Failure Prediction Model for Oil Pipelines

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Abstract

Failure Predicting Model for Oil Pipelines

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Oil and gas pipelines are considered the safest means to transport petroleum products comparing to railway and highway transportations. They transport millions of dollars' worth of goods every day. However, accidents happen every year and some of these accidents inflict catastrophic impact on the environment and result in great economic loss. In order to maintain safety of the pipelines, several inspection techniques have been developed in the last decades. Despite the accuracy of these techniques, they are very costly and time consuming. Similarly, several failure predicting and condition assessment models have been developed in the last decade; however, most of these models are limited to one type of failure, such as corrosion failure, or mainly depend on expert opinion which makes their output seemingly subjective.

The present research develops an objective model of failure prediction for oil pipelines depending on the available historical data on pipelines' accidents. Two approaches were used to fulfill this objective: the artificial neural network (ANN) and the Multi Nomial Logit (MNL). The ANN is used to develop a model to predict failure due to mechanical, corrosion or third party, which collectively account for 88% of oil pipeline accidents. This model had a prediction accuracy of 68.5%. Another ANN model is developed to predict only corrosion or third party failure with a prediction accuracy of 72.2%. The Average Validity Percentage (AVP) for the two models is 73.7 and 72.8, respectively.

The MNL approach is used to develop a model that predicts failures caused by mechanical, corrosion or third party elements with a prediction accuracy of 68.4% and Pseudo R Squared of 0.42. The Average Validity Percentage (AVP) for this MNL approach is 73.7%. This model also generates a probability equation for each type of failure.

The three developed models show convincing results, since they are based on solid historical failure data for the last 38 years, with no subjectivity or ambiguity. These models could easily be used by oil pipeline operators to identify the type of failure threatening each pipeline so that appropriate preventive and corrective measures can be planned. The models also help to prioritize in-line inspection of different pipeline segments according to the predicted type of failure.

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LIST OF ABBREVIATIONS

AE	Acoustic Emission
AHP	Analytical Hierarchy Process
AIP	Average Invalidity Percentage
ANN	Artificial Neural Network
ANSI	American National Standard Institute
API	American Petroleum Institute
ASME	American Society of Mechanical Engineer
ASTM	American Society of Testing Materials
AUV	Autonomous Underwater Vehicle
AVP	Average Validity Percentage
BPNN	Back Propagation Neural Network
C&RT	Classification and a Regression Tree
CIPS	Close Interval Pipe to Soil Potential
CP	Cathodic Protection
CVI	Close View Inspection
DCVG	Direct Current Voltage Gradient
DOT	US Department of Transportation
DV	Dependant Variable
ECDA	External Corrosion Direct Assessment
EMAT	Electromagnetic Acoustic Transducer
ET	Eddie Current Test
EWV	Elastic Wave Vehicle
FNN	Fuzzy Neural Network
GVI	General Visual Inspection
ILI	In Line Inspection
LL	Log Likelihood
MAE	Mean Absolute Error
MAOP	Maximum Allowable Operating Pressure
MFL	Magnetic Flux Leakage
MLE	Maximum Likelihood Estimate
MLF	Multi-Layer Feed Forward
MNL	Multi Nomonial Logit

NACE	National Association of Corrosion Engineers
NDT	Non Destructive Test
OPMG	Oil Pipelines Management Group
PNN	Probabilistic Neural Network
QA	Quality Assurance
QC	Quality Control
RBIM	Risk Based Inspections and Maintenance
REFC	Remote Field Eddy Current
RMSE	Root of Mean Square Error
ROC	Receiver Operating Characteristic
ROV	Remote Operated Vehicle
SCADA	Supervisory Control and Data Acquisition
SCC	Stress Crack Corrosion
UT	Ultra Sound

Chapter 1

INTRODUCTION

1.1 Overview

Pipelines are the backbone of the oil industry; they transport millions of dollars' worth of goods every day. While pipelines are considered to be the safest way to transport petroleum products, compared to rail and highway transportation, some pipeline accidents could have catastrophic environmental impact and severe economic lose (Dey, et al., 2004). According to the CONCAWE (a European associate of oil companies that investigates environmental, health and safety issues) pipeline failure occurs due to the following: mechanical, operational causes, corrosion, third-party activity and natural hazards. The CONCAWE organization was established in 1963 to carry out environmental research related to the oil industry. Most of the European oil companies are now members of CONCAWE (CONCAWE, 2010).

Over the last 20 years, several new inspection techniques have been developed to detect pipeline anomalies or defects without stopping production (or flow), such as Magnetic Flux Leakage (MFL) or Ultrasonic testing (UT). While these techniques are effective, they are costly and time consuming. As an example, for the DOLPHIN PIPLINE in Qatar it costs 260,000 dollars (US) and takes one week to inspect an 80 km pipeline using the MFL technique (Husein, 2011). The high costs in time and money for these techniques have encouraged researchers to develop condition assessment models (or failure prediction models) for oil pipelines to prioritize inspections and to identify the actions that need to be taken to prevent predicted threats.

1.2 Problem Statement and Research Objectives

More than 60 countries have oil and gas pipeline networks exceeding 2000 km; the longest pipeline network is located in the United States of America followed by Russia (Goodland, 2005). These huge networks transporting such a dangerous product must be in safe working condition to avoid catastrophic accidents. Mandatory frequent inspections are required to maintain these networks. While pipeline inspection techniques have developed to provide very accurate results, they are very expensive and time consuming. Therefore, most pipeline operators use condition assessment models to prioritize inspection, set a reasonably economical inspection interval and assure that they will take suitable precautions against failure.

Most of the current models are either dependent on expert opinions, which makes them subjective, or they are limited to evaluating only one type of failure. Therefore, a more robust objective model is needed, one that can use historical data to predict the failure type menacing a section of oil pipeline. This model would help pipeline operators to take the necessary actions to mitigate the risk that threatens a pipeline.

The main objective of the current research is to provide an impartial failure prediction model for oil pipelines that is capable of identifying the failure type menacing a pipeline by knowing some basic pipeline attributes. The developed model is able to predict the failure type threatening a pipeline from among the main three failure causes (mechanical, corrosion and third-party), which together cause 88% of oil pipeline accidents according to CONCAWE (Davis, et al., 2010).

The sub-objectives of this research may be summarized as follows:

- Identity and study the main failure causes of pipelines
- Identify the pipeline factors that contribute to pipeline failure
- Develop a failure prediction model for oil pipelines

1.3 Research Methodology

This research aims at developing a failure prediction model for oil pipelines. This model will allow oil pipeline operators to take those actions required to protect pipelines against the threats predicted and to prioritize inspections. The following procedure was carried out to achieve this objective.

1.3.1 Literature review

A comprehensive literature review was prepared, which includes information on different types of oil and gas pipelines, types of pipeline failure, a review of the effect of pipeline attributes on types of failure, a review of the recent studies for oil and gas pipeline condition assessment, a review of the various inspection techniques and a presentation of the Artificial Neural Network ANN and the Multinomial Logit Model techniques.

1.3.2 Data Collection

Historical data were collected from the CONCAWE report published in 2010. That report contains summaries of all of the oil pipeline accidents in Europe over the last 38 years, including the causes of failure and some pipeline characteristics. The collected data were processed by the following steps. First, all the accidents that had missing data were eliminated. Two data sets were then prepared. The first set includes all the accidents caused by mechanical, corrosion or third-party failure. The second data set contains the accidents caused by corrosion failure and third-party failure. These two sets were used two develop two different models.

1.3.3 Development of Failure Prediction Model

Three failure models are developed:

- An Artificial Neural Network (ANN) model that predicts failure caused by mechanical failure, corrosion failure or third-party failure (3 outputs);

- An Artificial Neural Network (ANN) model to predict failure caused by corrosion failure or third party-failure (2 outputs);
- A Multinomial Logit (MNL) model that can predict failure caused by mechanical failure, corrosion failure or third-party failure (3 outputs).

1.4 Thesis Organization

To accomplish the research objectives, a literature review illustrating condition rating models for oil and gas pipeline types is represented in chapter 2. The literature review covers the oil and gas pipeline types, the types of pipeline failures, factors contributing to pipeline failures, and inspection techniques. Chapter 2 also includes an overview of Artificial Neural Network techniques and presents the Multinomial Logit technique.

Chapter 3 provides an overview of the research methodology including a layout for building the ANN and the MNL models.

Chapter 4 contains the data collection and data preparation procedures, a description of the different data sets used for the different models and the exclusion method deployed for the random samples used for validation purposes are also presented.

Chapter 5 describes the development of two ANN models; it identifies the inputs and the outputs of each model, explains the models' development and presents the training and tests utilized for each model. It also shows the validation process and the sensitivity analysis for each model.

Chapter 6 illustrates the development of the MNL failure prediction model, including the model evaluation and validation processes. This chapter also includes a sensitivity analysis for the developed model.

Chapter 7 presents the conclusion, including the limitations of the developed models, the research contributions and recommendations for the future research.

Chapter 2

2 LITERATURE REVIEW

2.1 Overview

This chapter consists of seven parts. Section 2.2 presents a literature review on the different types of petroleum pipelines and their characteristics. Section 2.3 demonstrates the main causes of failure, such as mechanical failure, corrosion failure, operational failure, natural hazards, and third party failure. Section 2.4 illustrates the factors that contribute to petroleum pipeline deterioration. These factors are classified according to the failure category that they contribute to. Section 2.5 provides a literature review of current practices followed by pipeline line operators to assess the condition of existing pipelines. Section 2.6 presents a literature review of the current practices for inspecting oil and gas pipelines. This includes direct inspection methods, which are divided into in-line inspection and external inspection. This subsection also shows how most pipeline operators manipulate with the inspection data to help them make maintenance decisions. Section 2.7 provides a literature review of the failure prediction and condition assessment models for oil and gas pipelines developed to date. Section 2.8 and 2.9 present an extensive literature review on logistic regression analysis modeling and artificial neural network (ANN) analysis respectively and their application.

2.2 Petroleum Pipeline Material and Specifications

Pipelines are the back bone of the petroleum industry. They can be classified by the type of product they transport: crude oil, natural gas and products pipelines (Canadian Energy Pipeline Association, 2007). Most major pipelines are made of steel with diameters that vary from 8 to 47 inches, while distributive pipelines are mostly made of plastic with small diameters of up to only 2 inches. In this research we are concerned with main oil pipelines, which are made of steel that can be of different steel grades (grade B to grade X90) and that operate at various pressures (10 to 220 bar) (Ali, 2011).

2.2.1 Pipeline Types

There are five major types of pipeline, classified according to their usage (Hopkins, 2002):

Flow lines and gathering lines: are usually small and short pipelines that transport crude product to the processing facilities. Their diameter varies from 2" to 6" and they are made of carbon steel.

Feeder lines: these transport oil or gas from a processing facility or storage to the main line. The diameter can be up to 20", and they are composed of carbon steel.

Transmission lines: these are the main conduits of transported oil and gas, and can reach a diameter of 56". These lines are usually very long and are made of carbon steel.

Product lines: carry refined products from refineries to distribution centers. They are also made of carbon steel.

Distribution lines: are used for local distribution and function at low pressure. Their diameter can be up to 6 ", and they are made of cast iron or plastic.

2.2.2 Pipeline Material

As mentioned earlier, main pipelines are made of carbon steel. Carbon steel pipelines are manufactured according to the American Petroleum Institute (API 1994-2004), the American Society of Mechanical Engineer (ASME), the American National Standard Institute (ANSI) and the American Society of Testing Materials (ASTM) standards (Pharris, et al., 2007). There are two ways of manufacturing main pipelines; seamlessly, which means fabricated without longitudinal welds, or welded. Welded pipes can be spirally welded or longitudinally welded (Mikhail, 2011). The pipes are transported to the construction site certified by the manufacturer, and then they are welded together to form the pipeline network (Hasan, 2011). The steel grade varies from grade A to grade X 80. The higher the grade, the higher the yield stresses as shown in figure 2.1. Usually higher grade steel is used for high-pressure pipeline and offshore pipeline. One problem with these pipelines is that pipelines made of high-grade steel require special welds. Also high steel grades are highly affected by the existence of impurities, especially H2S. Generally, oil and gas are mixed with some impurities when extracted from the field. These impurities increase the risk of internal corrosion. The most common impurities are cited below (Mikhail, 2011):

H2S (sour gas): H2S forms sulphuric acid in the presence of water, which then causes pitting, lamination and corrosion.

CO2: When exposed to water, CO2 forms carbonic acid, a highly corrosive acid.

Chlorides: chlorides are highly corrosive substances.

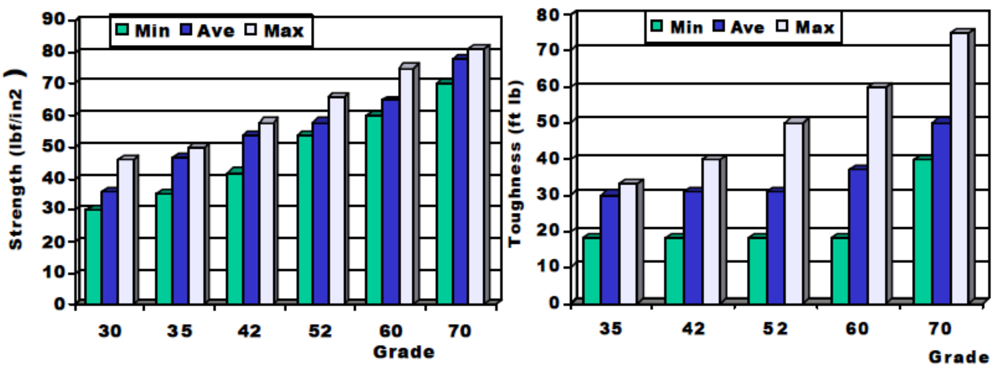

Figure 2-1 Overview of the Yield Stress and the Impact Toughness for Oil and Gas Pipeline (Hopkins, 2002)

2.3 Types of Oil Pipeline Failure

The Oil Companies' European Association for Environmental, Health and Safety issues in Refining and Distribution, CONCOWE, lists several types of failure for oil pipeline. The CONCAWE was established in 1963 by a group of leading oil companies to carry out research on environmental issues related to the oil industry. The CONCAWE publishes reports and collects and analyses pipeline accidents in Europe. The following section shows the main types of pipeline failure according to the CONCAWE (Davis, et al., 2010) .

2.3.1 Mechanical Failure

Mechanical failure includes all failure due to poor construction or the usage of low quality materials (Dey, 2004). Mechanical failure may be divided into two categories, dents and gouges, that appear as deformation in the pipe wall and which are sites where cracks develop. Dents are radial deformations, while a gouge follows along surface deformation. These defects usually occur during the construction phase. Mechanical damage can cause immediate failure, delayed failure or no failure, depending on the severity of damages. Presently the most common way to detect mechanical damage is by performing In-line Inspection (ILI), such as Ultrasound Pig or Magnetic Flux Pig (Panetta , et al., 2001).

2.3.2 Corrosion Failure

Corrosion is formed because of the tendency of manufactured metals to revert to their original mineral form; this process is usually very slow. Corrosion causes a loss of pipeline wall metal that could lead to failure. Corrosion failure is considered the second-most common cause of pipeline failure after third-party interference. To evaluate the change potential of corrosion, the type of corrosion should be clearly identified. There are three main types of corrosion, as presented below (Muhlbauer, 2004).

a. External Corrosion

External corrosion could be an atmospheric corrosion for above-ground pipeline components exposed to the atmosphere. This is a rare failure mechanism due to the slow rate of the atmospheric mechanism. External corrosion can also occur because of subsurface corrosion in buried pipelines. Subsurface corrosion is more dangerous than atmospheric corrosion due to the complicated mechanism underlying this corrosion. Subsurface corrosion can be minimized by using cathodic protection and pipeline coating (Muhlbauer, 2004).

b. Internal Corrosion

This type of corrosion attacks the inner surface of a pipeline. It is less severe than subsurface corrosion but more dangerous than atmospheric corrosion. It is typically a function of the product being transported by the pipeline (Ali, 2011).

c. Stress Crack Corrosion.

Stress crack corrosion is a type of corrosion induced from the combined influence of the tensile stress and the corrosive environment (Cotis, 2011).

2.3.3 Third-Party Activity and External Interference

Third party failure is a result of any damage caused by people who are not associated with a pipeline. This includes undetected accidents, and can result in a failure at any later point (Davis, et al., 2010). The US Department of Transportation (DOT) pipeline statistics show that third-party activities are the major cause of pipeline failure. 20 to 40 percent of all pipeline failures are caused by third-party damages. Despite this reality, third-party damage is the least-considered factor in pipeline hazard assessment (Muhlbauer, 2004). There are many factors that can affect the occurrence of third-party damage, such as the type of land use, pipeline location, political instability and its accessibility. These factors are discussed later in this chapter.

2.3.4 Operational Failure

Operational failure results from operational upsets: the malfunction or inadequacy of one or more safeguarding systems or operators' error (Bersani, et al., 2010). Operational failure is considered to be one of the more rare causes of pipeline failure, although it can cause catastrophic consequences. Eighty percent of operational failure is caused by human error. This type of failure could be significantly reduced by regularly performing safety programs and providing extensive training as well as drug testing of pipeline operators. Up-to-date safety devices and pressure monitoring could also reduce the risk of this failure (Muhlbauer, 2004).

2.3.5 Natural hazards

Natural hazards rarely cause pipeline failure, but they still should be considered in failure assessment because of their implications on public safety. Natural hazards include flooding, land movement, volcanic activity and earthquakes, all of which can severely damage a pipeline and the environment in most cases, geotechnical and hydro-technical studies are performed prior to pipeline construction.

The list above includes all the types of failure that could happen to a steel oil pipeline. Figure 2.2 represents the percentage of occurrence of each type of these failures for the last 38 years in the European pipeline system according to CONCAWE's data. The chart shows that 88% of accidents were caused either by mechanical failure, corrosion failure or third-party failure. Each of these types of failure could be affected by a number of factors, which means that researchers must investigate all the available pipeline parameters that could contribute to failure. The following section presents the pipeline parameters that contribute to the afore-mentioned types of failures.

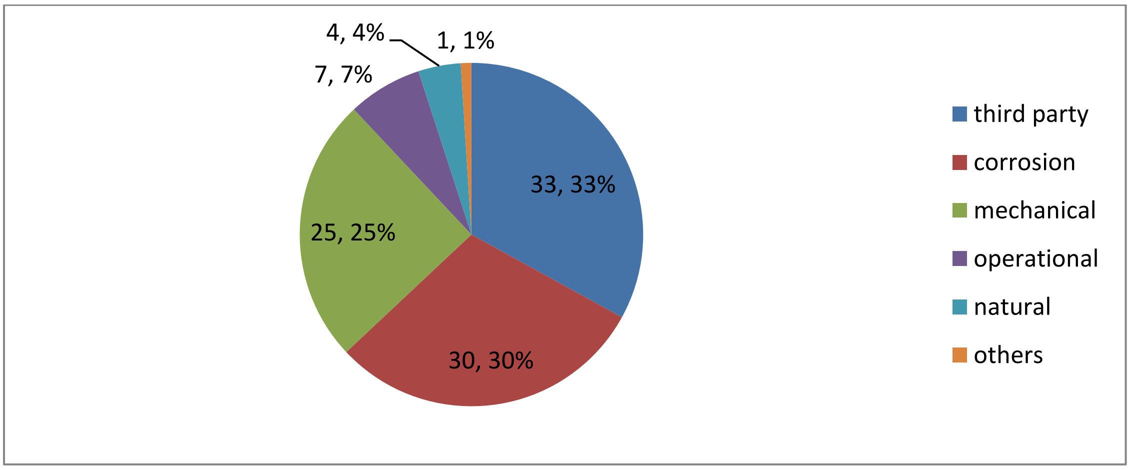

Figure 2-2 Percentages of Oïl Pipeline Failure Causes (Davis, et al., 2010)

2.4 Factors Contributing to Oil and Gas Pipeline Failure

The factors that affect pipeline failure are complicated, they in turn depend on several sub-factors, and all these factors should be taken into account in order to know the weight of their individual contribution to the pipeline deterioration. These factors are the pillars of any prediction model or risk-based inspection model. The model illustrated by (Muhlbauer, 2004) classifies factors contributing to oil pipeline failure according to the type of failure they may cause. In this section we will present these factors according to Muhlbauer's classification system which is shown in figure 2.3.

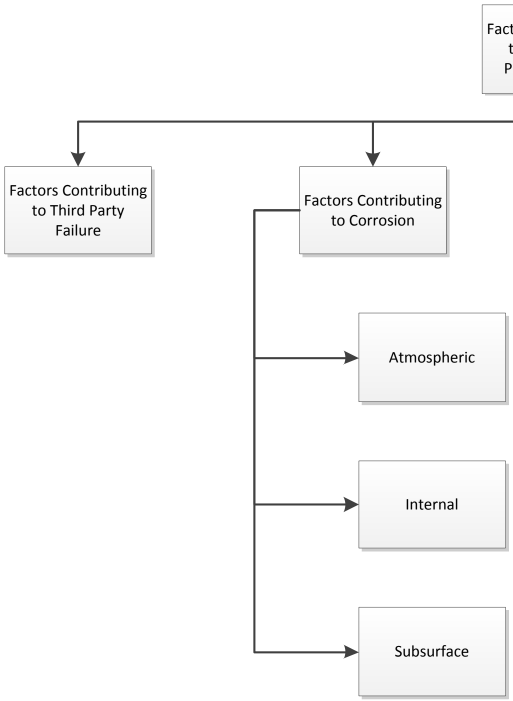

Figure 2-3 Types of factors Contributing to Pipeline Failure (Muhlbauer, 2004)

2.4.1 Factors Contributing to Third-Party Damages

a. <u>Minimum Depth of Cover</u>

The minimum cover depth highly affects the risk of third-party damage. Shallow buried pipeline is vulnerable to damage due to contractor excavation. The type of soil above the pipeline (sand, rock, etc.) and the type of pavement (if any) above (or close to) it could also affect the risk of third-party damage. The presence of burial warning tape, concrete coating or concrete slabs decreases the risk of third-party damage. In case of submerged pipeline, the depth of water affects the risk of third-party damage caused by anchoring (Muhlbauer, 2004).

b. Activity Level

The activity level, in terms of its effect on a pipeline, may be represented by population density. The presence of highways with heavy trucks or railways could apply an excessive load on buried pipelines. Other buried infrastructures could also cause threats because of their own need for excavations and maintenance. With submerged pipelines, the presence of ships and submarines could be a threat.

c. Line Locating

Line locating is a program that specifies the exact location of buried pipelines, thereby allowing third-party excavation to be conducted safely without risk of pipeline damage. The One Call System is a service that receives information about any digging activity and in turn notifies all owners of the affected underground facilities. These services decrease the risk of third-party failure. (Muhlbauer, 2004)

d. Public Education Program

A good public education program decreases the chance of third-party failure. This could be achieved by mailings and/or meetings with local contractors, as well as media publicity, (Public Service Announcements PSAs, billboards, etc.) (Muhlbauer, 2004).

e. Right-Of-Way Condition

This parameter measures the recognisability of a pipeline corridor. Pipeline corridors should be clearly indicated by appropriate clear signs to reduce third-party interruption.

f. Patrol Frequency

The frequency and the effectiveness of patrols should be considered in certain locations, as it can play an important role in reducing the risk of third-party damage and vandalism.

g. Pipeline Diameter

Pipeline diameter can contribute to third-party failure (Bersani, 2010), as small-diameter pipelines are more vulnerable to damage than larger ones (Ali, 2011).

2.4.2 Factors Contributing to Corrosion Failure

Corrosion failure could be caused by three different types of corrosion: atmospheric corrosion, internal corrosion and subsurface corrosion. Each types of corrosion are affected by several factors. In the factors contributing to each type of corrosion is cited showing how it could affect corrosion failure.

