ultrasonic (Yes, Null)
Material Failure of Pipe or Weld - Guided Wave Ultrasonic Year
Material Failure of Pipe or Weld - Handheld Ultrasonic Tool (Yes, Null)
Material Failure of Pipe or Weld - Handheld Ultrasonic Tool Year
Material Failure of Pipe or Weld - Wet Magnetic Particle Test (Yes, Null)
Material Failure of Pipe or Weld - Wet Magnetic Particle Year
Material Failure of Pipe or Weld - Dry Magnetic Particle Test (Yes, Null)
Material Failure of Pipe or Weld - Dry Magnetic Particle Year
Material Failure of Pipe or Weld - Other non-destructive examination (Yes, Null)
Material Failure of Pipe or Weld - Other non-destructive examination year
Material Failure of Pipe or Weld - Other non-destructive examination details
Equipment Failure Sub-Cause
Equipment Failure Malfunction of Control/Relief Equipment - Control Valve (Yes, Null)
Equipment Failure Malfunction of Control/Relief Equipment - Instrumentation (Yes, Null)
Equipment Failure Malfunction of Control/Relief Equipment - SCADA (Yes, Null)
Equipment Failure Malfunction of Control/Relief Equipment - Communications (Yes, Null)
Equipment Failure Malfunction of Control/Relief Equipment - Block Valve (Yes, Null)
Equipment Failure Malfunction of Control/Relief Equipment - Check Valve (Yes, Null)
Equipment Failure Malfunction of Control/Relief Equipment - Relief Valve (Yes, Null)
Equipment Failure Malfunction of Control/Relief Equipment - Power Failure (Yes, Null)
Equipment Failure Malfunction of Control/Relief Equipment - Stopple/Control Fitting (Yes, Null)
Equipment Failure Malfunction of Control/Relief Equipment - Pressure Regulator (Yes, Null)
Equipment Failure Malfunction of Control/Relief Equipment - ESD System Failure (Yes, Null)
Equipment Failure Malfunction of Control/Relief Equipment -Other (Yes, Null)
Equipment Failure Malfunction of Control/Relief Equipment - Other details
Equipment Failure Pump or Pump-related Equipment - Other Pump (Yes, Null)
Equipment Failure Pump or Pump-related Equipment - Other Pump Details
Equipment Failure Threaded Connection/Coupling Failure - Other Stripped (Yes, Null)

Equipment Failure Threaded Connection/Coupling Failure - Other Stripped Details
Equipment Failure Non-threaded Connection Failure - Other Non-threaded Connection (Yes, Null)
Equipment Failure Non-threaded Connection Failure - Other Non-threaded Connection Details
Other Equipment Failure - Details
Equipment Failure Additional factor - Excessive vibration (Yes, Null)
Equipment Failure Additional factor - Overpressurization (Yes, Null)
Equipment Failure Additional factor - No support or loss of support (Yes, Null)
Equipment Failure Additional factor - Manufacturing defect (Yes, Null)
Equipment Failure Additional factor - Loss of electricity (Yes, Null)
Equipment Failure Additional factor - Improper installation (Yes, Null)
Equipment Failure Additional factor - Mismatched items (Yes, Null)
Equipment Failure Additional factor - Dissimilar metals (Yes, Null)
Equipment Failure Additional factor - Breakdown of soft goods (Yes, Null)
Equipment Failure Additional factor - Valve vault (Yes, Null)
Equipment Failure Additional factor - Alarm/status failure (Yes, Null)
Equipment Failure Additional factor - Misalignment (Yes, Null)
Equipment Failure Additional factor - Thermal stress (Yes, Null)
Equipment Failure Additional factor - Other failure (Yes, Null)
Equipment Failure Additional factor - Other failure Details
Incorrect Operation Sub-Cause
Incorrect Operation - Specify Underground Gas Storage, Pressure Vessel, or Cavern Allowed or Caused to Overpressure
Incorrect Operation - Other reason of overflow Details
Incorrect Operation - Other Sub-cause Details
Incorrect Operation Incident related to - Inadequate procedure (Yes, Null)
Incorrect Operation Incident related to - No procedure established (Yes, Null)
Incorrect Operation Incident related to - Failure to follow procedure (Yes, Null)
Incorrect Operation Incident related to - Other (Yes, Null)
Incorrect Operation Incident related to - Other Details
Incorrect Operation - Category type that caused Incident
Incorrect Operation - Was the task(s) that led to the Incident identified as a covered task in your Operator Qualification Program (Yes, No, Null)
Individuals performing the task(s) qualified for the task(s)
Other Incident Cause Sub-Cause
Other Incident Cause - Miscellaneous Details
Other Incident Cause - Unknown Sub-type
Name of Operator's preparer
Title of Operator's preparer
Telephone number of Operator's preparer