2.4.2.1 Factors Affecting Atmospheric Corrosion

a. **Atmospheric Exposure**

Specific atmospheric characteristics affect atmospheric corrosion. Chemical composition could be air-borne naturally, such as salt and CO2, or manmade, as are chlorine and SO2. High temperatures and especially high humidity increase the chance and the rate of corrosion.

b. **Atmospheric Coating**

This factor describes the preventive precautions taken to minimise the chance of atmospheric corrosion. The age and condition of a coating have a great impact on corrosion prevention (Muhlbauer, 2004).

2.4.2.2 Factors Affecting Internal Corrosion

a. **Product Corrodibility**

This factor presents the relative corrosiveness of the pipeline content. Threats may be posed by product incompatibility with the pipeline material or the existence of corrosive impurities that migrate into the product. The corrodibility of a product may be categorized by the level of corrosiveness, as shown by Muhlbauer (2004):

Strongly corrosive: product that contains water, H2S etc.

Mildly corrosive: corrosion exists, but proceeds at a slow rate.

Corrosive in some conditions: product is normally benign but could become corrosive in the presence of other factors.

Never corrosive: a product that is always compatible with its pipeline material.

b. Internal Corrosion Prevention

In order to transport a corrosive product in a pipe susceptible to corrosion, some actions may be taken to reduce corrosion risk. These procedures are indicated in the following paragraphs (Salah, 2011).

Internal monitoring: can be conducted by an electronic probe that measures the corrosion, or with tabs coupon that corrode in the presence of a corrosive substance and thus give an indication of the probable corrosion rate.

Inhibitor injection: certain chemical products could be injected into a pipeline to reduce the reaction that causes corrosion**.**

Internal coating: an internal coating can be applied, including spray-on plastic, mortar or concrete. There is a broad assortment of internal coatings for pipelines.

Operational measures: maintaining certain temperatures and separating impurities from the products are the most effective operational measures for reducing corrosion risk.

Piging : involves a cylindrical instrument that is used to clean the inside walls of pipelines, removing residues (and corrosion).

2.4.2.3 Factors Affecting Subsurface Corrosion

a. Soil Corrosivity /Pipe Corrodibility

If there are any imperfections in a pipeline's external coating, the soil could be in contact with the pipeline. Soil works as an electrolyte, promoting the galvanic corrosion of a pipeline's metal. A soil's corrosivity is related to its resistivity, as shown in table 2.1. High moisture content and low PH increase soil corrosivity (Muhlbauer, 2004).

b. Cathodic Protection

Cathodic protection effectiveness: cathodic protection is the application of an electric current to a metal to offset the electromotive force of corrosion. The effectiveness of cathodic protection can be measured by different methods, and are described in appendix A.

Inference potential: because corrosion is an electrochemical process, cathodic protection works to prevent this process, the presence of other electric interference could defeat the cathodic protection effect (Muhlbauer, 2004).

c. Pipeline Age

The age of a pipeline is a main factor of pipeline deterioration, and the main sign of aging is corrosion. Since corrosion is a slow process, it becomes more severe for older pipelines (Henderson, et al., 2001). Figure 2.4 shows the oil spills recorded in an onshore pipeline in Western Europe. The figure shows how proper inspection and maintenance could decrease the effect of age on failure.

Table 2-1 Relation between Soil Resistivity and Corrosivity (Muhlbauer, 2004)

Soil resistivity	Soil corrosively
1.000 ohm – cm	High
Medium 1.000-15.000 Ohm – cm or moderately active corrosion indicated	Medium
High resistivity (low corrosion potential) 15.000 ohm – cm and no active corrosion indicated	Low

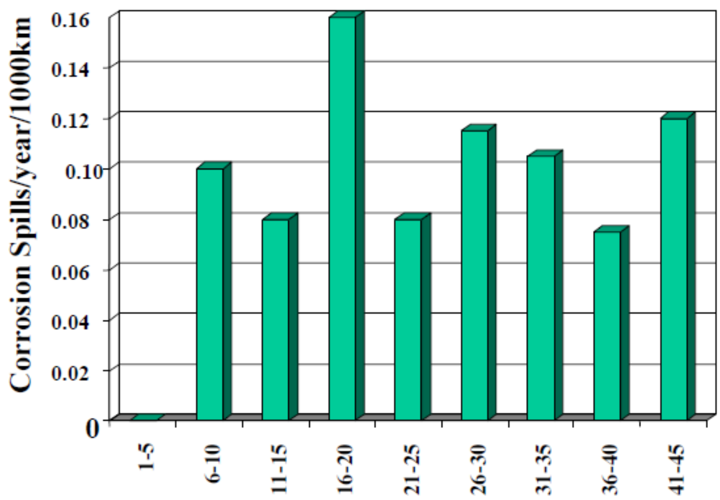

Figure 2-4 Age of Pipeline at Time of Spill (Henderson, et al., 2001)

2.4.3 Factors Contributing to Operational Failure

Operational failure can be caused by human error or by system error (Dey, 2004). The following factors must be considered to assess the risk of operational failure (Muhlbauer, 2004).

- Operational procedures;
- Supervisory Control and Data Acquisition SCADA communication;
- Drug testing;
- Safety programs;
- Surveys, maps and records;
- Training level of the operators; and
- Mechanical error preventers (e.g. safety and relief valves).

2.4.4 Factors Contributing to Mechanical Failure

Mechanical failure could be a result of design error, of the use of inappropriate materials and/or due to faulty construction (Davis, et al., 2010). A list of the factors contributing to faulty construction and contributing to desiegn errors is presented next.

2.4.4.1 Factors Related to Materials Failure and Construction Fault

The American Society of Mechanical Engineers (ASME) defines some regulations and recommendations to reduce the risk of mechanical failure. These factors can be summarised as follows (The Hartford Steam Boiler Inspection and Insurance Company, 2000):

- Material selection;
- The appropriate installation procedure;
- Leak inspection;
- The application of QA, QC to the installation and fabrication processes; and
- The proper construction method.

2.4.4.2 Factors Related to Failure Caused by Design Error

One of the main causes of mechanical failure is design error; some important subjects that could lead to design error as described by (Muhlbauer, 2004) include:

a. <u>Safety</u>

The safety factor is calculated by comparing the designed load of a pipeline with the actual load. This load could be an external load, the internal pressure in case of gas pipeline or a special load.

b. <u>Fatigue</u>

Fatigue failure mainly depends on the repetition of load cycles. For pipelines, the most important factor that affects the fatigue is the frequency of internal pressure cycles.

c. <u>Surge Potential</u>

Surge pressure or 'water hammer' occurs when there is a sudden change in a fluid's velocity, which could be caused by a closed valve, a tripped pump trip, or other situations (EMERSSON Prosess Management, 2012). The power of a surge depends on a fluid's density, elasticity and velocity, as well as the stoppage speed. Surge protection devices are used to reduce any mechanical failure risk caused by a surge.

d. **Integrity Verification**

The existence of an integrity system could decrease the risk of mechanical failure by detecting any threats or anomalies. The performance of the following actions has a direct effect on a pipeline's integrity:

- Verification dates;
- Pressure tests;
- In-line inspection techniques and schedule; and.
- In-line inspection accuracy.

2.5 Pipeline Condition Rating

Condition rating is vital to define inspection frequency and to extend service for aging pipelines. An inspection interval varies from six months, for some aging pipelines, to 10 years. These intervals are set after performing a risk-based analysis (Ali, 2011). Some software systems have been developed to optimally set inspection frequency, such as ORBIT+ developed by Det Norsik Veritas (DNV) and PIPEVIEWER developed by General Electric (GE). These software systems mainly depend on expert opinions (Mikhail, 2011).

Usually, condition rating is used for assessing an aging pipeline to have a better idea about the possibilities for service extension. The main challenges facing oil pipeline condition assessment are (Ali, 2011):

1. A significant percentage of the pipelines are unpigable (not suitable for in-line inspection); and
2. A lack of data and the absence of data management.

2.5.1 Overview of the Condition Assessment Procedure for Petroleum Pipelines

The pipeline condition assessment process is generally used by pipeline operators to ensure that a pipeline is in safe operational condition. Condition assessment is used to identify the life extension capacity of aged pipelines, to prioritize inspections and/or to pinpoint when and where to perform necessary maintenance. The following section illustrates the processes of identifying the pipeline condition in order to set the inspection frequency or to keep an aging pipeline in service.

2.5.2 Calculation of the Remaining Strength

In-line Inspection (ILI) reports contain thousands of anomalies and pipeline defects. Pipeline operators need a safe and cost-effective solution to deal with this huge amount of data (General Electric, 2010). To meet this challenge, the spots that have been identified by the ILI as having the highest metal loss should be compared to the allowable metal loss identified by the codes and the design criteria. The most commonly-used methods to assess the remaining strength of corroded pipeline are the ASME 31.G and the DNV RP 101 (Hopkins, 2002). After calculating the remaining strength, a new Maximum Allowable Operating Pressure (MAOP) should be calculated.

Case 1: If the operating pressure is below the calculated new maximum allowable pressure then no maintenance is needed. The next inspection will be scheduled based on the corrosion growth and the risk analysis.

Case 2: If the operating pressure is higher than the newly-calculated maximum allowable pressure, the operator must repair the affected areas or reduce the operating pressure (Mikhail, 2011).

2.5.3 Calculation of Corrosion Growth

Different models have been developed by researchers and organisations to predict corrosion growth. The ASME 31.8S gives a prediction for external corrosion growth depending on environmental factors such as soil resistivity, as shown in table 2-2 (Morbier, 2009). Others models involve several factors (e.g. type of product, existence of impurities, water content

…etc.). Most pipeline operators utilise in-line inspection comparison to calculate the corrosion rate. By analysing multiyear ILI data for pipelines, all of a pipeline's corrosion activities can be identified and the corrosion rate can be accurately calculated (Hashisha, 2011). General Electric developed the RUNCOM software to calculate the corrosion growth for pipelines based on multiyear ILI comparison (General Electric, 2010).

Table 2-2 External Corrosion Growth (Morbier, 2009)

Corrosion Rate (MILS/YEAR)	Soil Resistivity (OHM-CM)
3	More than 15,000 No Active Corrosion
6	1,000-15,000
12	Less than 1000

2.5.4 Risk-Based Inspection and Maintenance (RBIM)

For the past 10 years, the pipeline industry has relied on risk analysis to prioritise inspection and maintenance. Before then, inspection intervals were defined according to pipeline operators' experience and knowledge (Mikhail, 2011). Most regulatory bodies, such as the ASME and the American Petroleum Institute (API) have approved risk-based inspections for pipelines and have outlined some guidelines for its implementation (Ali 2011). Risk analysis is usually done by consultants, such as DNV or GE, but some companies have their own research departments that perform these studies by identifying the risk by performing ILI then studying the failure consequences. The final step is to quantify the risk and to recommend inspection and maintenance plan according to the risk analysis (Salah, 2011). General Electric implements a post-inspection program, which involves the following steps (Hashisha, 2011):

- Collecting In-Line Inspection (ILI) data;
- Identifying the spot(s) with high metal loss;
- Identifying corrosion growth using RUNCOM software;

- Defining and recommending the new maximum allowable pressure (MAOP);
- Identifying the factors causing defects, for example; soil type, incomplete cathodic protection, the coating condition, etc. as well as other factors that cause defects such as third-party damages or internal corrosion.
- Identifying the risk of failure and the likely consequences of failure using the PIPEVIEWER software, a system based on expert experience.
- Finally, recommending the most suitable maintenance program and the date of the next inspection.

As previously mentioned, most pipeline operators depend mainly on risk-based inspection which is based on expert opinion to set inspection frequency and/or to identify the condition of pipelines; in other words, there is no robust objective model capable of assessing petroleum pipeline condition or of predicting the failure type that threatens a pipeline.

2.6 Current Practices for Inspection Techniques and their Appropriate Use

Due to large the number of pipeline networks and their positioning (buried, above ground, onshore and offshore), various operating pressures (10 bar to 220 bar) and different steel grades (grade B to grade X80), inspection is the most important practice to ensure pipeline integrity. An inspection interval varies from six months, for some aging pipelines, to 10 years. These intervals are set after performing a risk-based analysis (Ali, 2011).

A set of new technologies have been developed in the last 20 years to overcome this challenging issue and to provide an effective, accurate and economical solution for pipeline operators. An inspection gives operators a view of several parameters that could cause pipeline failure. The most important parameters measured by inspection are (Ali, 2011):

- Free span (for offshore pipeline);
- Coating condition;

- Cathodic protection condition;
- Existence of dents or cracks;
- Calculating the metal loss caused by internal or external corrosion;
- Wall thickness measurement; and
- Geometric measurement.

Pipeline inspection can be categorized as external inspection and internal inspection. For external inspection techniques, offshore techniques are different than onshore techniques due to the very different types of insulation and environment. In-line inspection techniques are the same in onshore and offshore pipelines.

2.6.1 Onshore Pipeline Inspection

Since in-line inspection is expensive and time consuming, onshore pipelines are usually inspected externally, according the National Association of Corrosion Engineers (NACE). In-line inspection is performed at long intervals compared to offshore pipeline because of the particular challenges of carrying out external inspection of offshore pipelines. The External Corrosion Direct Assessment (ECDA) procedure is shown below (Mikhail, 2011):

- Perform DCVG tests and CIPS tests to assess the coating condition and the cathodic protection effectiveness, respectively;
- Perform a soil resistivity test to identify the level of corrosivity;
- Analyze the data from the above tests in order to select the critical points to use for verifying it with Ultrasonic testing (UT) devices to assess the metal loss; and
- Perform UT tests at the selected points and do suitable repairs if needed.

2.6.2 Offshore Pipeline Inspection

Offshore pipeline inspection is very dependent upon in-line inspection due to the physical difficulties involved with external inspection. The common techniques used by pipeline operators are MFL and UT. Most pipeline operators prefer MFL over UT, for the following reasons (Mikhail, 2011):

- MFL can be used for pipelines that carry gas or oil, while UT requires a liquid environment. UT is thus not convenient (or even possible sometimes) for gas pipelines.
- UT requires extensive cleaning of the pipeline inner surface.
- An MFL tool usually runs at a speed of 4m/sec, while a UT tool runs at a speed of 1m/sec, so the MFL process takes much less time than UT.
- MFL is less expensive than UT (in part because of the above two aspects).

2.7 Previous Studies on Oil and Gas Pipeline Condition Assessment

Some significant efforts in pipeline condition assessment have been made in the last decade. A Fuzzy Neural Network (FNN) model was developed in 2008 to calculate the rate of failure for oil and gas pipelines (Yu Peng, et al., 2008).The main goal of this research was to calculate the rate of failure of pipelines. Since corresponding pipeline history failure data is difficult to collect, a fault tree fuzzy analysis method was applied and a fault tree for external corrosion constructed. Experts evaluated the probability of events using natural language and then these linguistic variables were transformed into fuzzy numbers. All the incidents identified by the fault tree can be fed to the neural network model which then calculates the probability of pipeline failure as an output. It is obvious that this study does not eliminate subjectivity because of its dependence on expert opinion to evaluate the probability of events. Moreover, the model only predicts the probability of failure caused by corrosion.

A risk assessment model created in 2010 takes historical data from the US Department of Transportation (DOT) and treats it with artificial neural network techniques to predict third-party failure (Bersani, et al., 2010).The main data factors that were considered in this study are:

- Average population density per square km;

- Land use (forests, grassland, farmland (including crops)… etc);
- Number and types of road crossings;
- Number and type of river/stream crossings; and
- Number of railway crossings.

The neural network was trained with 128 positive results (failures) and 128 negative results (non-failure). Bersani et al. presented a prediction model that can calculate the probability of failure due to third-party causes by knowing the site boundaries. This model depends mainly on historical data, but it is limited to third-party failure. Historical failure data have also been used to develop a tool that predicts the class of each spillage, using statistical analysis Classification and a Regression Tree (C&RT) (Bertolini, et al., 2006)

The Analytical Hierarchy Process AHP was used develop a model that will help decision makers to select the most suitable types of inspecting or monitoring techniques for pipeline segments that need to be evaluated (Dey, 2004). The AHP model was developed by predicting the risk factor and analyzing the effect of risk on pipelines. The result makes it possible to identify the appropriate inspection and maintenance programme, analyze the cost and benefits to justify the investments required, and finally suggests improvement in pipeline design, construction and operation. The methodology adopted in this study involves (Dey, 2001):

- Classifying the pipeline into segments and collecting all the data about each segment;
- Identifying the risk factors that can cause failure (corrosion, third party, acts of god, …etc.);
- Constructing the AHP and then performing a pair-wise comparison between factors and sub-factors in order to determine the likelihood of pipeline failure due to factors and sub-factors; and
- Finally, the most-suitable inspection/repair method for each segment can be selected and a cost of failure calculated.

This model was applied in a case study for a 1500 km length pipeline located in Western India. The data was collected during a workshop with executives who operate various pipelines. About 30 executives participated. The case study divides the pipeline into five segments and the model was applied to determine the likelihood of risk menacing each segment. While this model covers all types of failure, it is mainly depending on expert opinion.

Dawotola proposed a combined Analytical Hierarchy Process and fault tree analysis to support the design, construction and inspection of oil and gas pipeline. The model chooses an optimal selection strategy based on probability and failure consequences (Dawotola, et al., 2009).

An earlier study developed a simulation-based probabilistic neural network model to estimate the probability of failure of aging pipelines vulnerable to corrosion (Sinha, et al., 2002). That paper used the Probabilistic Neural Network technique (PNN) to calculate the probability of failure in oil pipelines due to corrosion, using magnetic flux MFL data.

In conclusion, all of the models developed to date are either subjective or do not cover all of the oil and gas pipeline failure causes. In other words, there is no objective model available that can predict different pipeline failure types.

2.8 Artificial neural network (ANN) technique

2.8.1 Overview

The human brain is living proof of the existence of massive neural networks. The human brain is capable of performing different complex actions (identifying faces, language, movement, etc.) because it contains a collection of 10 billion connected neurons. Artificial neural networks have been developed which are capable of generalizing a mathematical model of a biological nervous system. (Abraham, 2005). The ANN technique mimics the human brain’s techniques for learning and recalling patterns. An ANN technique is useful in problems where a solution is not clearly identified, and where the relations among inputs and outputs are not adequately defined. (Barqawi, 2006). Neurons are randomly connected in three different layers (input layer, hidden layers and output layer) to form the artificial neural network. The hidden layers are connected to the input layer and the output layer; therefore they are not connected to the external world (black box) (Zayed, et al., 2005)

Artificial Neural Networks are used in this research because of their ability to deal with the complex relationship between predictors and output. ANNs can also deal with categorical outputs and categorical predictors, which makes this technique suitable when the available data contains categorical variables.

2.8.2 Artificial neural network application

Artificial neural networks have been widely used in computer science fields and in image processing. In the past ten years, many engineering disciplines have used ANNs because of their ability to solve complex problem. The ANN technique is used to assess the condition of buried pipeline. It is widely used to assess the condition of water pipelines and sewer pipelines. A condition rating model for water mains has been developed using the back propagation neural network (Barqawi, 2006).

For oil and gas pipeline, several ANN models have been developed. Sadr et al. developed a model to identify erosion defects detected by magnetic flux inspection (Sadr, et al., 2006). Another failure prediction model using ANN was created to predict third-party failure. This model uses the site boundary as the input and predicts the output, which is the probability of failure due to third-party interference (Bersani, et al., 2010).

The models mentioned above are just a few of the examples of the application of neural networks in the field of pipeline condition assessment. Artificial neural networks are now used in many engineering domains (e.g. construction, foundations, transportation, planning and scheduling …etc)

2.8.3 Types of Artificial Neural Networks

There are three types of neural networks, classified according to their learning paradigms; unsupervised, hybrid and supervised. In a supervised neural network the network is provided with a correct answer (output) for each pattern, then weights are generated to allow the network to produce output as close as possible to the real output. Unsupervised learning does not require providing an output to the network; instead, it perceives the underlying correlations of data patterns and organizes these patterns into categories. Hybrid NNs combine the supervised and unsupervised learning processes to provide part of the weights using supervised learning while the remaining weights are provided through unsupervised learning (Anil, et al., 1996).

2.8.4 Multi-Layer Feed Forward (MLF) and Back Propagation (BPN) Learning

The most popular neural network is the Multi-Layer Feed Forward trained with Back Propagation learning algorithm (Daniel, et al., 1997). Back propagation neural networks are one of the most common neural network structures; they are simple and effective. BPNNs learn by example, which makes them very effective at prediction (Barqawi, 2006). An MLF forward network consists of at least three layers: an input layer, a hidden layer and an output layer. Units are connected in feed forward fashion. Input neurons are connected to a hidden layer and then to output layers. In other words, each neuron is connected to all the neurons in the next layer. The connection between the *ith* and the *jth* neuron is the weight coefficient w_{ij}. The *ith* neuron has a threshold (activation function) of v_i , as shown in figure 2-5 (Daniel, et al., 1997).

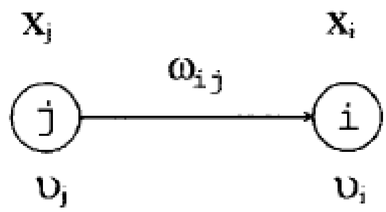

Figure 2-5 Connection Between Two Neuron (Daniel, et al., 1997)

The composition of a common MLF network is elaborated below, as shown in figure 2.6:

Input layer: This layer receives all the information from the input pattern.

Hidden layer: Neural networks can have more than one hidden layer, but should contain at least one. This layer is connected to the input layer and to the output layer by an activation function. The hidden layer is formed by receiving values from the input layer and then computing a value to send to an output neuron. This layer is totally formed by the neural network.

Output layer: this layer contains the weighted output received from the hidden neurons and compares it with the real output to adjust the weight.

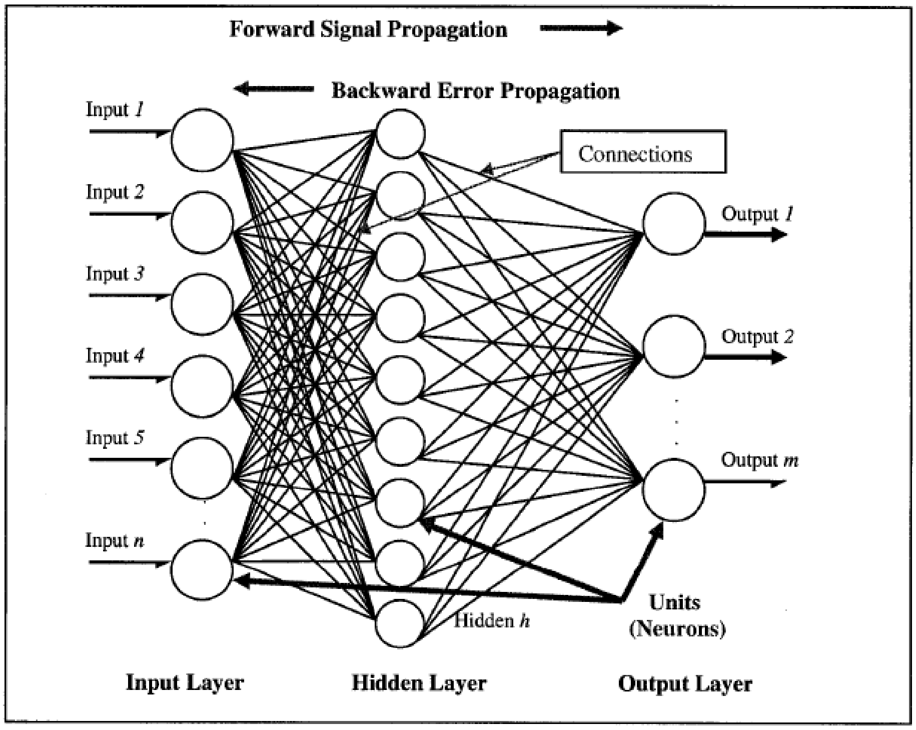

Figure 2-6 BPNN Architecture With one Hidden Layer (Barqawi, 2006)

A BPNN training algorithm is commonly used to supervise neural networks where the output is provided to instruct the ANN. The network learns by taking the partial derivative of the error of the network with respect to each weight. If we take the negative of this derivative and add it to the weight, the error will decrease until it reaches the local minima.

This process is called back propagation because it involves taking this derivative and adding them both to the weight starts from the output layer back to the input layer. (Abraham, 2005)

2.8.5 Learning and Recalling Process

The learning process of supervised ANNs using a BPNN learning algorithm is accomplished by providing the network with data sets that include inputs and outputs so that it can be trained. The network pattern is introduced and then the output pattern is estimated using random weights. The generated output is compared to the actual output, and then the error value between the 2 outputs is backward propagated into the network to adjust the connections weights. This procedure is repeated until an allowable error is reached, or a maximum number of epochs is reached, or any other stopping condition is satisfied (Barqawi, 2006). Once the neural network is trained it may be recalled to predict the output for any input pattern using the connections weights calculated during the learning process.

2.8.6 Neural Network Validation Process

One of the advantages of neural network models is that they can be used with continuous data or with categorical data. Common error metrics can be used to validate an ANN model for continuous output, such as the Mean Absolute Error (MAE) or the Root of Mean Square Error (RMSE) (Dikmen , et al., 2005) methods, or by using the Average Validity Percentage (AVP) and the Average Invalidity Percentage (AIP) (Zayed, et al., 2005). For categorical modeling the model is validated by introducing a new set of data to it and then calculating the percentage of correct predictions.

2.9 Statistical models

A statistical model is a probability distribution constructed to enable inferences to be drawn or decisions made from data (Davison, 2003). In other words, a statistical model is a formalization of relations between a set of independent and dependent variables. Many statistical models have been developed in the last few decades. The most important criterion to use to choose a suitable model is the type of data subjected to modeling. The different types of dependant and independent variables are listed and compared below.

2.9.1 Continuous vs. Discreet Variables

Variables can be categorised as continuous or discreet according to the number of values they can take. Continuous variables are those variables that take a large number of values, such as Pipeline Diameter, while discreet variables take only a few values, such as course grade (Agresti, 2002).

2.9.2 Nominal vs. Ordinal Variables

Categorical variables can be ordinal or nominal. Ordinal variables have an order relationship between the values. as in ‘course grade A is better than course grade B’, while with nominal variables there is no value relation (as can be the case with colors, for example).

2.9.3 Logistic Regression

In our case, the dependent variables are nominal (type of failure) and all the independent variables are discrete except for pipeline age and diameter, which are continuous. Since the output (dependent variables) is nominal and discreet, we are obligated to choose a discreet choice model. The basic form of logistic regression is used for the binary response and the Multinomial Logit (MNL) model uses the same methodology to deal with multiple outputs.

For binary categorical variables using the usual least squares deviation criteria, the best-fit approach of minimizing error around the line of best fit is inappropriate. Instead, logistic regression applies the binomial probability theory, which has only two values to predict: probability is 1 or 0. The logistic regression develops a best-fitting function (logistic function) using the maximum likelihood method, which is based on computing several iteration to maximize the probability of the observed data to be part of the appropriate category given the regression coefficient (Burns, et al 2009)

For a binary output Y=0 or Y=1 and multiple independent variable X, logistic regression does not calculate the value of X like linear regression does, but calculates the probability of Y being 1. The linear regression equation of Y is (Agresti, 2002):

$y = w1x1 + w2x2 + \cdots + wnxn$ ………………………………………………Equation 2-1

Where y is the dependent variable, w_1 to w_n are the estimators and x_1 to x_n are the independent variables. The logistic regression of Y is (Agresti, 2002):

$p(y = 1) = \frac{1}{1+e^{-z}}$ ………………………………………………………Equation 2-2

Where e is the natural logarithm number and Z is the logit (Agresti, 2002)

Z = (Logit) = $w1x1 + w2x2 + \cdots + wnxn$ …………………………………..Equation 2-3

From equations 2 and 3 we can conclude that the Logit is the log of odds, as shown in equation 2-4 (Agresti, 2002)

$Logit = \ln\left(\frac{p(y=1)}{1+p(y=1)}\right) = w1x1 + w2x2 + \cdots + wnxn$ ………………………...Equation 2-4

Figure 2.7 shows a set of data classified into categories 0 and 1. The continuous line represents the linear regression and the solid S curve represents the logistic function for the logistic regression, in which the vertical value of each point on the curve represents the probability of the Dependant Variable (DV) being equal to 1.

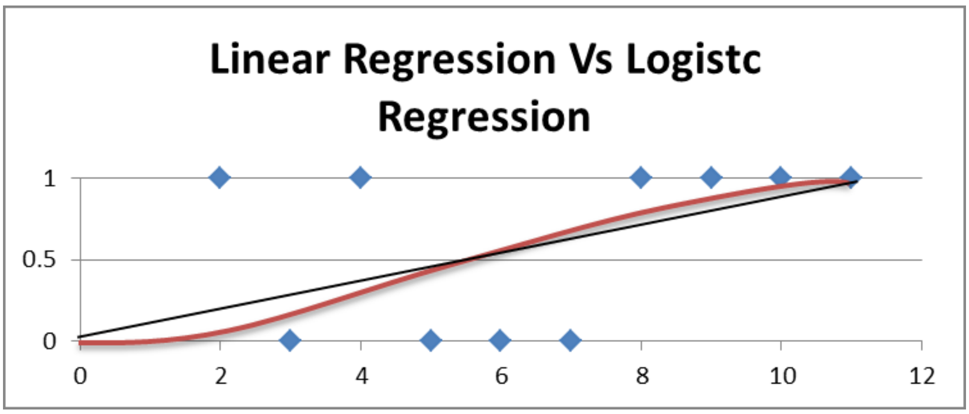

Figure 2-7 Comparison between Linear Regression and Logistic Regression

<u>Assumption and Limitation for Logistic Regression</u>

According to Burns the assumptions and limitations are as follows:

- Logistic regression does not assume a linear relationship between the dependent and the independent variables;
- There must be dichotomy (2 categories) among the dependent variables;
- The categories must be mutually exclusive;
- Large samples are required -- larger than for linear regression;
- The independent variables should not be intervals, nor normally or linearly distributed; and
- related, nor of equal variance within each group

2.9.4 Multinomial Logit (MNL) Model

MNL is a straight forward extension of logistic regression. For a dependent variable (DV) that has M categories, one value the first, the last, or the one that has the highest frequency of the DV is chosen to be the reference category. The probability memberships of each of the other dependent variables are compared to the probability membership in the reference category. For a DV with M categories, M - 1 equations are required to describe the relation between the dependent variables and the independent variables (Williams, R, 2011). When there are more than two categories, the equations used to calculate the probability for the outcome from m=2 to M are: (Agresti, 2002) .

$$\boldsymbol{p(y=m)=\frac{e\hat{}z}{(1+\sum_{h=2}^{M}e^{Zhi}}}$$ ……………………………………………………Equation 2-5

The probability for the reference category is (Agresti, 2002)

$$\boldsymbol{p(y=1)=\frac{1}{(1+\sum_{h=2}^{M}e^{Zhi}}}$$ ……………………………………………………..Equation 2-6

Where Z is the Logit defined in equation 2.3.

The MNL model was used because it can deal with categorical variables. Moreover, the MNL model generates probability equations for each output category, which gives a clear view of the failure that menaces a pipeline, thereby helping pipeline operators to make decisions about the actions required.

2.9.5 Goodness of Fit and Validation

The Log Likelihood (LL) is the criterion for selecting parameters in logistic regression. However, it is always used by multiplying by -2 and is thus called -2LL. The highest positive value of -2LL indicates the worst prediction. In order to identify the significant predictor, -2LL is calculated for a model with only an intercept and compared with the -2LL of the full model with all predictors. The difference between the -2LL for the full model and the model with only intercept is the CHI SQUARE for the model. Moreover, a model is considered significant if the statistical significance for the full model is less than 0.05. Models are also validated by comparing predicted values to the actual values for new data sets (Menard, 2002).

2.10 Summary

Oil pipeline's attributes have significant effect on the likely types of pipeline failure. This effect could be direct or indirect. As mentioned, all the condition assessment models and failure predicting models developed to date depend on expert opinions which makes them subjective, or they are limited to predicting only one type of failure. This research proposes a failure prediction model that employs five pipeline attributes to objectively predict the failure that threatens a pipeline, based on historical data, from among the three major causes of failure (mechanical, corrosion and third-party). The MNL and ANN techniques are used to develop this model because of their capability to analyse categorical variables.

Chapter 3

3 METHODOLOGY

3.1 Overview

The main objective of this research is to identify the type of failure that menaces an oil pipeline by knowing some basic pipeline features. All of the failure modes threatening oil pipelines are studied as a perquisite to this identification process. Moreover, an extensive study of pipeline attributes and their influence on each type of failure cause is performed. The model's development is based mainly on historical data presented in the CONCAWE report for 2010, which displays all of the accidents that transpired in the European pipeline system over the last 38 years. The report cites the cause of each accident, which is the model's output, as well as some pipeline attributes, which are the model's inputs. The methodology followed to achieve this goal consists of five main stages, as presented in figure 3.1:

1. A literature review which presents the main causes of pipeline failures, the current practices of oil and gas pipeline inspection techniques and a review of factors those contribute to pipeline failure.

2. Data collection and data preparation.

3. Development of a failure prediction model using Artificial Neural Networks.

4. Development of a failure prediction model using the Multi-Nomial Logit (MNL) technique.

5. Sensitivity analysis and validation of the developed models.

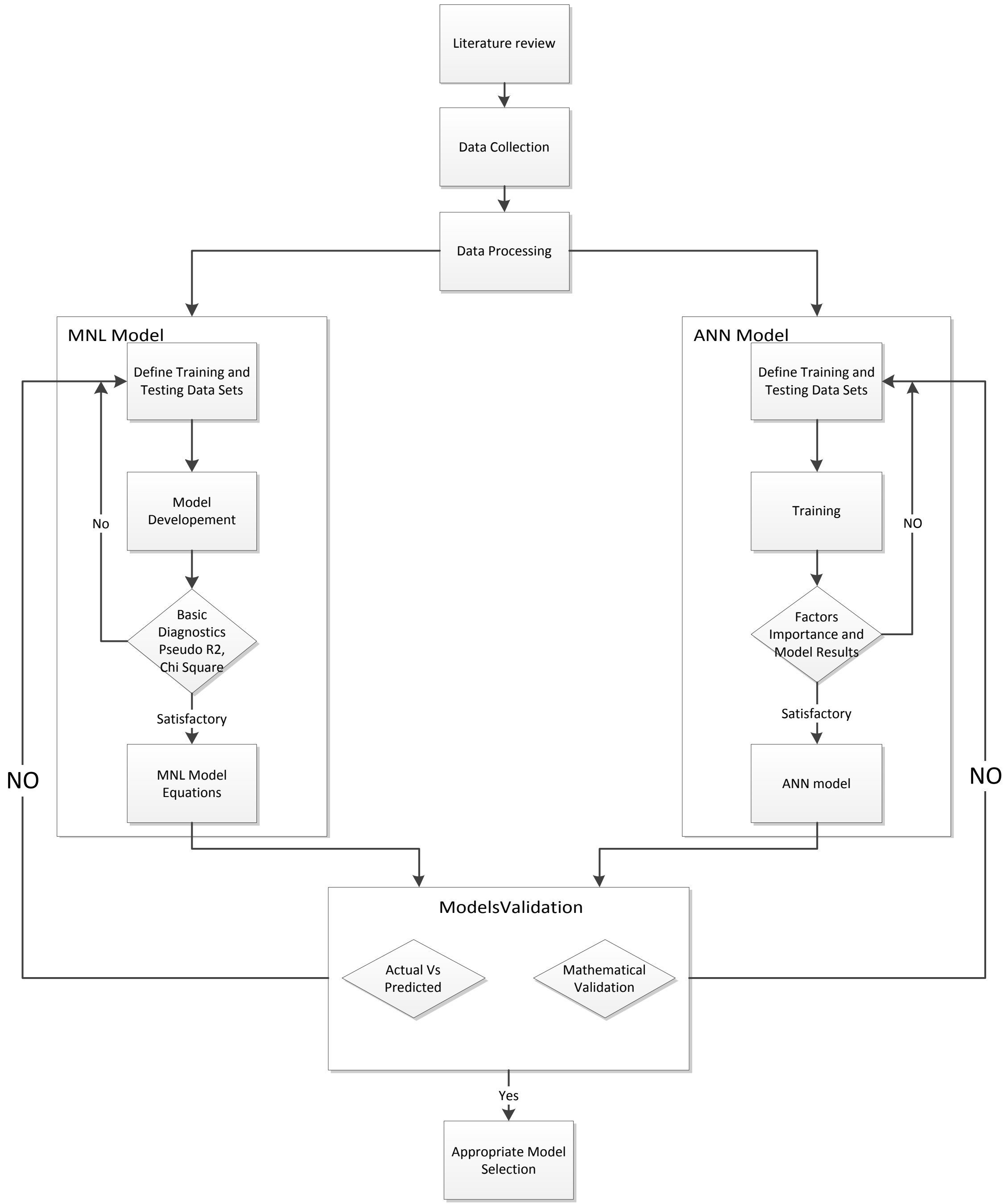

Figure 3-1 Research Methodology

3.2 Literature Review

The literature review consists of 8 sections. Section 2.2 in chapter 2 shows the different types of pipelines, identifying the different materials and specifications used for oil and gas pipelines.

Section 2.3 represents the different types of failure for oil pipelines (mechanical, operational, corrosion, third party and natural). This section also clarifies the cause of each failure type and the percentage of occurrence of each failure cause according to historical failure data for the last 38 years in Europe according to CONCAWE.

In section 2.4 we illustrate the pipeline factors and parameters that contribute to each failure type. Each failure's cause(s) are identified and explained, along with the pipeline attributes that led to each type of failure and how it (they) contributes to that failure.

An overview of the current condition rating procedures used by the oil industry is presented in section 2.5. This section also shows the usage and limitation of these condition rating procedures.

A literature review for the current practices of pipeline inspection techniques is presented in section 2.6. This section illustrates the different types of inspection (internal and external) and their appropriate uses.

Finally, a review of the recent studies and research developed for oil and gas condition assessment and failure prediction models is presented in section 2.7, followed by a detailed literature review of the Artificial Neural Network ANN techniques and an analysis of the Multi-Nomial Logit (MNL) model in sections 2.8 and 2.9, respectively.

3.3 Data Collection

The data used in this research was collected from the CONCAWE report issued in 2010, which lists all of the spillage accidents that occurred in the European oil pipeline system in the last 38 years. The report lists 467 accidents showing the cause of spillage and some pipeline attributes of the damaged pipeline. These lists of accidents were used to develop a model that is capable of predicting the cause of failure that could menace a pipeline given certain pipeline attributes, based on historical data. Table 3.1 represents the five factors considered in the failure prediction models and their descriptions.

Table 3-1 Description of the Factors Used in the Failure Predicting Models

No	Factor	Description of Factor
1	Pipeline Age	The age of pipeline (Year)
2	Pipeline Diameter	The diameter of the pipeline (Inch)
3	Pipeline Location	The position of pipeline, either buried or above ground
4	Land Use	The area where the pipeline is located (residential, industrial,… etc.)
5	Service	The type of product transported (Crude oil, Product,… etc.)

3.4 Data Processing

In this section, the data collected from the CONCAWE report were refined to exclude any accidents with missing data. Moreover, all accidents caused by operational failure and natural hazards were excluded due to the impossibility of their prediction using the given pipeline parameters provided in the report. The remaining data, which consists of 289 accidents caused by mechanical, corrosion or third-party factors (Data set 1), are used to develop a model that predicts the three stated failure causes, which represents 88% of the total accidents. In addition, the previous list of accidents (Data set 1) was further refined by excluding accidents caused by mechanical failure to form Data Set 2, comprised of that 225 accidents, in order to develop another model that predicts failure caused by corrosion and by third-party interference, which represents 63% of the total accidents. This step is done to achieve higher accuracy by decreasing the number of output to reduce the complexity of prediction.

For validation purposes, 20% of accidents are randomly extracted from Data Set 1 and called Data Set 1 (Test) while the remaining 80% are enclosed in Data Set 1 (Training) which is used for model training. The same procedure is applied on Data Set 2 to form Data Set2 (Test) that contains 20% of the total accidents with the remaining 80% comprising Data Set 2 (Training).

Table 3-2 Data Sets Used for Modeling

Name	Number of Accidents	Types of Failures
Data Set 1	289 Accidents	Mechanical, Corrosion and Third-Party
Data Set 2	225 Accidents	Corrosion and Third-Party

3.5 ANN Failure Prediction Models

A supervised neural network developed with the Back Propagation algorithm is used to develop two failure prediction models for oil pipelines. The ANN technique was used because of its capability to analyze complex relationships between predictors and output and its ability to treat categorical variables. The models development procedure is represented in figure 3.2, which represents the two main phases. The training phase employs the Data Set (Training) that includes 80% of the total accidents to train the ANN models. If the model shows satisfactory results, we go through the test phase where the developed model is applied to the Data Set (Test) to compare the predicted outputs with the real outputs. Based on this comparison, the accuracy of the model will be calculated and the model will be accepted if its outcomes achieve a satisfactory percentage.

3.5.1 ANN Model 1-A (3 failure causes)

This model is designed to predict oil pipeline failure caused by mechanical, corrosion or third-party failure, employing the following five pipelines attributes as input:

1. Pipeline Diameter (in inches);
2. Pipeline age (year) which reflect the deterioration state of the pipeline;
3. Pipeline position, which indicate the position of pipeline as either buried or above-ground;
4. Land use, which describes the land usage where the pipeline failure occurred; industrial, agricultural or residential; and

5. Type of transported product, which could be crude oil, hot product or white product.

In the refined accident list, which contains 289 accidents (Data Set 1), each accident contains the pre-mentioned pipeline factors and the failure type that caused the failure. A spreadsheet containing 80% of these accidents was introduced to the SPSS platform to train the ANN model using the back propagation learning algorithm, and then the preliminary result was verified. The next phase is to test the model using the randomly excluded 20% of the data by providing the developed model with the inputs only and then comparing the output predicted by the model with the actual output. Moreover, a mathematical validation is performed on the developed model, such as the Average Validity Percentage.

This model is able to predict the failure cause that could menace the pipeline given the above-mentioned five pipelines attributes. The failure causes considered in this model represent 88% of the oil pipeline accidents according to CONCAWE (Davis, et al., 2010). By using this model pipeline operators will be able to identify the risk threating the pipeline among corrosion, mechanical failure or third-party interference. Identifying this risk will allow pipelines operators to take suitable actions to prevent it.

3.5.2 ANN Model 1-B (2 Failure Causes)

Another model was developed to predict failures caused by corrosion and by third parties in order to achieve prediction accuracy higher than was possible with the previous model by decreasing the number of output that could add some complexity. A new data set was prepared by excluding all the accidents caused by mechanical failure; the new data set contains 225 accidents (Data Set 2). The data set was treated in the same fashion as the previous model by excluding twenty percent of the accidents for validation purposes and using the remaining eighty percent for training the artificial neural network. The failure causes considered in this model, corrosion failure and third-party failure are responsible for 63% of all oil pipeline accidents according to CONCAWE.

3.6 MNL Failure Prediction Model

The Multi-Nomial Logit (MNL) technique is usually used to analyse nominal (categorical) data with nominal output, which would be challenging to analyse using ordinary linear regression. The advantage of using MNL over using ANN is that the MNL gives failure prediction equations as an output. This equation can then be used to predict the failure mode that threats the pipeline. The model development procedure is represented in figure 3.3. The figure shows that Data Set (Training) that contains 80% of the total accidents data will be introduced to the SPSS software to be modeled using the MNL technique. If the analysis results are satisfactory we proceed to the testing phase where the generated equations will be applied to the Data Set (Test) which contains the randomly excluded 20% of accidents. Then the predicted outputs will be compared with the actual outputs and the accuracy percentage is calculated accordingly. The model will be accepted if the percentage of correct predictions is satisfactory.

3.7 MNL Model 2 (3 Failure Causes)

This model is also designed to predict the type of failure threating a pipeline, corrosion, mechanical or third-party failure, using the same five pipeline attributes mentioned in the previous models. The model uses Data Set 1 which consists of 289 accidents, the same as for Model 1-A. The model development procedure has two main phases; the modeling phase and the testing phase. In the modeling phase 80% of the data was introduced to the SPSS software in a spreadsheet. Next, the inputs and the outputs were defined to the software. The model then produces equations that calculate the probability of occurrence of each failure type and some basic diagnostics such as the Chi square and the Pseudo R square. The next phase is to validate the model by applying the generated equations to the randomly excluded data which contains 20% of the total number of accidents. This is to compare the actual output with the predicted output and produce useful statistics such as the average validity percentage and the percentage of right prediction. The model is accepted if it shows satisfactory validation results.

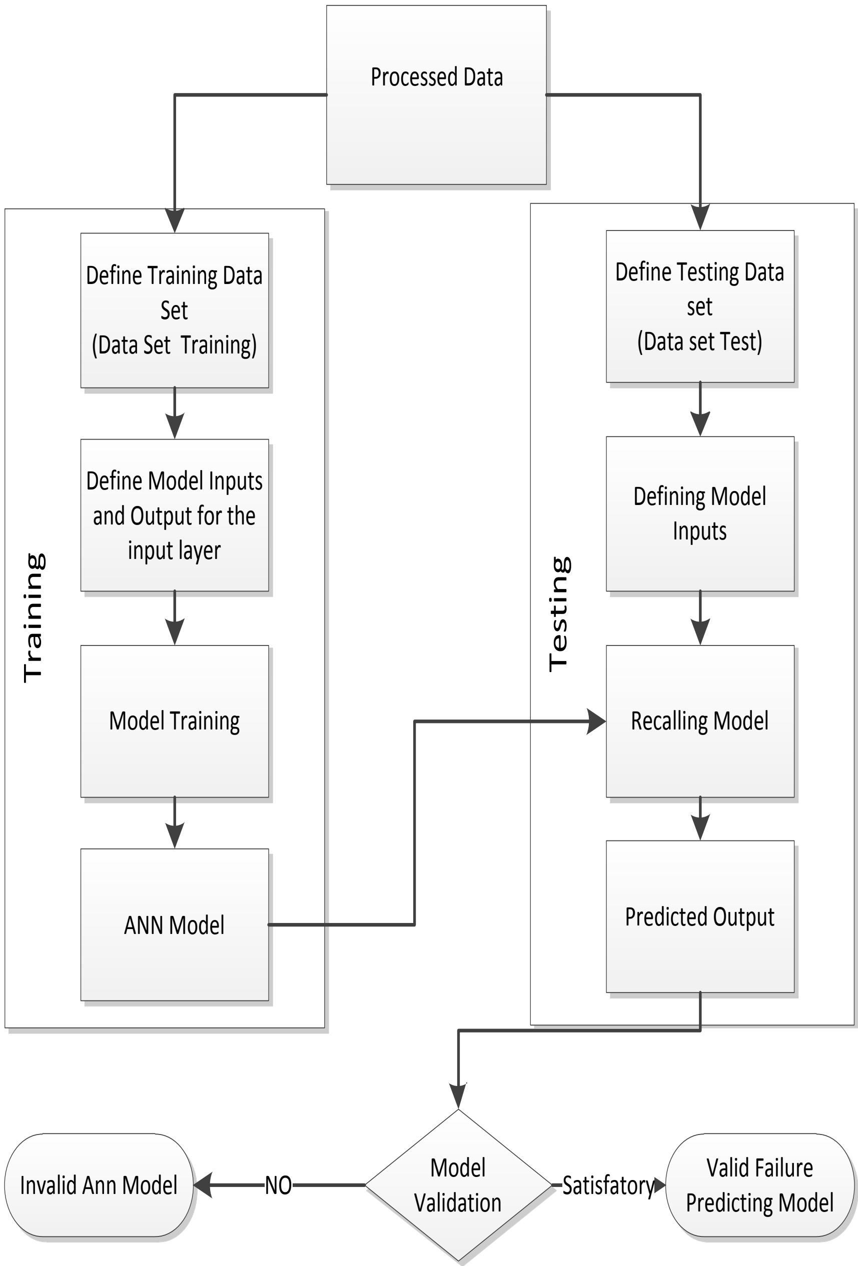

Figure 3-2 ANN Models Development

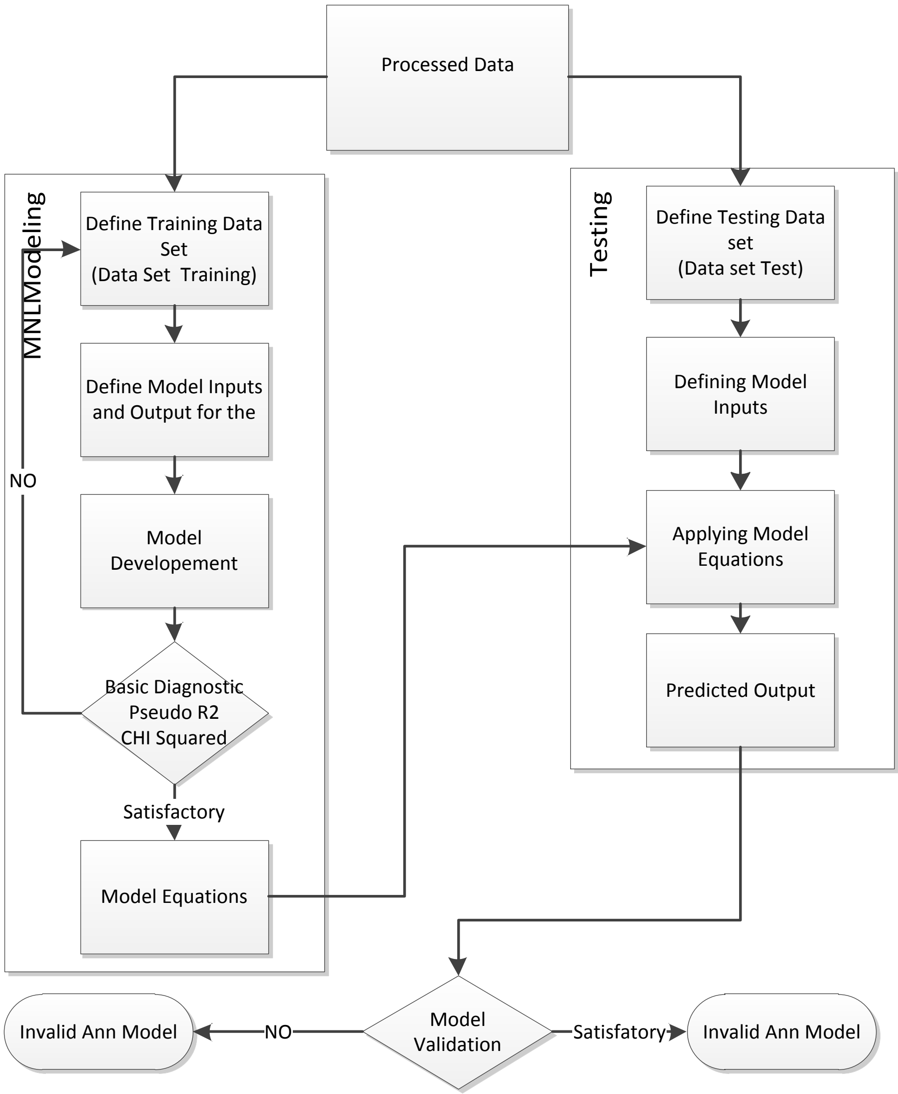

Figure 3-3 MNL Models Development

3.8 Validation and Sensitivity Analysis

The goal of validation is to check the developed model's effectiveness. This is done by applying the developed models to the validation data set to compare the predicted versus actual values, and then calculate the percentage of correct predictions, the average validity percentage and the average invalidity percentage. In addition, a sensitivity analysis was performed for each predictor to recognise the influence of variations in the input on the model's outputs. This is done by changing each predictor under study between its maximum value and its minimum value while keeping other predictors constant.

3.9 Summary

The methodology of the current research includes an extensive literature review, data collection and data preparation, development of oil pipeline failure prediction models using ANN and MNL techniques. Moreover, it details the procedure followed in this research to develop failure predicting models for oil pipelines by demonstrating each step, from data collection to model validation.

Chapter 4

4 DATA COLLECTION

4.1 Introduction

The data used in this research are collected from the report published on 2010 by CONCAWE, an association of European oil companies established to address environmental, health and safety issues related to refining and distribution. The CONCAWE was founded in 1963 by a small group of oil companies to carry out research on environmental issues related to the oil industry. Most of the oil companies operating in Europe are now members of CONCAWE. Its research efforts cover a range of environmental field such as fuel emissions, soil contamination and cross-county pipeline performance (CONCAWE, 2010).

The report prepared by the CONCAWE Oil Pipelines Management Group (OPMG) in 2010 recorded 38 years of spillage data for 35000 km of oil pipelines that transport 780 million m^3 of crude oil and petroleum products across Europe. The spillage causes are grouped into five main categories: mechanical failure, operational failure, corrosion, natural hazards and third-party failure. The report indicates all the accidents that occurred since 1971, showing their failure cause and some of the respective pipeline attributes (Davis, et al., 2010).

4.2 Data Organization

The collected data, which consists of 467 spillage accidents in cross-country oil pipeline, is composed of a set of oil pipeline characteristics, the cause of failure and the spillage consequences, as shown in figure 4.1. The following represent the pipeline criteria for inclusion in the accident inventory (Davis, et al., 2010)

- Pipelines that transport crude oil or petroleum product.

- Minimum length of 2 kilometers in the public domain.
- Running cross country, including short estuary or river crossings but excluding lines serving offshore production facilities and offshore tanker loading/discharge facilities.
- Including pump stations and intermediate storage facilities but excluding origin and destination terminal facilities and tank farms.
- Minimum spillage size of 1 m^3, unless there are exceptional safety or environmental consequences reported for spillage less than 1 $m^{3.}$

Spillage ID	Year	Pipe dia (")	Service	Fatalities	Injuries	Spillage volume ($m^{3)}$		Leak first detected by	Facility	Facility part	Age	Land use	Cause		Impact	
						Gross	Net loss				Years		Category	Reason	Water bodies	Contaminated land area
458	2008	16	2			4	4	6	1	3	40	4	Aa Ab	5		25
459		40	1			6		5	2	7	36	7	Ab Ab	2		
460		11	2			30		3	3	5	29	4	Aa Ab	2		40
461		11	2			52	37	3	1	4	29	3	Ea Ea	4		50
462		11	2			12		1	2	4	20	4	Ea Ea	7		
463		11	2			129	108	3	1	3	29	3	Ab Ca	2		90,000
464		9	2			44	17	3	1	3	16	3		17		3,600
465		6	2			40		2	1	3	52	4				5,000
466		4	2			28		5	1	3		3		18		250
467		16	1			294		3	1	3	46	4		17		11,000
468		16	1			328		3	1	3	46	4		4		3,600
469		18	1			1	1	5	1	3	1972	2		14	S	

Figure 4-1 Sample of the List of Accidents as Stated in the CONCAWE Report 2010 (Davis, et al., 2010)

4.3 Model Inputs

4.3.1 Pipeline age

Pipeline age is one of the main factors that have a direct influence on corrosion failure, as mentioned in the literature review. Since corrosion is a slow process, an aging pipeline is usually more vulnerable to corrosion failure (Henderson, et al., 2001). It also reflects the deterioration state of a pipeline. The age of pipelines cited in this study varies from one year old to 40 years old.

4.3.2 Pipeline diameter

Pipeline diameter is one of the physical factors that has a direct influence on third-party failure, as elaborated in chapter 2. Pipelines with a relatively small diameter are more vulnerable to third-party damage caused by activities such as excavation. Moreover, smaller pipelines can be mechanically damaged during construction (Ali, 2011). The pipeline diameter is measured by inch and varies from 1 inch to 60 inch.

4.3.3 Service

This factor shows the type of product transported in pipelines, as it has a direct influence on corrosion failure. The types of product considered are shown in table 4.1. Since service types 4 and 5 contributed to only 8 accidents there were excluded to simplify the analysis. Table 4.2 shows the service types considered in this research. The crude oil represents the crude product extracted from a well without any refining process. White products include Naphthas, gasoline, gas oils (diesel) and Kerosenes. Finally fuel/hot oil is considered heavy fuel oils and lubricating oils and in some cases very heavy crude oils are part of this type. The product is heated before entering the system, to assure it has adequate flow characteristics (Haan, 2012).

Table 4-1 types of product (Davis, et al., 2010)

Service	Type of Product
1	Crude Oil
2	White Product
3	Fuel Oil (HOT)
4	Crude Oil or Product
5	Lubes Hot

Table 4-2 Types of Transported Product Considered in this research

Service Code	Type of Product
1	Crude Oil
2	White Product
3	Fuel Oil (HOT)

4.3.4 Facility

This factor describes the location of a pipeline. In this research we considered only underground and above-ground pipeline as shown in table 4.3. All the pump station accidents (31) were excluded. This factor has a great influence on both corrosion failure and third-party failure, as described in detail in chapter 2.

Table 4-3 Location of Pipeline Considered in this Research

Facility	Location of Pipeline
1	Underground Pipe
2	Above-round Pipe

4.3.5 Land Use

This factor describes where the failure occurred. To simplify the analysis we merged the land uses of residential high-density and residential low-density into one factor, named as residential. Moreover, we excluded all those accidents that occurred in forested hills, the Barren Lands, and in water bodies because of their small numbers (only 7 accidents). Table 4.4 shows the types of land use reported in the CONCAWE report while table 4.5 shows the types of land use considered in this research.

Table 4-4 land use reported in the CONCAWE Report (Davis, et al., 2010)

Land Use	Location of Pipeline
1	Residential High Density
2	Residential Low Density
3	Agricultural
4	Industrial or Commercial
5	Forested hills
6	Barren Lands
7	Water Body

Table 4-5 Land Use considered in this Research

Land Use	Location of Pipeline
1	Residential
2	Agricultural
3	Industrial or Commercial

4.4 Model Outputs

This section describes the failure causes reported in the CONCAWE report and their sub-factors as shown in table 4.6. Also the percentage of accidents related to each failure cause is represented in figure 4.2.

1- Mechanical Failure (Considered): Includes failure resulting from either a design or material fault (e.g. metallurgical defect, inappropriate material specification) or construction fault (e.g. defective weld, inadequate support,…etc.). This also includes the failure of sealing devices.

2- Operational Failure (Not Considered): This means a failure resulted from operational upsets, malfunction or inadequacy of safeguarding systems (e.g. instrumentations, mechanical pressure relief system) or from operator error.

3- Corrosion Failure (Considered): Failure as a result of external and/or internal corrosion or stress crack corrosion.

4- Natural Hazard (Not Considered): Includes failure resulting from a natural occurrence such as land movement, flooding …etc.

5- Third-Party Failure (Considered): Includes all failure resulting from third-party actions, accidental or intentional. Also includes incidental third-party damage that was undetected and resulted in a failure at some later time.

Table 4-6 Accident Failure Causes (Davis, et al., 2010)

Failure Cause	**A**	**B**	**C**
A. Mechanical Failure	Design & Material	Construction	
B. Operational	System	Human	
C. Corrosion	External	Internal	Stress Corrosion
D. Natural Hazard	Ground Movement	Other	
E. Third Party	Accidental	Intentional	Incidental

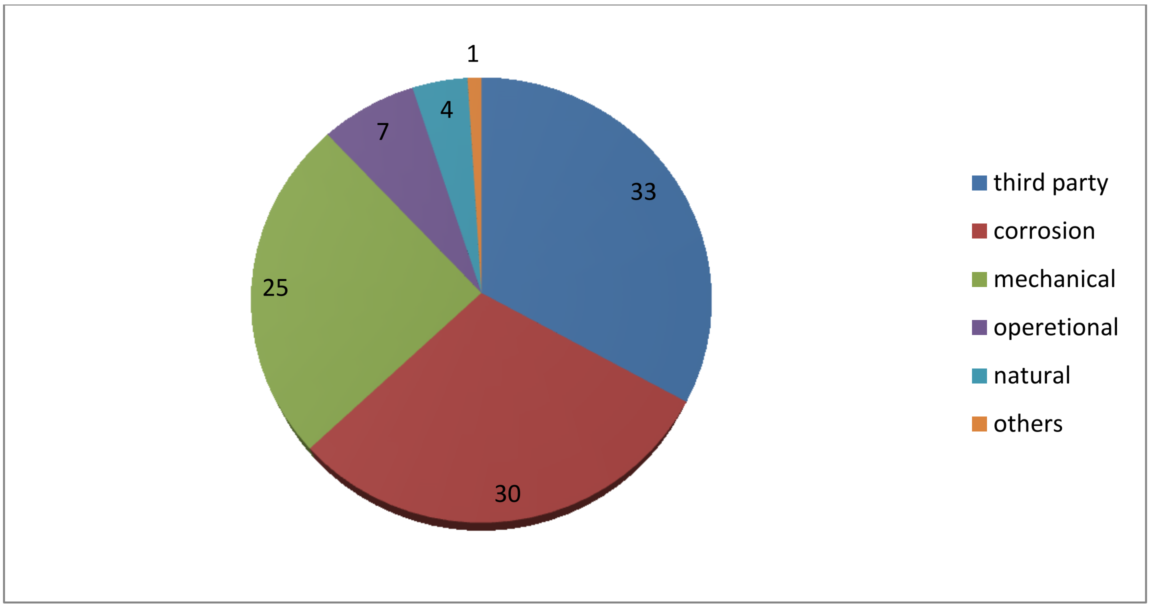

Figure 4-2 Percentage of Accidents Related to Failure Types

4.5 Data preparation

The data gathered consists of 467 accidents caused by five failure causes. Since the report only provides five pipeline characteristics, as discussed earlier, it is challenging to develop a model that can predict the five failure causes only from these five parameters. According to the literature, these five parameters are only related to mechanical failure, corrosion failure and third-party failure. There is no significant relation between these parameters and the other failure causes (operational and natural). Based on this assessment, two models were developed.

Model A: predicts failure caused by mechanical failure, corrosion failure and third-party failure.

Model B: predicts failure caused by only corrosion and third-party failure.

4.5.1 Data Set 1

The first step of the data preparation is to exclude the accidents with missing data; next all of the accidents caused by operational failure and natural failure are also excluded. Moreover, some other accidents related to the eliminated input categories are excluded. Finally, we were left with 289 accidents due to mechanical, third-party or corrosion failures. This set of accident data were organized into EXCEL spreadsheets with six columns. The first five columns represent the pipeline attributes, some of which are continuous variables and some are nominal variables, as shown in table 4.7. The last column represents the output, which is the failure cause as shown in table 4.8. For validation purposes twenty percent of Data Set 1 were randomly excluded and named as Data Set 1 (Test). The remaining 80 % were used for the model training and called Data Set 1 (Training).Figure 4.3 represent a sample of the Spread sheet for Data Set 1.

Table 4-7 Models predictors

Predictor	Unit	Form
Pipeline age	Year	Continuous
Pipeline diameter	Inch	Continuous
Land use	Category	Nominal
Facility	Category	Nominal
Service	Category	Nominal

Table 4-8 Models output

Failure Cause (output)	Code
Mechanical Failure	1
Corrosion Failure	2
Third Party Failure	3

4.5.2 Data Set 2

Data set 2 was prepared for the failure prediction model to predict only corrosion failure and third-party failure. Therefore, all the accidents caused by mechanical failure were removed from Data set 1. Data set 2 contains 225 accidents caused by either corrosion failure or third-party failure. As with Data Set 1, twenty percent of Data Set 2's items were randomly excluded for validation and named as Data Set 2 (Test). The remaining 80% were used for training and called Data Set 2 (Training).

Dia/inch	Service	Facility	Age/year	Land use	Output
22	1	1	18	1	2
9	1	1	46	1	2
16	1	1	23	1	3
12	2	1	30	1	1

Figure 4-3 Sample of Spread Sheet for Data Set 1

4.6 Summary

This chapter presented the data collection and preparation of two sets of data required to develop two failure prediction models. It also identifies and explains the inputs reported on the original data and the inputs considered in these models showing the reason behind this selection. More over the original data outputs were illustrated in this chapter and the outputs considered in theses model were identified.

Chapter 5

5 ARTIFICIAL NEURAL NETWORKS' APPLICATION TO FAILURE PREDICTION MODELING

5.1 Introduction

In the real world, historical data is usually very noisy. It is challenging to create a robust prediction model using historical data. One of the main advantages of using Artificial Neural Networks is their ability to deal with historical data because they mimic the human brain in its capacity to predict patterns based on learning and recalling processes. In other words, the ANN technique is applicable when the causal relationships among predictors are unknown (Sadik, et al., 2004).

This section presents the development of two failure prediction models for oil pipelines using the artificial neural network technique. These two models consider as inputs five pipelines attributes: diameter, age, pipeline positioning, the area where the failure occurred, and the type of product transported. The first model predicts the type of failure from among three failure types, mechanical, corrosion and third-party, as those three types of failure are the main cause of 88% of all oil pipeline spillage according to the CONCAWE. The second model is developed in order to achieve a high accuracy of prediction, but it only predicts failure caused by corrosion or third-party interference, which together represent 63% of pipeline failures according to the CONCAWE.

5.2 Factors Included in the ANN Models

Various physical, environmental and operational factors contribute to pipeline failure, as discussed in chapter 2. The factors considered in this research are selected based on the availability of historical data provided in the CONCAWE report, as shown in table 5.1. However, some of the other factors presented in chapter 2 could be considered in future studies. The physical factors include pipeline diameter and pipeline age, and are considered as continuous variables. The facility and land use are considered environmental factors and both are nominal variables. Finally, the only operational factor considered in this research is that of service type, which is also considered as nominal. The description of these factors and their effect on pipeline failure was presented in detail in chapter 2.

Table 5-1 Factors Included in the Failure Prediction Model

Factor Type	Variable	Categories	Scale
Physical Factors	Pipeline Diameter	Continuous	Inch
	Pipeline Age	Continuous	Year
Environmental Factors	Facility	Under ground Above ground	1 2
	Land use	Residential Agricultural Industrial or commercial	1 2 3
Operational Factor	Service	Crude Oil White Product Hot Oil	1 2 3

5.3 Model 1-A: Pipeline Failure Prediction Model for Three Failure Types

This model is designed to objectively predict the type of failure that could menace a pipeline among mechanical failure, corrosion failure and third-party failure based on historical data. Five factors are selected as the model's inputs based on the availability of the historical data, as represented in table 5.1. Since three of these factors are nominal, each category of nominal factors is represented by one neuron at the input layer; for the other two continuous factors, each is represented by one neuron. The input layer thus consists of 10 neurons. The output layer consists of 3 neurons, each neuron representing a type of failure (mechanical, corrosion and third party). The SPSS 19 software is used for the ANN model development because of its following qualities:

1. Ease of use;
2. Short training time;
3. Its flexibility in modifying the training parameters; and
4. Its ability to deal with nominal variables and output.

Data Set 1, which includes 289 accidents, was used for this model. Data Set 1 (Training), containing 80% of the Data Set 1 accidents, was fed to the SPSS software via Excel and used to train the model, while the remaining twenty percent were used to test the model.

The network architecture consists of one input layer with 10 neurons, one hidden layer containing 35 neurons and an output layer that contains 3 neurons. The gradient decent was used as an optimization algorithm. The training process uses the Back Propagation algorithm. The learning rate is 0.05 and the momentum is 0.9. The Tanh activation function was used between the input layer and the hidden layer. The stopping rule is 10 steps without any error decrease. Figure 5.1 shows the network information, while figure 5.2 represents the model summary.

Twenty percent of the accidents in Data Set 1 (Training) were used by the SPSS software to test the model accuracy of prediction for predicting each output of the three outputs. The percentage of correct prediction for the test sample shows that 73.8% of the data are correctly classified. The SPSS package also displays the Receiver Operating Characteristic (ROC) curve for each output. Each curve treats the category at issue as the positive state versus the aggregate of all other categories. Basically, the Y axis is the (sensitivity), which is the true positive rate, and the X axis is the (1-specificity (true negative rate)), or the false positive rate. The area under the ROC curve measures the prediction accuracy (1 is the best and 0.5 is the worst. .Figure 5.3 represents the ROC curve for the Dependent Output, while table 5.2 represent the area under the ROC curve for each output (Hanley, et al., 1982). The results show that the area under the ROC curve for each output is generally more than 0.75, which indicates good prediction accuracy. For further details, please see (Fawccet, 2004).

Network Information

Input Layer	Factors	1	service
		2	facility
		3	land use
	Covariates	1	dia/inch
		2	age
	Number of Units[a]		10
	Rescaling Method for Covariates		Standardized
Hidden Layer(s)	Number of Hidden Layers		1
	Number of Units in Hidden Layer 1[a]		35
	Activation Function		Hyperbolic tangent
Output Layer	Dependent Variables	1	output
	Number of Units		3
	Activation Function		Identity
	Error Function		Sum of Squares

Figure 5-1 Network Information Model 1-A

Training	Sum of Squares Error	47.459
	Percent Incorrect Predictions	35.3%
	Stopping Rule Used	10 consecutive step (s) with no decrease in error
	Training Time	00:00:00.400
Testing	Sum of Squares Error	9.222
	Percent Incorrect Predictions	26.2%

Figure 5-2 Summary for Model 1-A

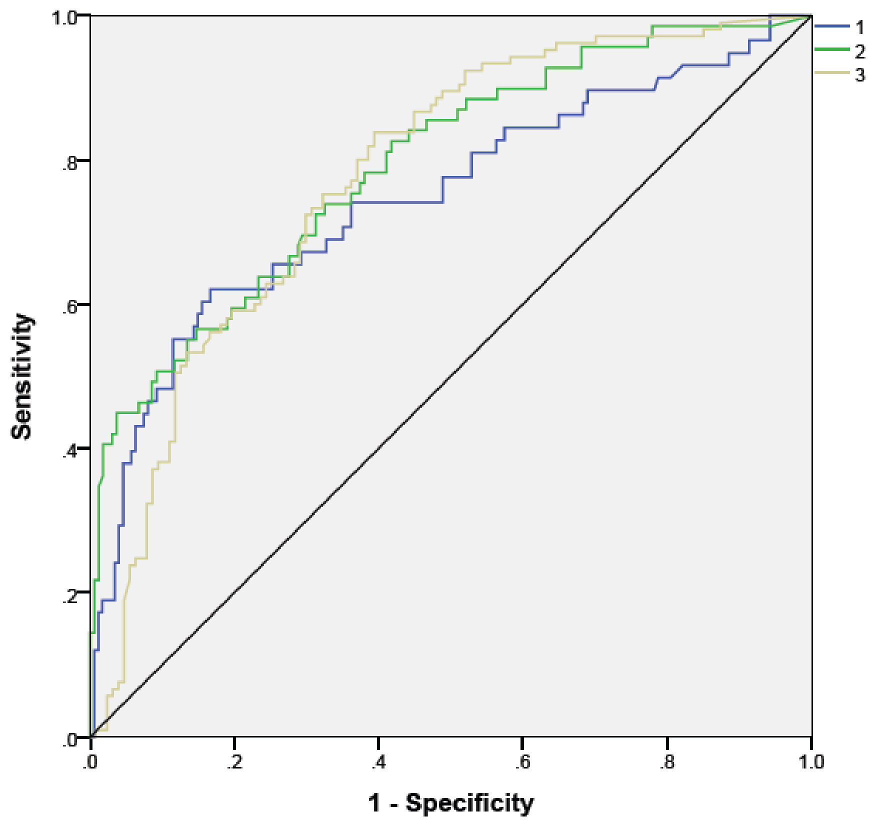

Figure 5-3 ROC Curve for 3 Outputs for Model 1-A

Table 5-2 Area under the ROC Curves Model 1-a

Output	Area
1 Mechanical Failure	0.746
2 Corrosion Failure	0.792
3 Third-Party Failure	0.776

5.3.1 Factors' Importance

The SPSS software can determine the importance of each predictor contributing in the neural network. Table 5.3 represents the importance of each predictor, while figure 5.4 displays a chart of the normalized importance of each predictor. It is clear that the most important factor is the type of service (type of transported oil), while the least important predictor is the pipeline's age.

Table 5-3 Predictor Importance

Model Inputs	Importance	Normalized Importance
Service	0.270	100%
Facility	0.193	71.7%
Land use	0.142	52.8%
Diameter	0.263	97.4%
Age	0.132	48.9%

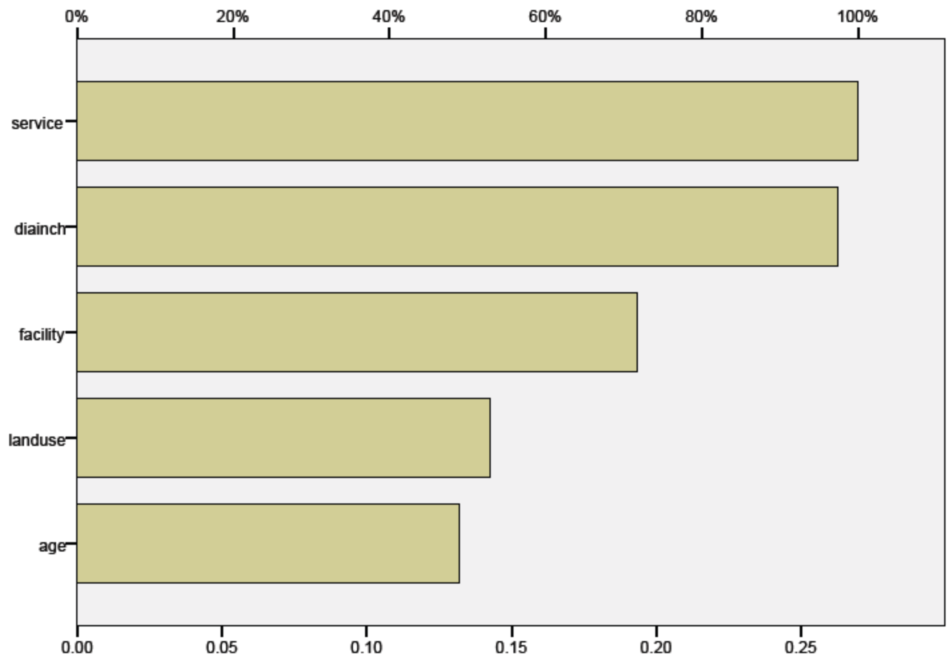

Figure 5-4 Normalized Importance Chart

5.3.2 Model Validation

As mentioned above, twenty percent of Data Set 1's accidents were kept aside for validation and called Data Set 1 (Test). Since the data is nominal, the main validating test is to determine the percentage of correct predictions for the developed model. In order to identify this percentage the ANN model is recalled and applied to the records in Data Set 1 (Test) without introducing the failure cause to the software. The output obtained by the developed model is compared to the actual cause of failure, and the percentage of correct predictions is calculated. It was found that the prediction percentage was 68.5%, which is fairly good. A plot was prepared (figure 5.5) to display the failure cause predicted by the developed model versus the actual failure cause for the validation data set (here consisting of 57 accidents).

In accordance with Zayed and Halpin's (2005), the Average Validity Percentage (AVP), which shows the validity percentage out of 100 and the Average Invalidity Percentage (AIP), which shows the prediction errors, were applied to validate the ANN model using the following equations.

$$\boldsymbol{AIP} = \left(\sum_{i=1}^{n} \left|\mathbf{1} - \left(\frac{Ei}{Ci}\right)\right|\right)/\boldsymbol{n} \quad \text{……Equation 5-1}$$

$$\boldsymbol{AVP} = \mathbf{1} - \boldsymbol{AIP} \quad \text{……Equation 5-2}$$

Where:

AIP = Average Invalidity Percentage;

AVP = Average Validity Percentage;

Ei = Predicted Value; and

Ci = Actual Value.

After applying the previous equations on the test sample the results indicate that:

AIP =26.3%

AVP =73.7%.

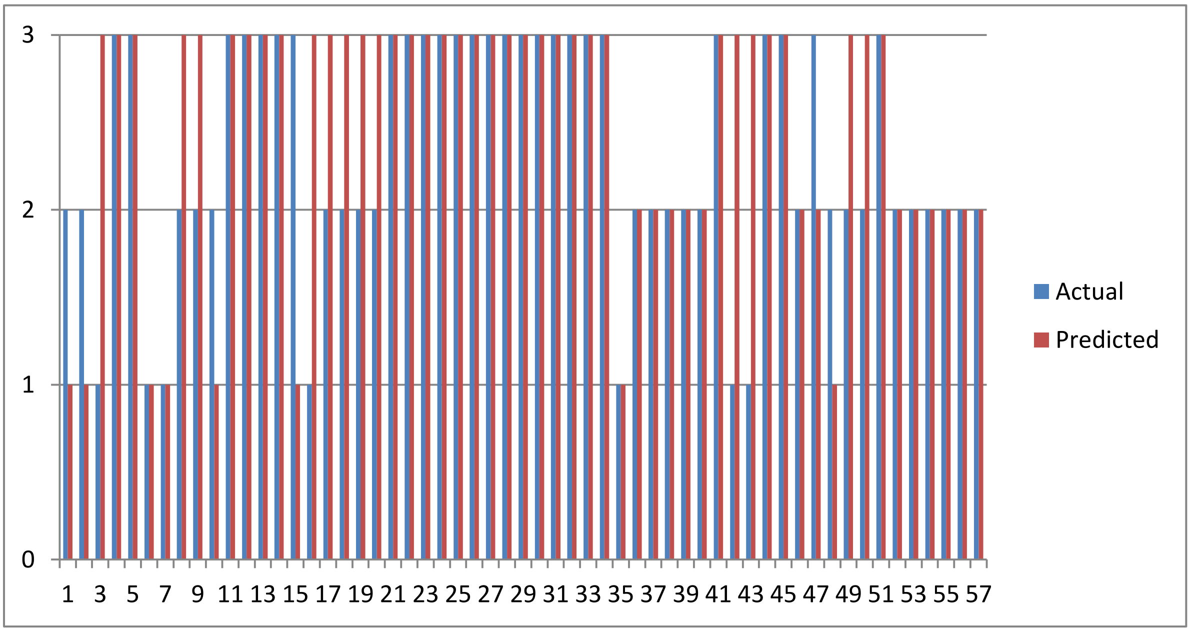

Figure 5-5 Actual Vs Predicted Failure Cause

5.3.3 Sensitivity Analysis

A sensitivity analysis is carried out on the developed model in order to identify the effect of the variation of predictor values on the failure type. An accident was randomly chosen (where the diameter was 11, service was type 2, facility was type 1, age was 40 and the land use was type 1), and then each predictor under study was changed between its maximum value and its minimum value while keeping the other predictors constant. The procedure was repeated for each input. In those cases where there was no change in output related to a particular input we maintained other inputs at a different value, one at time, to study the co-relation between inputs. The sensitivity analysis almost completely confirms the inputs' importance that was previously determined by the SPSS software in the predictor importance table, which shows that 'service' is the most sensitive predictor while 'age' has the smallest affect. The following subsection shows the sensitivity analysis chart for each predictor.

a. <u>Effect of Service Variation</u>

The following chart shows the effect of changing the type of transported oil on the failure cause. Figure 5.6 also shows that for this particular case, when the type of oil is white products, the failure that occurs is due to a third-party cause, while when the transported product was crude oil or hot products the failure cause changes to corrosion because of the impurities and heat of these types of product that induce corrosion.

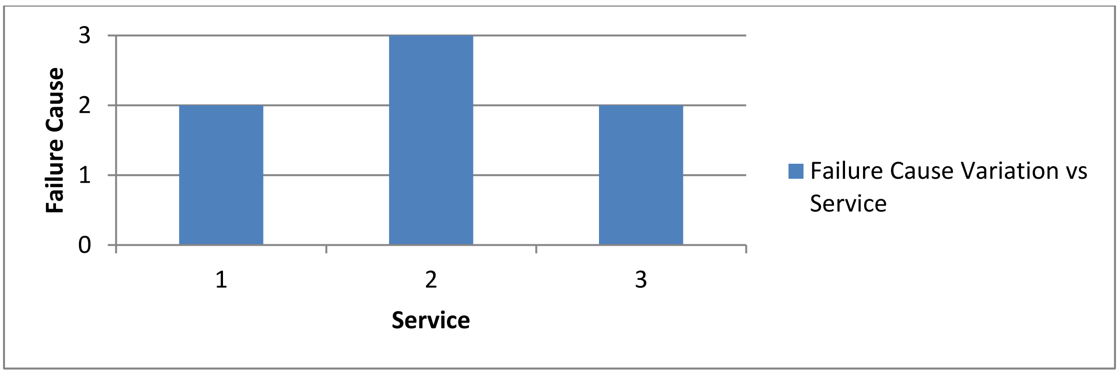

Figure 5-6 Failure Cause versus Service

b. Effect of Facility Variation

The change in failure cause due to pipeline location is presented in figure 5.7. With buried pipeline, the predicted failure cause was third-party failure, while with above-ground pipeline the failure causes become mechanical-based.

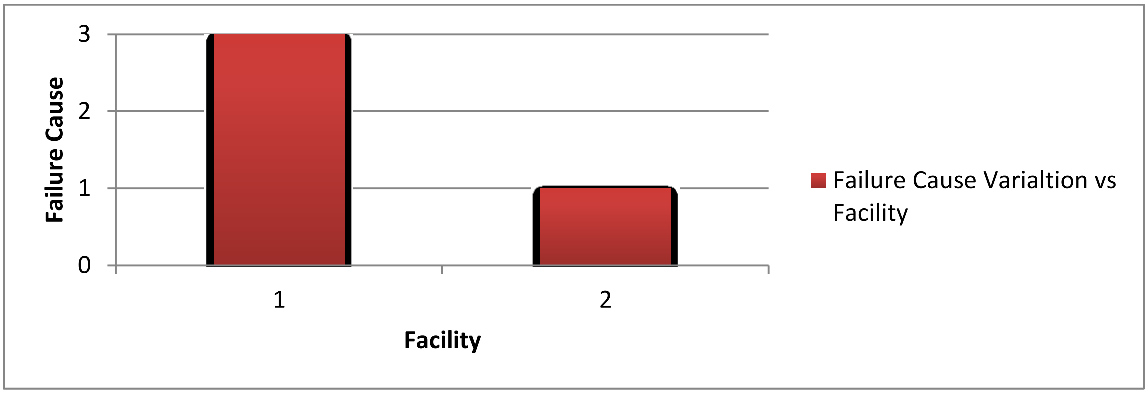

Figure 5-7 Failure Cause versus Facility

c. Effect of Land Use Variation

We found that there is no variation in the type of failure due to the change of the land use for the chosen accident. We then changed the other inputs once at a time to identify any co-relation between the inputs, as presented in figure 5.8. The figure indicates a significant correlation between land use and age, diameter and service.

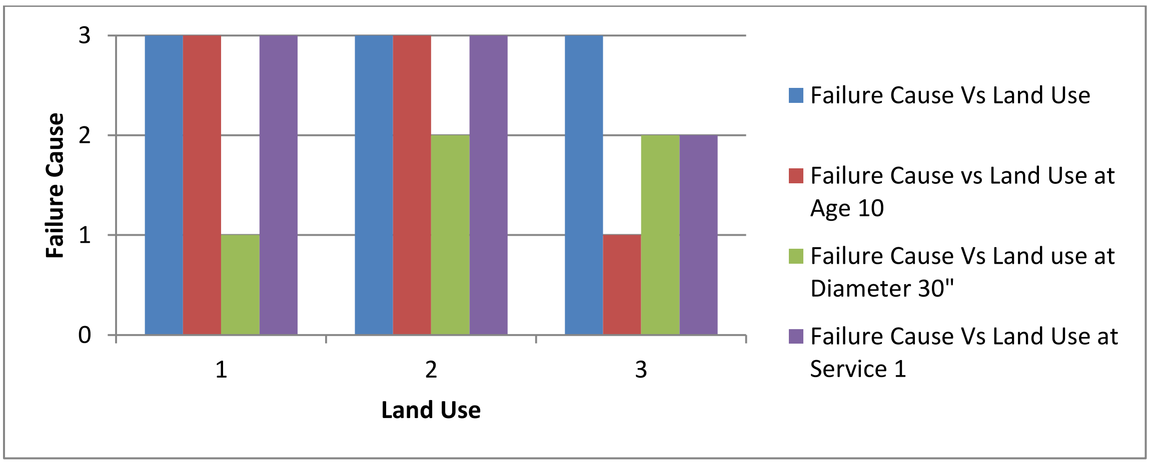

Figure 5-8 Failure Cause versus Land Use Variations

d. Effect of Diameter Variation

Figure 5.9 represents the failure cause change due to diameter variation. It shows that pipelines with small diameters are vulnerable to third-party failure, as mentioned previously in the literature, while the failure cause changes when pipe diameter is larger.

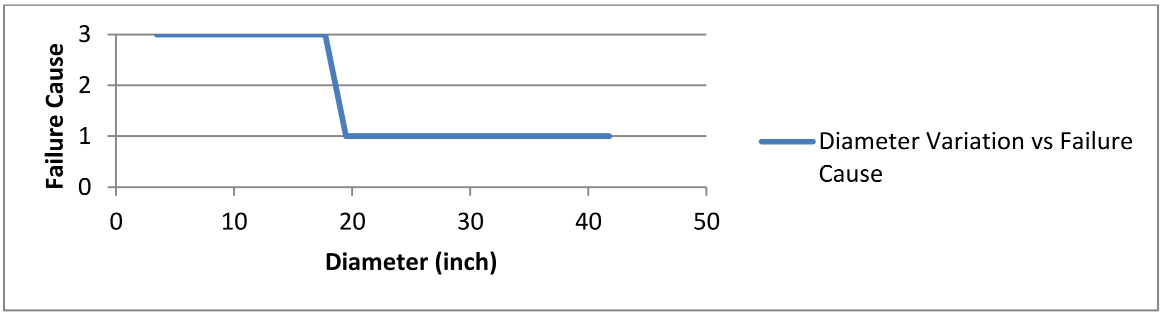

Figure 5-9 Failure Cause versus Diameter

e. Effect of Age Variation

As mentioned earlier, pipeline age has the lowest importance weight. Figure 5.10 shows that there is no effect from age variation on the type of failure, but when the diameter is changed to a larger diameter of 30 inches the effect of age became stronger, as indicated in figure 5.11.

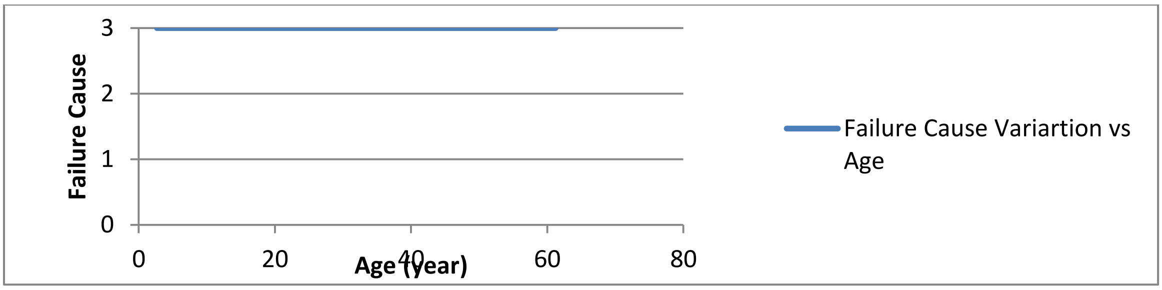

Figure 5-10 Failure Cause versus Age

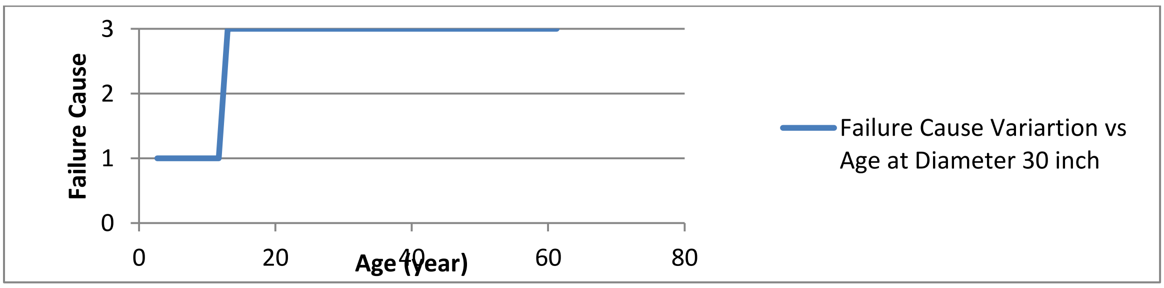

Figure 5-11 Failure Cause versus Age (30 inch Diameter)

5.4 Model 1-B: Failure Prediction Model for Oil Pipeline for Two Failure Types

As mentioned previously, this model is able to predict oil pipeline failure caused by corrosion failure and by third-party failure, which together cause 63% of oil pipeline failure according to CONCAWE. The model uses Data set 2, which contains 225 accidents caused only by corrosion or third-party failure. This model follow the same procedure presented earlier, by using Data Set 2 (training) which contains 80% of the total accidents for training, while Data Set 2 (Test) containing the remaining 20%, are used for validation.

The network architecture is comprised of one input layer with 10 neurons, one hidden layer containing 26 neurons, and the output layer with 2 neurons. The gradient decent was used as an optimization algorithm. The training uses the Back Propagation algorithm. The learning rate is 0.05 and the momentum is 0.9. The Tanh activation function was used between the input layer and the hidden layer. The stopping rule is 20 steps with no error decrease. Figure 5.12 shows the network information, and figure 5.13 represents the model summary. The percentage of correct predictions shows that 73.3% of the data were classified correctly. The Receiver Operating Characteristic (ROC) curve for each output is represented in Figure 5.14 while the area under the ROC curve measures the accuracy of prediction and is represented in table 5.4. The calculated area is close to 0.85, which is better than the three-output model.

Network Information

Input Layer	Factors	1	service
		2	land use
		3	facility
	Covariates	1	age
		2	dia/inch
	Number of Units[a]		10
	Rescaling Method for Covariates		Standardized
Hidden Layer(s)	Number of Hidden Layers		1
	Number of Units in Hidden Layer 1[a]		26
	Activation Function		Hyperbolic tangent
Output Layer	Dependent Variables	1	output
	Number of Units		2
	Activation Function		Identity
	Error Function		Sum of Squares

Figure 5-12 Network Information Model 1-B

Training	Sum of Squares Error	21.511
	Percent Incorrect Predictions	20.7%
	Stopping Rule Used	20 consecutive step (s) with no decrease in error
	Training Time	00:00:00.248
Testing	Sum of Squares Error	5.463
	Percent Incorrect Predictions	26.7%

Figure 5-13 Model 1-B summary

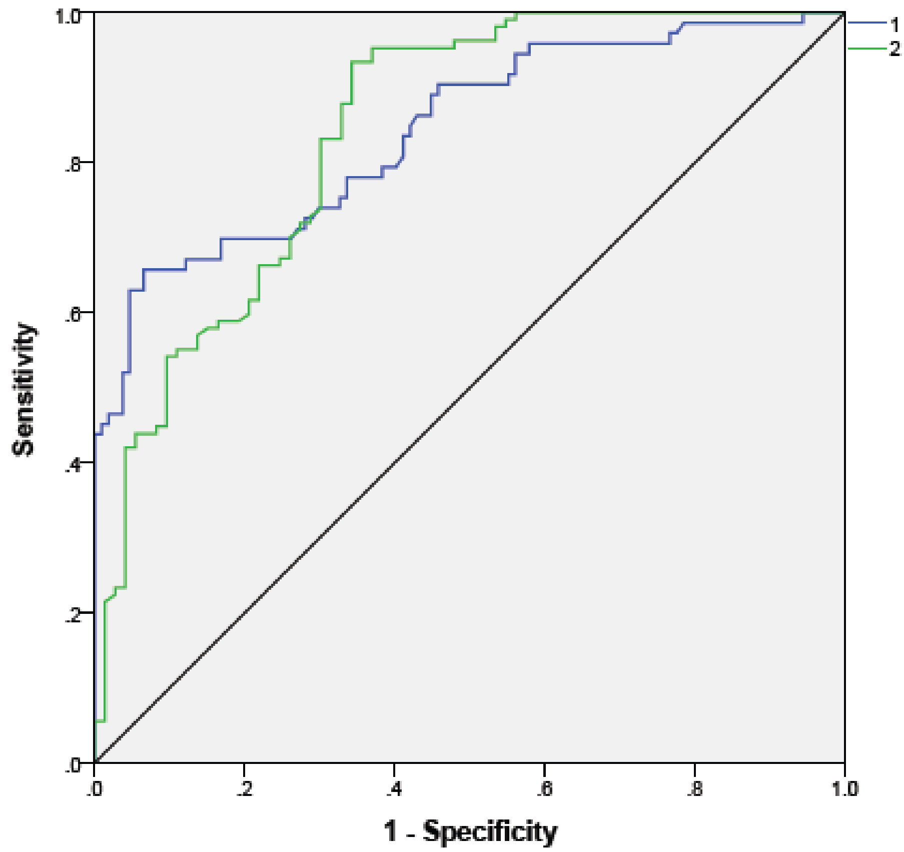

Figure 5-14 ROC Curve for 2 Outputs for Model 1-B

Table 5-4 Area under the ROC Curve for Model 1-B

Output	Area Under The R.O.C Curve
1.Corrosion Failure	0.842
2.Third Party Failure	0.842

5.4.1 Factors' Importance

As represented in the previous model, the SPSS software has the ability to determine the importance of each predictor contributing in the neural network. Table 5.5 represents the importance of each predictor while figure 5.15 displays a chart of the normalized importance of each predictor. It can be seen that the most important factor is the service (type of transported oil), while the least important predictor is the facility.

Table 5-5 Factors Importance for Model 1-B

Predictor	Importance	Normalized Importance
Service	0.418	100%
Land Use	0.166	39.8%
Facility	0.93	22.2%
Age	0.174	41.8%
Diameter	0.149	35.7%

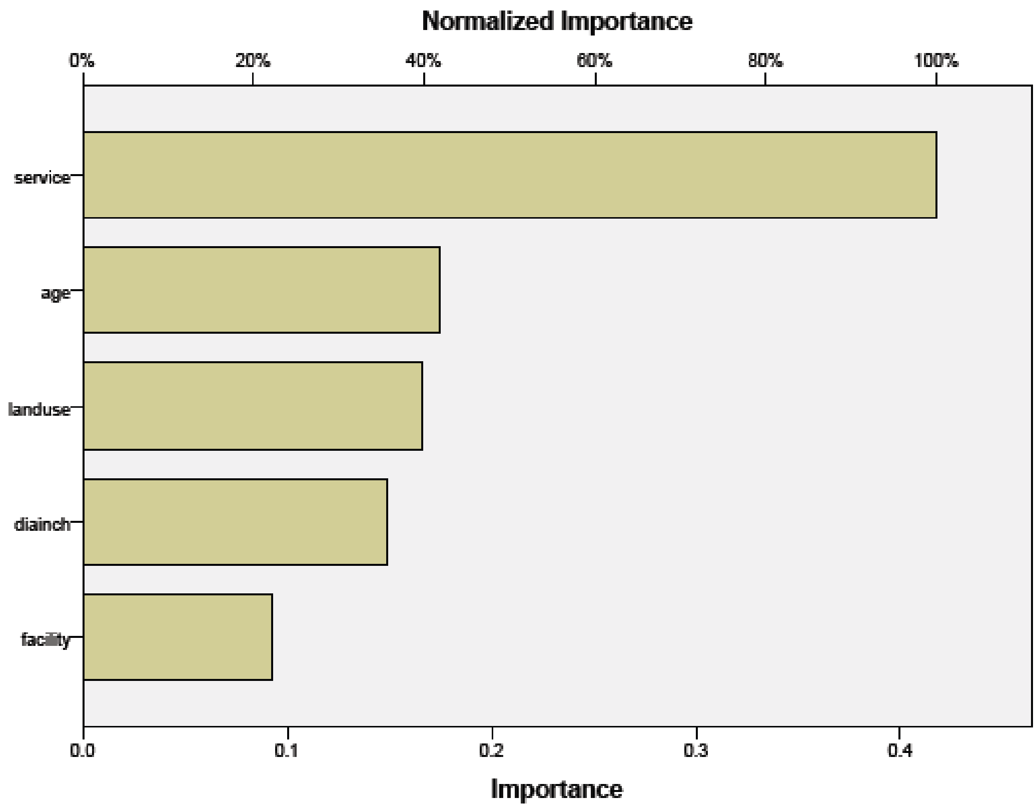

Figure 5-15 Normalized Factors Importance Chart for Model 1-B

5.4.2 Model 1-B Validation

As described previously, twenty percent of Data Set 2 were kept aside for validation and called Data Set 2 (Test). We found the percentage of correct prediction to be 72.2%, which is better than with the previous model. A graphic Figure 5.16 displays the failure causes predicted by the developed model versus the actual failure cause for the validation data set, consisting of 43 accidents. The model produces an AVP of 72.8% and an AIP of 27.2%.

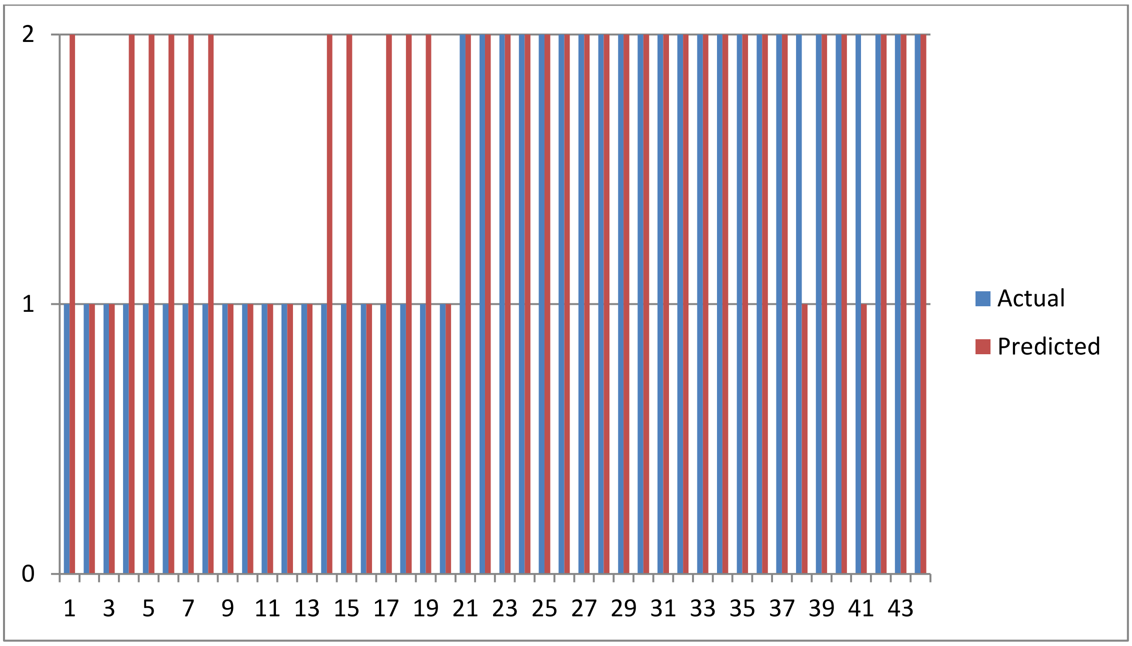

Figure 5-16 Actual versus Predicted Failure types, Model 1-B

5.4.3 Sensitivity Analysis for Model 1-B

A sensitivity analysis was carried out for the developed model to identify the effect of varying predictor values on the failure type. The sensitivity analysis follows the same procedure as in the previous model.

a. <u>Effect of service variation</u>

The following chart (figure 5.17) presents the effect of service variation on the type of failure. The chart also shows that for this particular case, when the type of oil was white products the failure occurs due to third-party causes, while when the transported product was crude oil or hot products the failure cause changes to corrosion because of the impurities and heat of these types of product which induce corrosion.

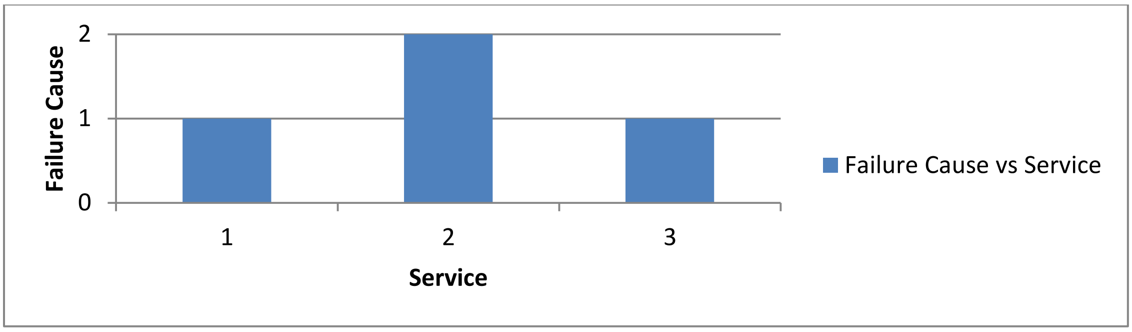

Figure 5-17 Failure Cause versus Service Variation

b. <u>Effect of Facility Variation</u>

The following figure 5.18 shows that the facility variation does not affect the failure cause in the case of the randomly-chosen accident, but that facility does become a factor when the diameter is changed from 9 to 30 inches.

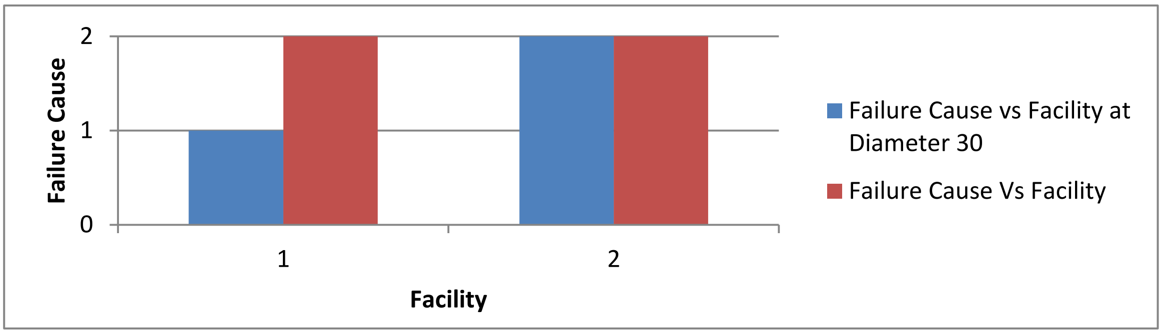

Figure 5-18 Failure Cause versus Facility Variation for Model 1-B

c. <u>Effect of Land Use Variation</u>

The land use did not have an effect in this particular accident, but it shows some significant effect when the diameter is 30 inches and when the type of transported oil changes from white product to crude oil. The land use variation effect is presented in figure 5.19.

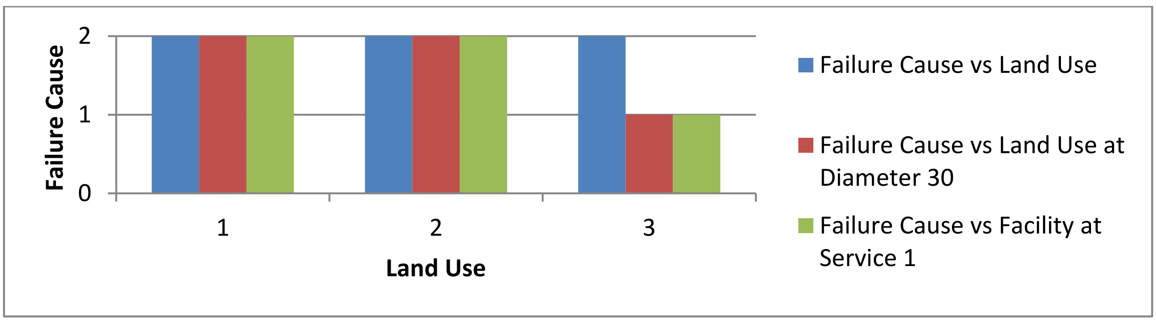

Figure 5-19 Failure Cause Variation versus Land Use for Model 1-B

d. Effect of Diameter Variation

The following figure 5.20 represents the effect of diameter variation on the failure type. It shows that small diameter pipelines are more vulnerable to third-party failure, which has been noted in the literature and summarized in chapter 2.

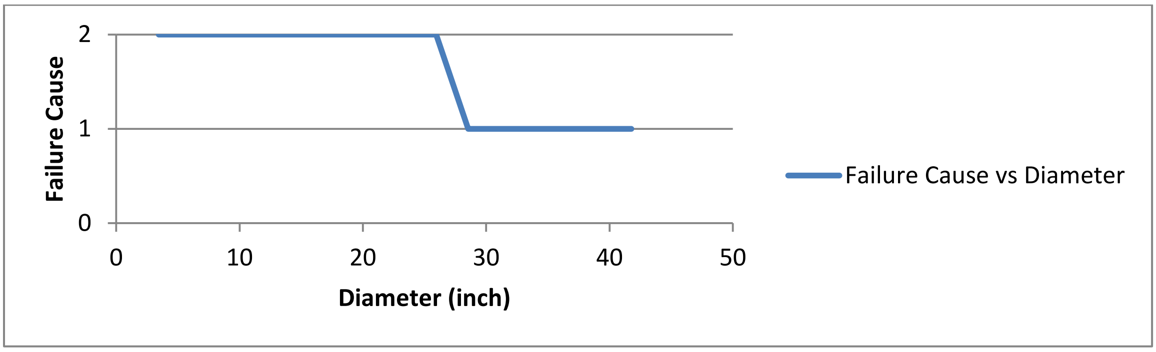

Figure 5-20 Failure Cause versus Diameter Variation for Model 1-B

e. Effect of Age Variation

The study of age variation shows that there is no effect of age variation on the failure type for the accident selected, as presented in figure 5.21. However, when the diameter is changed from 9 to 30 inches, pipeline age starts to have an effect on the failure type, as shown in figure 5.22.

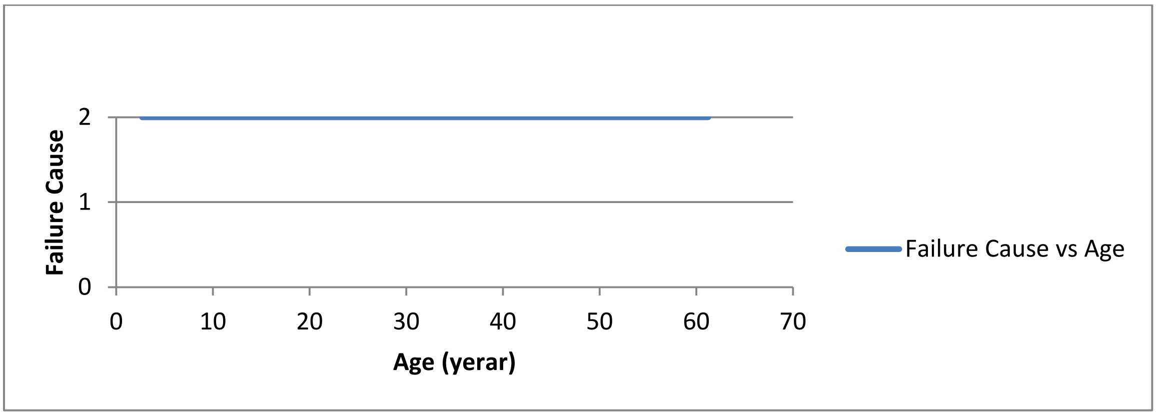

Figure 5-21 Failure Cause versus Age Variation for Model 1-B

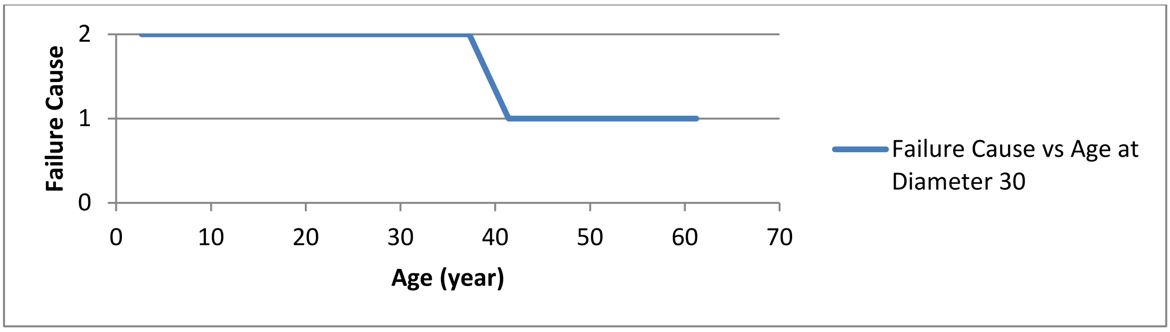

Figure 5-22 Failure Cause versus Age Variation at a 30-inch Diameter for Model 1-B

5.5 Summary

Two ANN models were developed to predict the type of failure that would most likely menace an oil pipeline, with five pipeline parameters known: diameter, age, type of transported product, land usage and position. The first model is designed to predict failure caused by mechanical failure, corrosion failure or third-party failure. The model validation showed that it has the ability to identify the failure cause with an accuracy percentage of 68.5%.The second model is designed to predict the failure caused by corrosion failure or by third-party failure and has the ability to identify the failure cause with an accuracy percentage of 72.2%.

Chapter 6

6 MULTINOMIAL LOGIT MODEL APPLICATION TO OIL PIPELINE FAILURE PREDICTION MODEL

6.1 Introduction

Logistic regression is a prediction approach, similar to an ordinary least square regression (OLS). The multinomial logit model is used when categories are unordered or nominal data exists (Burns, et al 2009). In our case, three of our predictors and the output are nominal unordered categories. In this section we show the development of our failure prediction model using the multinomial logit technique. This model is designed to predict the failure type among Mechanical failure, corrosion failure and third-party failure. The developed model is validated and a sensitivity analysis performed for each predictor.

6.2 Model 2: Failure Prediction Model for Oil Pipeline for Three Outputs

This model uses the same data set as model 1-A (see section 5.3). SPSS software is also used to develop the MNL model because of its ease of use and its detailed results. Data Set 1 (training), was introduced via an EXCEL spreadsheet to the SPSS software to perform the MNL analysis, while Data Set 2 (Test) was kept aside for validation. As mentioned in chapter five, the model has two continuous inputs (age and diameter), three nominal inputs (service, facility and land use) and three nominal outputs representing the failure cause (mechanical, corrosion, and third-party).

The multinomial regression performs the analysis by computing the probability of occurrence of each failure type, where the highest probability is set as a predicted value. The logit model pairs each category to a base line category, in our case the last output category (third-party failure) is the baseline category. For more details, please refer to Agresti 2002. Since the Ordinary Least Square Method (OLS) is inapplicable for the MNL model because

MNL models compute the probability of occurrence for the dependent variable and not its value, the Maximum Likelihood Estimate (MLE) method is used to measure the MNL model's performance. The MLE is the value of the parameter that makes the observed data most likely. Since the value of the likelihood is very small it is usually reported as the log likelihood or the initial log likelihood function that is equal to -2 Log Likelihood (-2LL) (Williams, 2011). The initial likelihood function (-2 Log Likelihood) is a statistical measure similar to the total sum square in linear regression. Table 6.1 shows the initial likelihood function value (498.091) for the model with no independent variable (constant only) and the initial likelihood value (387.59) for the model with all the variables independent in its first column of values. The decrease of the value indicates the improvement in the model's prediction because of the addition of independent variables. The difference between the two values is the Chi Squared (101.49) and has a significant that is less than 0.0001. Based on the results it can be concluded that there is a significant relationship between the independent variables and the dependent variable (Menard, 2002).

Table 6-1 Model Fitting Information

Model	**-2 Log Likelihood**	**Chi-Square**	**Sig.**
Intercept Only	489.091	N/A	N/A
Final	387.592	101.499	0.000

Since an ordinary R square does not exist in logistic regression, several pseudo R squares have been developed in order to evaluate the logistic models' goodness of fit. These pseudo R-squares have a scale similar to that of R-squares that varies from 0 to 1 with a higher value indicating a better model fit. The pseudo R squares calculations are shown in equations 6.1 to 6.3 (Menard, 2002). While table 5.2 represent the pseudo R Square value for our model.

a. Cox and Snell Pseudo R-Square

$$\boldsymbol{R^2 = 1 - \left(\frac{l(Mfull)}{l(Mintercept)}\right)^{\frac{2}{n}}}$$ ………………………………………………..Equation 6-1

Where:

M_{full} = the model with a predictor

$M_{intercept=}$ the model with all predictors,

L= the estimated likelihood

N= the number of observation.

Note: Cox and Snell R-squared cannot reach 1.

b. Nagelkerke Pseudo R-Square

$$\boldsymbol{R^2 = \frac{1-\left(\frac{l(Mfull)}{l(Mintercept)}\right)^{\frac{2}{n}}}{(1-l(mintercept))^{\frac{2}{n}}}}$$ …………………………………………………..Equation 6-2

This is an adjustment for Cox and Snell R-Square to reach the 1.

c. McFadden Pseudo R-Square

$$\boldsymbol{R^2 = 1 - \frac{lnL(Mfull)}{\ln L(Mintercept)}}$$ …………………………………………………….Equation 6-3

Table 6-2 Three Pseudo R-Square Values

Pseudo R-Square	Values
Cox and Snell	0.354
Nagelkerke	0.42
McFadden	0.205

In order to identify the importance of each predictor the SPSS software calculates the initial likelihood value for the reduced model. The reduced model is formed by omitting one effect from the final model, in other words, it is the likelihood of the model that includes all predictors except the predictor under study. This likelihood is compared with the likelihood achieved by the model when all predictors are included (full model). The Chi Square is then calculated for each model by subtracting the full model value from the reduced model value. The predictor with a high Chi Square and a low significant is considered to be an important variable. The results generated by the SPSS process are presented in table 6.3, indicating that the type of service is the most important variable while pipeline age is the lowest.

Table 6-3 Likelihood Ratio Test for Model 2

Effect	-2 LL of Reduced Model	Chi Square	Significance
Intercept	387.592	0	.
Diameter	399.623	12.031	0.02
Age	389.872	2.279	0.320
Service	436.608	49.016	0.000
Facility	404.405	16.813	0.000
Land Use	398.546	10.954	0.027

6.2.1 Model Equation

As discussed earlier, the concept driving the logistic regression is to calculate the probability of occurrence of each failure type. In order to calculate the probability of each dependant variable we must first calculate the Logit of each dependant variable. The Logit is similar to the linear regression equation, as shown in the following equation (Menard, 2002).

$$\boldsymbol{Logit = Z = B + B1X1 + B2X2 + \cdots + BnXn} \qquad \text{Equation 6-4}$$

Where; B are the variable coefficients (see table 6.4) and X are the predictor values. The SPSS program generates the coefficient for outputs one and two, but output three (the reference category) could be calculated by subtracting the probability of output one and the probability of output 2 from one (P3 = 1 - (P1+P2)).

Table 6-4 Variable Coefficients

Variables	Coefficients (Output1)	Coefficients (Output2)
Intercept	2.005	3.949
Diameter	0.097	0.008
Age	-0.008	0.016
Service 1	-1.453	-3.358
Service 2	-1.493	-4.5
Facility 1	-2.351	-0.307
Land Use 1	-0.193	-1.213
Land Use 2	0.044	-1.823

The following equations show the Logit equations for each output.

$Z_1 = 2.005 + 0.0097*D - 0.008*A – 1.453*S_1 - 1.493*S_2 – 2.351* F_1 – 0.193*L_1 + 0.044*L_2$ ……………………………………………………………………………Equation 6-5

$Z_2 = 3.949 + 0.008*D + 0.016*A – 3.358*S_1– 4.5*S_2 – 0.307* F_1 – 1.213*L_1 + 1.823*L_2$ ……………………………………………………………………………Equation 6-6

$Z_3 = 0$ (Reference Category) ………………………………………………Equation 6-7

Where; D is the pipeline diameter in inches, A is the pipeline age by year, S is the service type, F is the facility and L is the land use. The probability of each output is calculated by the following equations (Agresti, 2002).

$$\boldsymbol{P1(Mechanical\ Failure)} = \frac{e^{z1}}{e^{z1}+e^{z2}+e^{z3}}$$ …………………………...……..Equation 6-8

$$\boldsymbol{P2(Corrosion\ Failure)} = \frac{e^{z2}}{e^{z1}+e^{z2}+e^{z3}}$$ …………………………………Equation 6-9

$$\boldsymbol{P3(Third\ Party\ \ Failure)} = \frac{e^{z3}}{e^{z1}+e^{z2}+e^{z3}}$$ ………………………………Equation 6-10

Where; e = the natural logarithm. The previous equations can be used to determine the probability of which failure type menaces an oil pipeline when certain pipeline attributes are known.

6.2.2 Model Validation

To measure the accuracy of the predictions provided by the developed Multinomial Logit Model, we applied the generated equations to Data Set 1 (Test). The outputs from the equations are compared to the actual failure cause, thereby calculating the percentage of correct predictions. We found that 39 out of 57 accidents were correctly identified, or correct predictions 68.5% of the time. The model also shows an Average Validity Percentage of 73.69% and an Average of Invalidity Percentage of 26.31%. The actual outputs versus the predicted outputs are represented in figure 6.1.

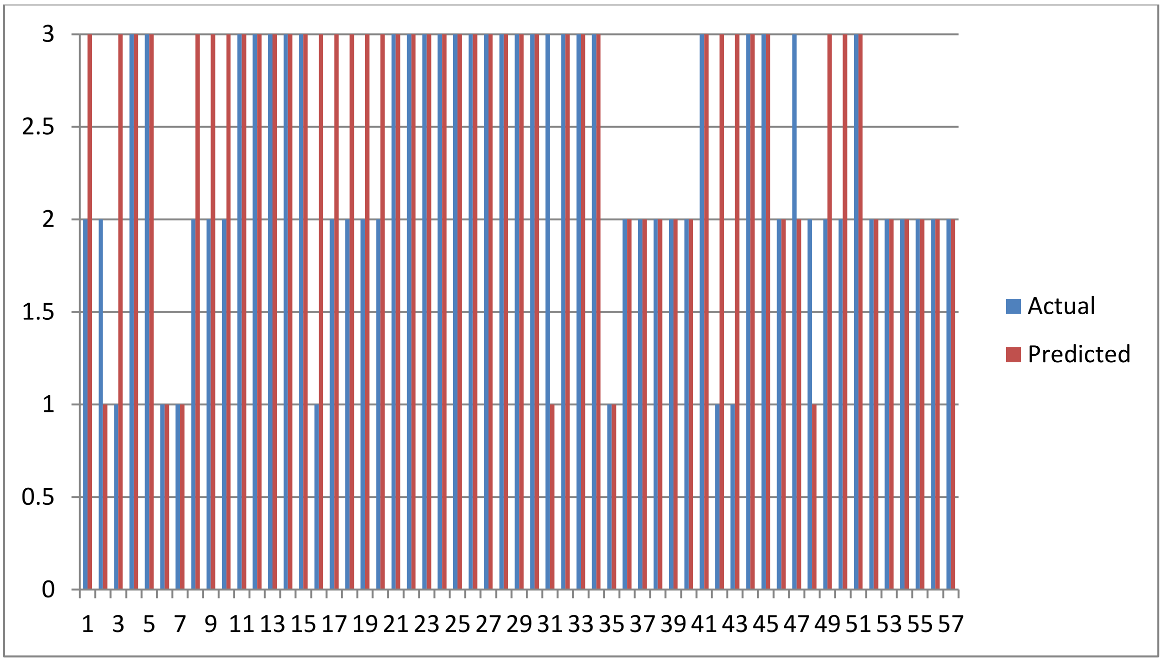

Figure 6-1 Actual versus Predicted Outputs

6.2.3 Sensitivity Analysis

A sensitivity analysis was performed, similar to that done for the artificial neural network models, to identify the effect of varying each predictor on the failure cause. The following shows the effect of varying each predictor of the MNL model.

a. <u>Effect of Service Variation</u>

As shown in figure 6.2, changing the type of transported product has a direct effect on the failure type. Figure 6.2 shows that, when the type of oil is white products, the failure happens due to third-party causes, while when the transported product was crude oil or hot products, the failure cause changes to corrosion because the impurities and heat of these types of product induce corrosion. This aspect also follows the same trend as the ANN model.

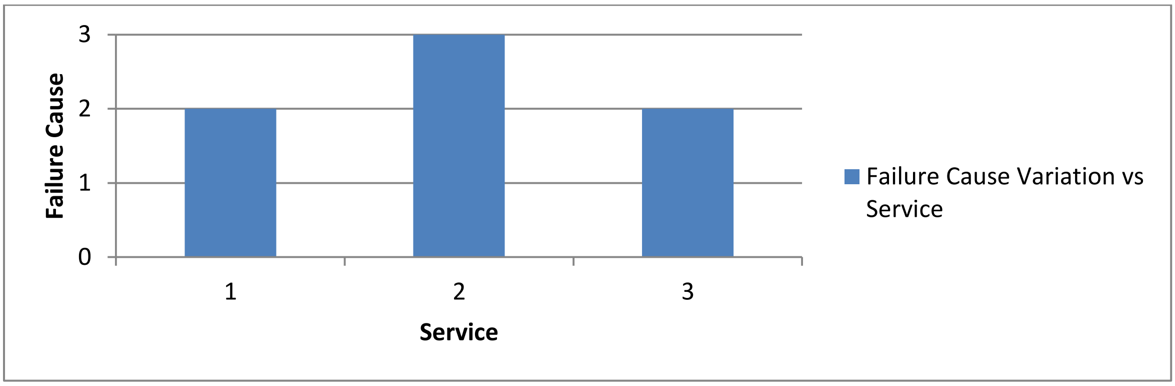

Figure 6-2 Failure Cause versus Service Type

b. <u>Effect of Facility Variation</u>

Figure 6.3 indicates that the position of a pipeline, either aboveground or buried, affects the failure type that could menace it, buried pipelines are more vulnerable to third-party failure and above-ground pipelines are more vulnerable to mechanical failure.

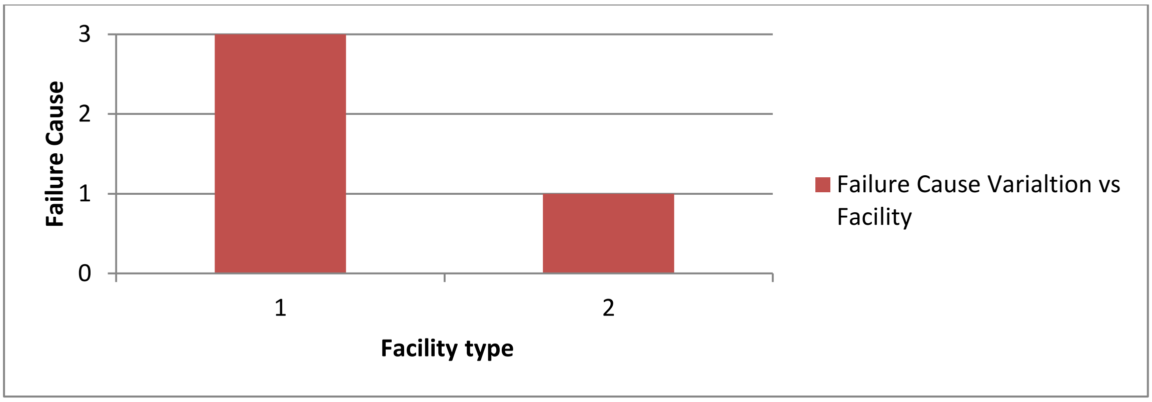

Figure 6-3 Failure Cause versus Facility Type

c. <u>Effect of Land Use Variation</u>

The change of land use did not display any effect on the output in our evaluation, but when the service type changed from white product to crude oil a significant effect appeared, as shown in figure 6.4.

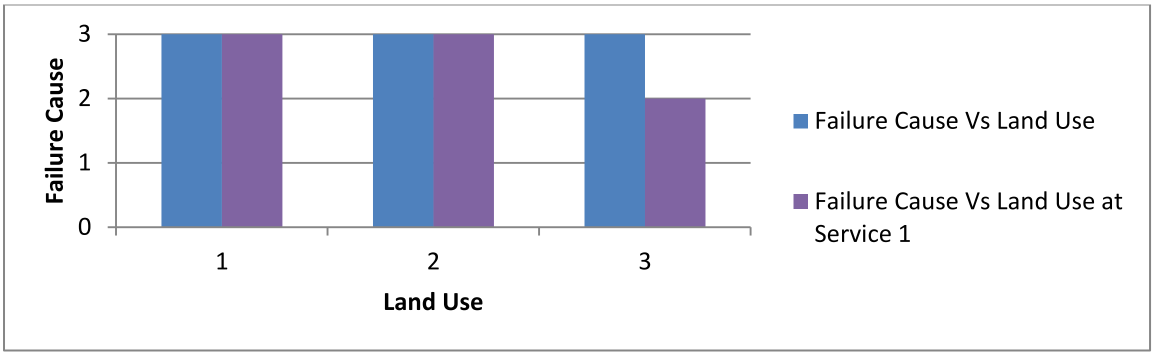

Figure 6-4 Failure Cause versus Land Use Variation

d. Effect of Diameter Variation

Examining the effect of pipe diameters indicated that it has an effect on the failure cause; small diameter pipelines are more susceptible to third-party failure while when larger diameter pipelines are more likely to experience mechanical failure, as shown in figure 6.5.

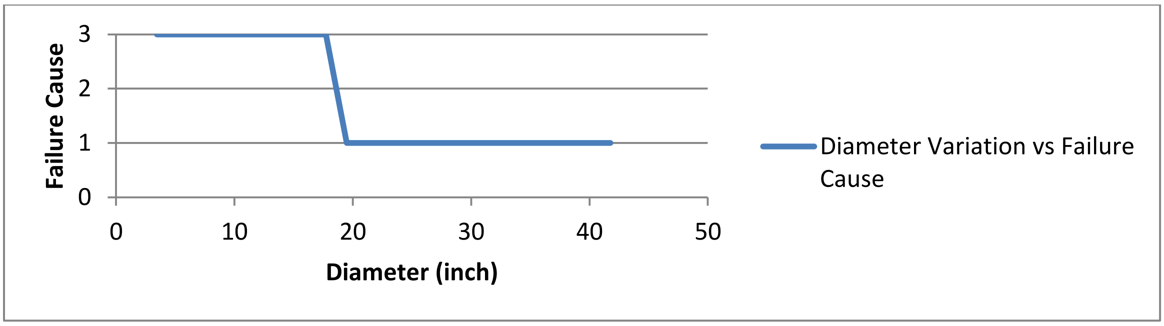

Figure 6-5 Failure Cause versus Diameter Size

e. Effect of Age Variation

Figure 6.6 shows the effect of the age variation on the failure cause. The figure shows that for newer pipelines, mechanical failure has the highest probability, while for older pipelines third-party failure has the highest probability.

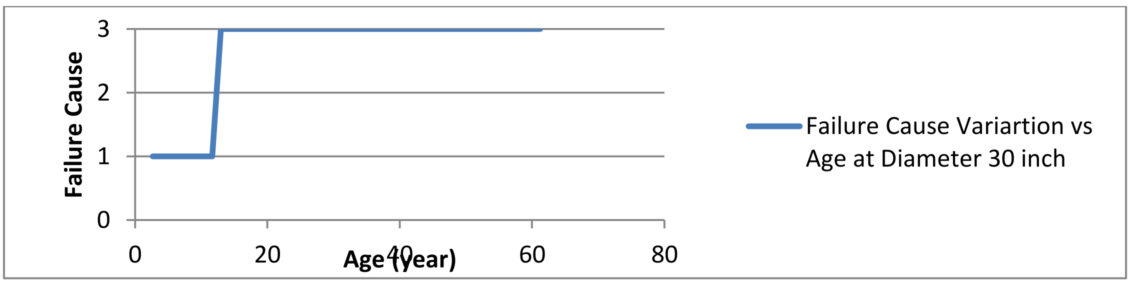

Figure 6-6 Failure Cause versus Age Variation, pipe diameter of 30 inches

6.3 Models' Summary

The different approaches used in this research (ANN and MNL) had similar results, as displayed in table 6.5. The multinomial logit model developed for this study was used to calculate the probability of each major type of failure that threatens pipelines, given five pipeline attributes. By knowing the probability of each failure type, we could identify the failure cause that would be most likely to threat a pipeline; the failure cause with the highest probability. The results show the the model has an accuracy of 68.5% -- which is fairly good for a model developed from pure historical data. This model has two obvious advantages over the ANN model:

- The MNL model utilizes an equation, which makes it easy to use for pipeline operators.
- The MNL model gives the probability of each failure cause, which can help operators to have a better idea about a pipeline's condition.

Table 6-5 Models Summary

Model	**Approach**	**Accuracy**	**AIP**	**Pseudo R Squared**	**Factors with high Sensitivity**
1-A(3 Outputs)	ANN	68.5%	73.7%		Service, Facility and Diameter
1-B(2 Outputs)	ANN	72.2%	72.8%		Service and Diameter
2 (3 Outputs)	MNL	68.4%	73.69%	0.42	Service, Facility, Diameter and Age

The true capacity of the developed models can be revealed by considering how they are neatly fitted at the very beginning of the costly and time consuming inspection process. An example of these models usage is when an oil company intends to inspect one of the lines, through knowing the age, diameter, product type, land use and location, the company would use the model to pin point expected failures in the line, and consecutively plan their course of action. For example by knowing that a 10 years old pipe with a diameter of 40 inch above ground carrying fuel oil (Hot) in industrial area, the model would indicate that this pipe is likely to fail due to corrosion. This would dictate a course of action that examines the degree corrosion using ILI and accordingly plan the suitable corrective actions. In a different case, the input might result in predicting a third party failure, which would direct the company towards a different course of action. These cases reveal the importance of using this model, instead of inspecting the whole pipeline and not knowing what type of failure to watch for.

CHAPTER 7

7 CONCLUSIONS AND RECOMMENDATIONS

7.1 Conclusions

The present research proposes an objective failure prediction model for oil pipelines built on historical data from real failure incidents. This model will help decision makers and oil pipeline operators to plan the strategies and actions required to maintain a pipeline in safe operating condition by knowing the threats that any particular pipeline would be faced with. This research implemented three different failure prediction models using two different approaches (ANN and MNL) to predict the types of failure menacing a pipeline based on specific physical, operational and environmental factors. The first two models (1-A and 1-B) were developed using the ANN technique. Model 1-A is able to predict a failure type among three different types of failure (mechanical, corrosion, third party failure) with an accuracy of 68.5%, which is fairly good and acceptable for such a model based exclusively on historical data. While model 1-B is designed to predict failure caused by either corrosion or third-party damage, and does so with an accuracy of 72.2%. This small increase in accuracy is not high enough to exclude mechanical failure, and therefore Model 1-A is more advantageous, as it can predict failure among the three failure types that are the main cause of 88% of oil pipeline accidents.

The MNL approach was used to develop the third model (model 2), whose results are very similar to those of model (1-A) in predicting three types of failure, with a prediction accuracy of 68.4%. The MNL model generates equations that calculate the probability of each type of failure, which is very helpful for decision makers.

This study also determined that the type of transported product has the highest impact on the failure types, while pipeline age has no significant effect on the type of failure. All three models supported this conclusion. The models developed here can help to reduce unnecessary inspections, as they can be prioritised. These models provide a clear view of the risks that threaten a pipeline, allowing decision makers to take some actions to reduce those risks and keep the pipeline in safe condition.

7.2 Research Contributions

The contributions of this research to the current oil pipeline condition assessments process are that it:

- Develops an ANN failure prediction model for oil pipelines that helps to forecast mechanical, corrosion or third-party failure;
- Develops an ANN prediction model for oil pipelines that anticipates either corrosion or third-party failure; and
- Develops an MNL model to predict for oil pipeline mechanical, corrosion or third party-failure.

The added value of this research is the development of an objective failure prediction model capable of predicting different types of failure from some basic pipeline attributes. This is the only model that can predict different types of oil pipeline failure objectively, based only on historical data.

7.3 Models' Limitations

The developed models still have some limitations which are described below:

- The developed models are only for oil pipelines;
- The models are only valid for main oil pipelines, which are made of carbon steel;
- These models are not suitable for offshore pipelines; and
- All the model inputs need to be available in order for these models to be utilised.

7.4 Recommendations and Future Works

Recommendations for the extension of this research can be summarized as follows:

Current research enhancement areas:

- To enhance the model accuracy more predictors could be added, such as steel grade, type of soil and effectiveness of cathodic protection, which have a direct effect on corrosion failure. Adding the area population and proximity of highways could improve the prediction of third-party failure. In general, adding more predictors will improve the models' accuracy.
- More historical data would also enhance the developed model. This could be done by gathering more data from additional pipeline operators in different regions.
- The ANN models could be integrated with Fuzzy Theory (NeuroFuzzy). This approach will allow expert evaluations to be used for some predictors that do not exist in historical data; thereby enriching the models' accuracy.

Current study extension:

- Develop a failure prediction model that can predict all of the failure causes listed by CONCAWE by adding more predictors related to operational failure and natural failure.
- Develop an integrated model for oil and gas pipelines. This could be achieved by adding the capacity for historical data for gas pipelines. The type of transported product would then include gas and predictors relevant to gas pipelines added; their values could simply be set to zero if an oil pipeline is being evaluated.
- Design a condition scale for oil and gas pipelines, which reflects the state of deterioration of a pipeline using a scale from 0 to 10 where 0 is the worst condition and 10 is the best state. This scale could be developed using expert opinions to evaluate pipeline condition.

- Develop a condition assessment model for oil and gas pipelines. This model would give the condition of a pipeline as the output which would help decision makers to assess the state of a pipeline and take the appropriate maintenance action(s).

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APPENDIX A

LIST OF ACCIDENTS HAPPENED TO OIL PIPELINE IN THE LAST 38 YEARS REPORTED IN THE CONCAWE REPORT 2010

Service

1	Crude oil
2	White product
3	Fuel oil (hot)
4	Crude oil or product
5	Lubes (hot)

Leak first detected by

1	R/W surveillance by pipeline staff
2	Routine monitoring P/L operator
3	Automatic detection system
4	Pressure testing
5	Outside party
6	Internal Inspection

Land use

1	Residential high density
2	Residential low density
3	Agricultural
4	Industrial or commercial
5	Forest Hills
6	Barren
7	Water body

Facility

1	Underground pipe
2	Above ground pipe
3	Pump station

Facility part

1	Bend
2	Joint
3	Pipe run
4	Valve
5	Pump
6	Pig trap
7	Small bore
8	unknown

Reason

1	Incorrect design
2	Faulty material
3	Incorrect material specification
4	Age or fatigue
5	Faulty weld
6	Construction damage
7	Incorrect installation
8	Equipment
9	Instrument & control systems
10	Not depressurised or drained
11	Incorrect operation
12	Incorrect maintenance or construction
13	Incorrect procedure
14	Coating failure
15	Cathodic protection failure
16	Inhibitor failure
17	Construction
18	Agricultural
19	Underground infrastructure
20	Landslide
21	Subsidence
22	Earthquake
23	Flooding
24	Terrorist activity
25	Vandalism
26	Theft (incl. attempted)

Categories of spillage causes

Main		Secondary		
		A	b	c
A	Mechanical Failure	Design & Materials	Construction	
B	Operational	System	Human	
C	Corrosion	External	Internal	Stress Corrosion
D	Natural Hazard	Ground movement	Other	
E	Third Party Activity	Accidental	Intentional	Incidental

Spillage ID	Year	Pipe dia (")	Service	Fatalities	Injuries	Spillage volume (m^3)		Leak first detected by	Facility	Facility part	Age	Land use	Cause		Impact	
						Gross	Net loss				Years		Category	Reason	Water bodies	Contaminated land area (m^2)
1	1971	11	2			1	1	2	1	2	3	2	Aa	7		
2			1			4		2	3	2			Aa Aa			
3		11	2			0		5	1	3	6		Ab Ba	5		
4		20	1			40	5	3	3	2	5		Bb Ca			60,000
5			1			350		2	3	8	9	4	Ca Ea	9		
6			1			25		2	3	7			Ea Eb	11		
7		5	3			3		5	1	3	8					
8		8	2			6	6	2	1	3	20					
9		20	1			300	50	5	1	3	5			19		1,000
10		34	1			2000		5	1	3	9			19		
11		8	2			2	2	5	1	3	20			25		
12	1972	16	2			5		2	1	4	4		Ab Ab	12		
13		28	1			800	150	2	3	1	12	4	Ab Ca	5		
14		12	2			70	39	5	1	2	5	2	Ca Ca			
15		9	1			10	5	5	1	3	29		Ca Ca			
16		9	1			40	35	5	1	3	29		Ca Ca			
17		10	1			1	1	2	2	3	39	4	Ca Ca			
18		10	1			1	1	2	2	3	39	4	Ea Ea			
19		12	3			500		5	1	3	12	4	Ea Ea			
20		12	3			5	1	5	1	3	12	4	Ea Ea			
21		10	2			150	50	2	1	3	7		Ea Ea			
22		4	3			0		5	1	3	15	4	Ec			
23		6	3			1	0	5	1	3	15					
24		20	1			200	60	2	1	3	8	4		17		
25		20	1			250	100	2	1	3	8			17		
26		28	1			60	12	5	1	3	16			17		
27		10	1			90		5	1	3	6					
28		8	1			7		5	1	3	8	2		17		
29		10	2			30		5	1	3	9			17		
30		8	2			400	350	2	1	3	2	2		18		
31		10	2			99	96	5	1	3	6	2				
32		12	3			0		5	1	3	5					
33	1973	5	3			4		1	1	3	8		Aa Aa	4		
34		20	1			25	3	5	3	2	1	4	Ab Ab			
35		16	1			0		2	3	4	3	4	Ab Ab			
36			1			4		2	3	7	11	4	Ab Ca	4		
37		24	2			25		2	3	2	2	4	Ca Ca			
38		18	1			11	1	2	3	5	13	4	Ca Ca	4		
39		6	2			12	6	5	1	2	1	4	Ca Ca			
40		9	1			12	12	1	1	3	32		Ca Da			
41		5	3			15		1	1	3	8		Ea Ec			
42		5	3			15		1	1	3	8		Ec Ec			
43		12	3			200	2	5	1	3	13					
44		12	3			12	2	2	2	3	13					
45		12	3			250	5	5	2	3	13					
46		12	3			150	2	1	2	3	13			14		
47		12	3			310	10	5	1	3	13	4				30,000
48		28	1			100	40	5	1	3	16					
49		10	3			8		5	1	3	9	2		18		
50		12	3			0		5	1	3	6					
51		12	3			1		5	1	3	6					
52		12	3			0		1	1	3	6					
53	1974		1			1	0	2	3	7	4	4	Aa Aa	7		
54			1			3	2	2	3	7	5	4	Aa Ca	4		1,000
55		6	1			20		5	1	1	15		Ca Ca	4		
56		9	1			10		1	1	3	33		Ca Ca			
57			2			2	2	2	2	7	6		Ca Ca			
58		10	3			1		2	1	3	9	4	Cb Cb	14		
59		12	3			5		5	1	3	8		Ea Ea	14		
60		13	3			5		5	1	3	8		Ea Ea	14		
61		4	3			1		5	1	3	17	4	Ea Ea	14		
62		6	3			0		5	1	3	16			14		
63		16	3			1		5	1	3	9	2			P	
64		7	1			1		5	1	3	8	2				
65		16	1			500		5	1	3	10			17		
66		5	2			1	0	5	1	3	21			19		
67		8	2			30	4	2	1	3	22			19		
68		8	2			200	2	5	1	3	22			17		
69		10	2			668	668	2	1	3	18			18		
70		10	2			489	405	2	1	3	18	2		17		

Spillage ID	Year	Pipe dia (")	Service	Fatalities	Injuries	Spillage volume (m^3)		Leak first detected by	Facility	Facility part	Age	Land use	Cause		Impact	
						Gross	Net loss				Years		Category	Reason	Water bodies	Contaminated land area (m^2)
71	1975	20	2			30	10	4	2	7	11	2	Ab	5		
72		34	1	4		30	2	5	1	2	12		Ab Ab	5		
73		10	3			3		2	2	2	5	1	Ba Ba			
74			1			10	2	2	3	8		4	Bb Bb	11		
75			2			4		3	3	7		4	Ca Ca	9		
76		8	2			20	10	2	3	7	4	4	Ca Ca	11		
77			1			5		2	3	7		4	Ca Ca	11		
78		10	3			50		2	1	3	11		Ca Ca	15		
79		12	3			3		5	1	3	9		Ea Ea	14		
80		6	3			25		1	1	3	9		Ea Ea	14		
81		10	3			1	0	2	3	6	6	4	Ea			
82		4	3			1		5	1	3	18					
83		8	3			0		6	1	3	6					
84		8	3			0		1	1	3	6	2				
85		12	3			0		2	3	3	6	4				
86		6	1			15	0	5	1	3	23	2		18		
87		18	1			5	0	2	1	3	12			19		
88		8	1			120	3	2	1	3	9			17		
89		8	2			60	60	2	1	3	23			19		
90		6	1			15	6	5	1	3		2		18		
91	1976	8	2					5	1	7	9		Aa Aa	5		
92		8	3					5	1	4	13	2	Ab Ab	2		
93			1			9		2	1	4	13	4	Ab Ca	2		
94		24	2			17	1	5	2	2	17	4	Ca Da	1		
95		16	1			1322	433	2	1	2	13		Da Ea	1		
96		10	3			80		2	1	3	11		Ea Ea	14		
97		4	2			90	90	5	1	3	16		Ea Ec	15		
98		24	1			200		2	1	3	10			21		
99		10	3			50	25	2	1	3				21		
100		10	1			40	2	5	1	3	13	2		18		
101		8	2			44	14	2	1	3	24	2		18		
102		18	1			802	606	5	1	3	7	2		18		
103		8	2			153	153	2	1	3		2		18		
104		14	2			358	358	5	1	3	23	2				
105	1977		2			32		2	3	4	9	4	Ab Ab			150
106			2			28		2	3	2	9	4	Ab Ab			140
107		20	2			2		5	1	2	8	2	Bb Bb	2		
108		36	1					2	1	4	3	4	Ca Ca	1		
109			1			50		2	3	4	19	4	Cb Da	11		
110			1			1		2	3	4	7	4	Da Db	11		
111		12	2			350	220	4	1	3	10	2	Ea Ea	15		
112		10	3			315	90	2	1	3	8	1	Ea Ea			
113			1			6		2	3	7	9	4	Ea Ea			
114		12	2			103		5	1	3	19		Ec	20		
115		20	1			550	500	1	1	3	13	2		23		
116		24	1			600	25	3	1	3	11	2				
117		10	1			160		2	1	3	12	2		17		1,500
118		18	1			80		2	1	3	5	2		18		400
119		8	2			3	3	2	1	3	25	2		18		
120		8	2			3	1	2	1	3	13	2		17		
121		12	2			191		2	1	3	19	2		17		
122		8	2			269		5	1	3	19	2		17		
123		20	2			2530	2500	2	1	2	9	2				
124	1978	34	1			2000	300	5	1	2	16	2	Ab Ab	2		
125		8	2			235	205	2	1	4	16	2	Ab Ca	2		
126		22	1			19		5	1	3	7	2	Ca Ca	2		1,800
127		6	2			12	6	5	1	3	18	4	Ca Ca	15		
128		10	2			100	10	2	1	3	14	2	Ca Ca	15		
129		12	3			2		5	1	3	14	2	Da Ea	15		
130		8	3			120	60	4	1	2	7	2	Ea Ea	15		
131		8	3			80	40	4	1	3	7	2	Ea	15		
132		12	3			2		1	1	3	12	4				
133		18	3			4	1	5	1	3	6	4		15		
134		16	4			400	250	2	1	3	14	2		23		
135		11	2			3	0	5	1	3	10	2		17		
136		12	2			58	40	4	1	8	10	2		19		
137		24	1			1		5	1	7	4			19		
138		16	1			255	245	2	1	3	15	2		18		5,865
139	1979	22	1			100	40	4	1	3	8	2	Aa Aa	6		16,000
140		24	1			100	1	5	1	3	5		Ca Ca	6		2,700
141		9	2			50		5	1	3	17	2	Ca Ca	14		350
142		12	2			300	200	1	1	3	23	2	Ea Ea	15		
143		18	3			20		1	1	3	12	4	Ea Eb	15		500
144		18	3			5		1	1	3	12	4		15		100
145		18	1	5		50	1	5	1	3	16	2		17		2,500
146		12	2			90	50	5	1	3	23	2		18		
147		8	1			245	150	5	1	3	23	2		18		
148		11	2			950	380	2	2	3	15	4		26	P	6,400

Spillage ID	Year	Pipe dia (")	Service	Fatalities	Injuries	Spillage volume (m^3)		Leak first detected by	Facility	Facility part	Age	Land use	Cause		Impact	
						Gross	Net loss				Years		Category	Reason	Water bodies	Contaminated land area (m^2)
149	1980	13	2			8	1	2	3	2	12	4	Ab	7		
150		40	1			4800	400	5	1	3	9	2	Ab Ca	2		10,000
151		10	3			80		5	1	3	10	2	Ca Ca	14		
152		10	3			10		1	1	3	10	2	Da Ea	14		
153		7	3			1		1	1	3	15	2	Ea Ea	15		10
154		12	3			111	12	5	1	3	15	2	Eb	21	P	10,000
155		10	4			762	135	2	1	3	15	2		18		10,000
156		12	2			270		5	1	3				19		
157		8	2			313		2	1	3				17		
158			1			30		5	3	4		4		25		
159	1981	34	4			10	2	5	1	4	6		Ab Ab			
160		40	1			10		5	2	2	5	4	Ab Ca			80
161		10	2			600	150	2	1	3			Ca Ca	2		
162		20	1			19	1	5	1	3	17	2	Ca Ca	14		
163		8	3			5		4	3	2	12	2	Ca Ca	14		
164		8	3			19		4	3	2	12	2	Da Db	14		
165		12	3			5	2	5	1	3	15	4	Ea Ea	14		50
166		10	2			92	58	2	1	3	25	2	Ea Ec	15		
167		20	1			5	3	5	1	7	15	4		14		
168		10	2			10		5	1	3				14		
169		26	2			125	45	5	1	2	18	2		20		
170		24	3			30	10	4	3	7	14	4				
171		7	1			132	132	2	1	3	15	2		18		
172		8	2			322	317	2	1	3	24	2		17		
173		5	1			96		5	1	3				19		
174		28	1			5	0	1	1	3	16	4				
175	1982	8	2			12	12	5	2	3	20	2	Aa Ab	6	P	
176		24	1			9		5	1	3	18	2	Ca Ca	2		1,000
177		8	1			2		1	1	3	20	2	Ca Cb			
178		12	3			8		5	1	3	16	4	Cb Cb	15		30
179		10	3			400	16	5	1	3	19	2	Ea Ec	15		
180		5	1			20		5	3	3	10	4				
181		7	1			140	140	5	1	3	16	2				3,000
182		22	1			15	5	5	1	3	18	1				
183		6	1			31		5	1	3	20	2		18		
184		8	2			7	1	2	1	3	30	4				
185	1983	4	5			10		2	1	2	22	2	Aa Aa	1		100
186		4	5			1		3	1	2	22	2	Ab Bb	1		9
187		4	5			4		5	1	2	22	2	Ca Cb	1		80
188		16	4			442	111	4	1	3	18	2	Ea Ea	11		
189		6	2			12		4	1	3	15	4	Eb Ec	15		3,600
190		7	1			182	120	2	1	3	17	2				20,000
191		7	1			148	110	5	1	3	17	2		17		18,000
192		10	2			213	171	5	1	3	29	2		17		
193		14	2			675	470	5	1	4	3	2		24		
194		12	1			1	0	5	1	3	20	4				15
195	1984	28	1			4363	3928	1	1	3	10	2	Aa Aa	6		6,500
196		24	1			141		5	1	1	18	2	Ab Ab	6		4,500
197		28	1			3		3	2	4	11	2	Ba Ba	2		120
198		8	2			16	3	5	2	2	17	2	Bb Ca	2		720
199		34	1			5	2	2	3	4	13	4	Ca Ca	8		1,000
200		16	1			10		2	3	6	18	2	Cb Ea	8		50
201			1			10	10	2	1	3	21	2	Eb	10		50
202		12	3			2		1	1	3	17	4				
203		6	1			20	16	5	1	3	24	4		15		250
204		16	2			5	1	5	3	3	11	4		14		10
205		9	2			236	236	5	1	3	11	2				200
206		10	1			150	1	5	1	3	23	5		17		100
207		11	2			244	240	3	1	4	21			24		
208	1985	24	1			1	1	1	1	8	14	2	Aa Ba	7		18
209		20	1			25	4	5	3	5	9	4	Ba Ba			
210		10	2			16		3	3	4	17	4	Ba Cc			
211		10	2			7		3	3	2	17	4	Ec			
212		6	2			4		3	3	4	17	4				
213		16	1			1100	756	2	1	3	9	2				13,000
214		8	2			211	195	2	1	3	33	2		18		1,000
215	1986	16	2			160	6	3	3	2	17	2	Ab Ab			200
216		20	1			53	6	2	1	3	12	2	Ab Ca	2		3,000
217		24	2			292	4	2	1	2	26	2	Ca Ca	7		3,000
218		16	3			20	5	5	1	3	38	1	Cb Cb	14		
219		20	2			2	2	5	1	3	22	1	Ea Ea	15		
220		8	3			10		4	1	3	25	2	Ea Eb			20
221		9	1			10	10	5	1	3	45	2				180
222		34	1			7	7	1	1	2	14	4				84
223		8	2			192	95	5	1	3	15	2		19		1,500
224		14	2			280	56	3	1	3	18	2		17		100
225		6	2			52	41	3	1	3	13	2		17		10
226		8	2			11	6	3	1	2	19	2		25		3

Spillage ID	Year	Pipe dia (")	Service	Fatalities	Injuries	Spillage volume (m^3)		Leak first detected by	Facility	Facility part	Age	Land use	Cause		Impact	
						Gross	Net loss				Years		Category	Reason	Water bodies	Contaminated land area (m^2)
227	1987	20	2			1000	120	4	1	2	20	4	Aa	5		
228		26	4			2	1	5	1	3	25	2	Aa Ab	7		1,000
229		9	1			25	2	5	1	1	46	2	Ca Cb	2		200
230		16	3			550	150	2	1	3	39	2	Da Ea	15		200
231		9	1			8	1	5	1	3	46	1	Ec			280
232		12	2			12	10	5	1	3	21	2		20	P	2,000
233		22	2			3	1	5	1	7	20	4		19		10
234		16	2			300	115	5	1	8	18	4			P	
235	1988	34	1			10	1	5	1	2	26	4	Ab Ab			200
236		12	2			90	42	5	1	1	30	1	Ab Ca	2	P	1,500
237		8	2			97	21	2	3	2	28	2	Ca Ca	4		500
238		34	1			81	1	5	1	3	17	4	Da Ea	15		5,000
239		11	2			80	80	2	1	3	35	1	Ea Ea	15		
240		28	1			5	1	5	2	2	31	1	Ea Ea	15		400
241		10	2			305	5	2	1	3	23	2	Ea Ea	20		5,000
242		20	2			40	10	5	1	3	24	4	Ea Ea	17		30
243		3	1			2	1	5	1	3	28	2		17		100
244		10	1			14	1	5	1	3	23	2		18		100
245		8	2			3	1	5	1	3	35	1		17		20
246		16	2			3	1	5	1	3	16	2		19		150
247		16	1		1	650	650	3	1	3	23	1		17		550
248		4	2			2	1	5	1	3	26	2		19		9
249		6	2			63	56	5	1	3	33	2		17		1,200
250		6	2			18	1	5	1	3	33	2		18		1,800
251	1989	26	1			3	2	5	1	2	26	2	Aa Aa	5		100
252		12	3			1		5	1	2		4	Aa Ab	5		6
253		1	2			25	7	5	2	7	1	2	Bb Ca	7		10,000
254		26	1			155	5	5	1	3	26	2	Ca Cb	5	P	2,000
255		10	2		1	66	16	2	1	2	27	2	Ea Ea	11		
256		9	1			25	5	4	1	3	48	2	Ea Ea	14		50
257		12	3			240	150	2	1	3	17	4	Ea Ea	15		
258		10	2			400	90	3	1	3	24	2	Ea Ec			2,000
259		16	2	3		253	253	5	1	3	22	2	Ec	19		500
260		16	2			660	472	3	1	3	20	2		18	P	
261		10	2			82	4	3	2	3	24	2		17		200
262		12	2			298	298	2	1	3	32	2		18		6,000
263		6	2			52	27	5	1	3	33	2		18		2,000
264		8	2			3		5	1	3	32	2		19		66
265		8	2			186	126	5	1	3	29	2		18		
266		40	1			40	5	5	1	3	17	2				4,000
267		11	1			2		5	1	3	26	2		18		
268	1990	13	2			105	105	5	1	4		2	Bb Bb	12		30
269		10	2			252	221	5	3	6	33	2	Bb Ca	11		1,500
270		8	2			9		2	2	4	48	2	Ea Ea	12		10
271		11	3			325	11	2	1	3	22	4	Ea	15		
272		11	2			225	194	5	1	3	11	2		17		3
273		6	2			3	1	5	1	3	34	2		18		324
274		10	2			189	34	5	1	3	24	2		18		
275	1991	20	2			275	118	3	1	3	24	2	Aa Aa	1		14,000
276			2			50	38	5	1	7	10	2	Aa Aa	1		1,200
277		20	1			20	13	5	1	3	24	2	Aa Ab	7		4,500
278		12	2			25	7	2	3	7	20	4	Ab Ab	6		150
279		12	2			5	2	5	1	7	21	2	Ab Ca	7		320
280		12	2			29	29	5	1	3	38	2	Cb Cb	2		600
281			2			4	1	3	3	7	31	4	Cb Ea	4		250
282			2			172	68	3	3	4	11	4	Ea Ea	2		100,000
283			2			2		5	2	2		2	Eb Eb			
284		10	2			80	4	5	1	3	26	2	Ec	15		1,500
285		7	1			20		5	1	2	30	2				300
286		8	2			100	60	4	1	3	17	2				10,000
287		8	2			15	10	4	1	3	17	4				25
288		8	2			4		5	1	3	49	2		19		6
289		6	2			21	13	5	1	3	34	2		18		500
290		6	2			1		5	1	3	37	2		19		2
291			2			84	75	3	3	4	1	2		25		
292		13	2			485	485	2	3	3	24	2		25		7,000
293		8	2			10	1	5	1	3	24	2				30
294	1992	8	2			1000	400	2	1	3	34	4	Aa Ab	2		
295			2			128	98	2	1	2		2	Ab Ab			5,400
296			2			113	8	2	3	4	12	4	Ab Bb	2		
297		8	2			30	15	2	2	2	33	4	Bb Bb	5		
298		8	2			5	5	6	1	3	13	5	Ca Ca	2		10
299			2			275	248	2	3	4		4	Ca Da	11		1,100
300			2			5	1	2	2	8	22	4	Ec Ec	10		1,350
301		10	2			2		2	1	4	30					
302		8	3			200		5	1	3	25	2				300
303		24	2			13	1	5	1	2	27	4				250
304		6	2			3	3	4	1	3	49	2		15		2
305		12	2			75	75	5	1	3	28	2		23		
306		8	2			50	50	4	1	3	25	2				20
307		8	2			25	25	4	1	3	25	2				60

Spillage ID	Year	Pipe dia (")	Service	Fatalities	Injuries	Spillage volume (m^3)		Leak first detected by	Facility	Facility part	Age	Land use	Cause		Impact	
						Gross	Net loss				Years		Category	Reason	Water bodies	Contaminated land area (m^2)
308	1993	34	1			248	18	4	1	3	31	2	Aa	2		45,000
309			2			3		5	3	2	2	4	Ab Ab			80
310		12	2			2	1	1	1	4	23	4	Ca Cb			400
311		18	2			14	13	6	1	3	27	4	Cb Da			400
312		13	2			580	500	2	1	8	26	2	Ea Ea			800
313		20	1			2000	500	2	1	3	19	2	Ea Ea			25,000
314		26	2			10	7	5	1	3	31	5	Ec Ec	20	P	
315		9	2			8	6	5	1	3	30	2				50
316		24	2			49	39	5	1	3	33	2		18		40,000
317		8	2			3	1	5	1	3	37	2		19		100
318		12	2			101	19	5	1	3	31	2		19		
319		20	2			3050	1450	2	1	3	29	4				
320		7	2			3	3	5	1	3	13	1				6
321	1994	16	1			200	160	3	1	3	31	2	Ab Ab	2		6,000
322		16	1			1350	1295	2	1	3	31	2	Ab Ab	2		25,000
323		6	2			250	14	2	3	2	16	4	Ab Ba			50
324		6	2			1	1	1	1	3	16	4	Ca Cb	2		25
325		11	2			5	5	5	2	2	9	2	Ea Ea			100
326			1			2	2	5	3	8		4	Ea	9		100
327		12	3			90	60	5	1	3	24	2		14		
328		32	1			10	5	2	2	3	21	4				500
329		10	2			285	285	5	1	3	26	2		17		
330		9	2			195	170	3	1	3	37	2		18	P	8,000
331		8	2			46		5	1	3	36	2		17		1,150
332	1995		2			280	80	2	2	6	22	4	Aa Aa	7		10,000
333		10	2			30	30	5	1	2	35	2	Ab Ab	5		750
334			2			53	41	5	1	7	5	2	Bb Ca	2		
335		6	2			115		1	1	3	36	2	Ea Ea	2		500
336		16	1			132	82	3	1	3	30	2	Ea Ea	11		6,500
337		10	2			1000	270	1	1	3	31	4		15		55,000
338		9	2			48	18	3	1	3	28	2		17		1,500
339		9	2			20	20	3	1	3	39	4		17		100
340		13	2			139	113	5	1	3	5	2		17		300
341		6	2			12		3	1	3	37	2		17		30
342	1996	9	2			165	99	2	3	2	5	4	Ab Bb			40
343		14	2			292	209	5	1	3	40	1	Ca Ea	10		300
344		12	3			1		5	1	3	30	4	Ea Ec			16
345		9	2	1		437	343	2	1	3	40	4		19		20
346		7	2			19	19	5	1	3	40	2		17		350
347		10	2			500	62	5	1	3	64	4				23,000
348	1997	12	2			19	3	1	1	3	27	2	Ca Cb	14		2,800
349		10	1			2	0	1	1	2	7	4	Cc Cc			20
350		12	2			422	341	2	1	3	30	2	Ea Ec			
351		12	2			435	267	2	1	3	30	1			P	
352		8	2			13	2	2	1	4	33	2		19		150
353		12	2			40	1	5	1	3	24	4		17		
354	1998		1			30	4	2	3	5	30	4	Ab Bb	1		400
355		6	3			0	0	5	1	3	34	2	Bb Ca	11		
356		13	2			486	247	2	1	3	42	2	Ea Ea	11		100
357		16	2			250	20	5	1	3	30	4	Ea Ea	14		
358		10	2			340	313	3	1	3	6	1	Ea	17		500
359		10	2			15	14	1	1	3	4	2		19		600
360		9	2			176	67	3	1	3	42	2		18		160
361			2			30	2	3	1	7		2		19		650
362		8	2			0		5	1	3	25	2		19		4
363	1999		1			7		2	3	6		4	Bb Ca	11		200
364		1	3			30		2	1	3	32	4	Ca Ca	14		300
365		11	2			167	64	2	1	3	32	2	Ca Ea	14		60
366		6	2			1	1	3	1	3	25	2	Ea Ea	14		5
367		4	1			1	1	5	3	8	35	4	Eb Eb	14		
368		8	2			80	20	5	1	3	48	2	Ec	17		500
369		13	2			84	13	3	1	3	10	4		17		
370		6	2			29	14	5	1	3	40	2		18		
371		8	2	1		80	30	5	1	3	35	2		26		1,000
372		11	2			36	28	3	1	7	5	2		26		100
373		12	2			1		2	1	3	36	4				
374	2000		2			175	3	5	2	4	24	4	Ab Cb			60
375		12	1			10	7	5	1	3	30	4	Ea Ea			150
376		12	2			8	8	5	1	3	31	2	Ea Ec	17		
377		11	2			159	64	3	1	3	8	2		17		5,000
378		12	2			7	1	5	1	3	26	1		19		
379		24	2			1	1	5	1	3	41	2		19		150

Spillage ID	Year	Pipe dia (")	Service	Fatalities	Injuries	Spillage volume (m^3)		Leak first detected by	Facility	Facility part	Age	Land use	Cause		Impact	
						Gross	Net loss				Years		Category	Reason	Water bodies	Contaminated land area (m^2)
380	2001	20	1			800	8	5	2	8	35	2	Aa	5		10,000
381		10	2			1	1	5	1	2	39	2	Aa Ab	5		10
382		10	2			5	5	5	1	3	38	2	Ab Ab	2		500
383		6	2			37	7	4	1	1	27	2	Ca Ca	2		900
384		12	2			10	2	5	1	1	15	4	Cb Ea	2		120
385		34	1			6	1	3	1	3	29	4	Ea Ea	14		500
386		12	2			4	4	5	1	3	26	2	Eb Eb	14		1,000
387		13	1			103	50	2	3	8	23	4	Eb Eb			225
388		11	2			55	51	5	1	3	9	2		17		
389		10	2			10	1	5	1	3	11	2		17		
390		6	2			5	5	5	1	3	47	1		18		400
391		12	1			10	7	5	1	3	30	2		26		250
392		12	1			17	12	5	1	3	30	2		26		400
393		16	2			2	2	5	1	3	18	2		26		350
394		8	2			85	24	2	1	3	47	2		26	P	404
395	2002	8	2			10	10	5	1	3	47	2	Ab Ca			325
396		20	1			100		2	1	3	36	4	Ca Ca	15		500
397		10	2			80	20	5	1	3	38	4	Ca Ca	14		10,000
398		10	3			1		5	1	3	28	2	Cc Da	15		14,000
399		6	2			17		2	2	3	33	4	Ea Ea			400
400		8	2			70		2	1	2	?	4	Ea Ea			
401		13	2			225	58	3	1	3	46	2	Eb Ec			400
402		24	2			250	20	5	1	7	39	4		22		5,000
403		30	1			2		5	2	2	40	4		19		40
404		8	2			170	120	4	1	3	57	2		18		
405		16	1			750	45	1	1	3	39	2		17		20,000
406		20	1			280	30	5	1	3	40	2		17		12,000
407		12	1			40	15	5	1	3	33	2		26		6,000
408		8	2			190		3	1	3		4		19		
409	2003	14	2			30	30	3	1	8			Aa Ca			
410		20	4			2		2	1	3	52	4	Ea Ea		S	2
411		12	2			2		5	1	3	32	4	Ea Ea		S	5
412		11	2			83	74	3	1	3	46	3	Eb Eb	18		1,800
413		11	2			45	31	5	1	3	46	4	Eb Eb	17		600
414		6	2			2		3	1	8			Ec Ec			
415		11	2			74	49	3	1	8	46	3		26		500
416		16	1			5	5	1	1	3	41	5		26		120
417		16	2			28	10	5	1	3	29	2		26		400
418		16	2			52	3	4	1	3	29	2		26		400
419		12	2			11	7	4	1	3	45	4				800
420		20	2			2500	1100	5	1	3	31	6		19	P	80,000
421	2004	16	2			2	0	1	1	3	32	3	Aa Aa			4,000
422		10	2			26	18	2	2	7	40	2	Ab Ea			6,000
423		22	1			20	6	2	3	8	5	4	Ea			200
424		8	2			90	50	5	1	1	5	3		18		1,500
425		10	2					3	1	8	29	1				2,000
426	2005	12	2			19	19	2	3	4		3	Aa Aa	7		
427		12	2					5	1	2		4	Ab Ab	5	G	
428		20	1			350	10	3	1	8	45	2	Ab Bb	1	G	15,000
429		6	2			20		2	1	1	28	3	Bb Ca	4	S	58
430		6	2			38		5	1	1	28	3	Cb Ea	4	S	42
431		9	1			30	4	3	1	8	14	2	Ec	12	G	1,000
432		10	1			15		5	2	4	22	3		12		1,000
433		10	2			3	1	5	1	3	25	4		14	S	50
434		24	1			64	1	2	1	8	40	4			G	150
435		8	2			15	8	5	1	3	41	2		17	G	1,000
436		24	2			0		5	1	3	46			19	S G	3,000
437	2006	12	2			75		5	1	4	58	4	Ab Ab			50
438		8	2			6	6	2	1	4	19	4	Aa Ab	2		60
439		9	2			5		1	2	2	1	3	Ea Aa	7		
440		14	2			5		2	2	4		4	Ea Ab	2		
441		11	2			245		2	1	3	13	3	Cb Cb	18		
442		11	2		1	37		5	2	3		3	Eb Eb	5		
443		11	2			223		5	1	3		5		17		
444		13	2			4		1	2	7		4		1		
445		20	2			2		3	1	3		4			S G	
446		12	1			10	3	5	1	1	8	4				50
447		6	2			23		3	1	3	41	5		26	G	100
448		6	2			16		3	1	3	41	5		26	G	80
449	2007	8	2			150	70	3	1	3		4	Ec Ea	4		400
450		8	2			30	1	5	1	3		2	Eb Ea	17		2,000
451		11	2			12	10	2	1	4	28	3	Ea Eb	26		1,600
452		13	2			301	38	5	1	3	17	3	Ea Ca	19		452
453		9	2			117	54	2	1	3	50	3	Cb	19		120
454		9	2			2	2	5	1	3	16	3		26		100
455		11	2			182	133	5	1	3	50	3		19	S	500
456		13	2			185	159	2	1	3	50	3		14		1,200
457		16	1			7		5	3	3	40	3			S G	700

Spillage ID	Year	Pipe dia (")	Service	Fatalities	Injuries	Spillage volume (m^3)		Leak first detected by	Facility	Facility part	Age	Land use	Cause		Impact	
						Gross	Net loss				Years		Category	Reason	Water bodies	Contaminated land
458	2008	16	2			4	4	6	1	3	40	4	Aa Ab	5		25
459		40	1			6		5	2	7	36	7	Ab Ab	2		
460		11	2			30		3	3	5	29	4	Aa Ab	2		40
461		11	2			52	37	3	1	4	29	3	Ea Ea	4		50
462		11	2			12		1	2	4	20	4	Ea Ea	7		
463		11	2			129	108	3	1	3	29	3	Ab Ca	2		90,000
464		9	2			44	17	3	1	3	16	3		17		
465		6	2			40		2	1	3	52	4				3,600
466		4	2			28		5	1	3		3		18		
467		16	1			294		3	1	3	46	4		17		5,000
468		16	1			328		3	1	3	46	4		4		250
469		18	1			1	1	5	1	3	1972	2		14	S	11,00

APPENDIX B

PIPELINE INSPECTION TECHNIQUES

Inspection Techniques

In the last decade a variety of technologies have been developed; to assess pipeline conditions and to accurately detect any metal loss. Most of the new developed technologies are for inline inspection. Pipeline inspection categories are illustrated in figure 2.4.

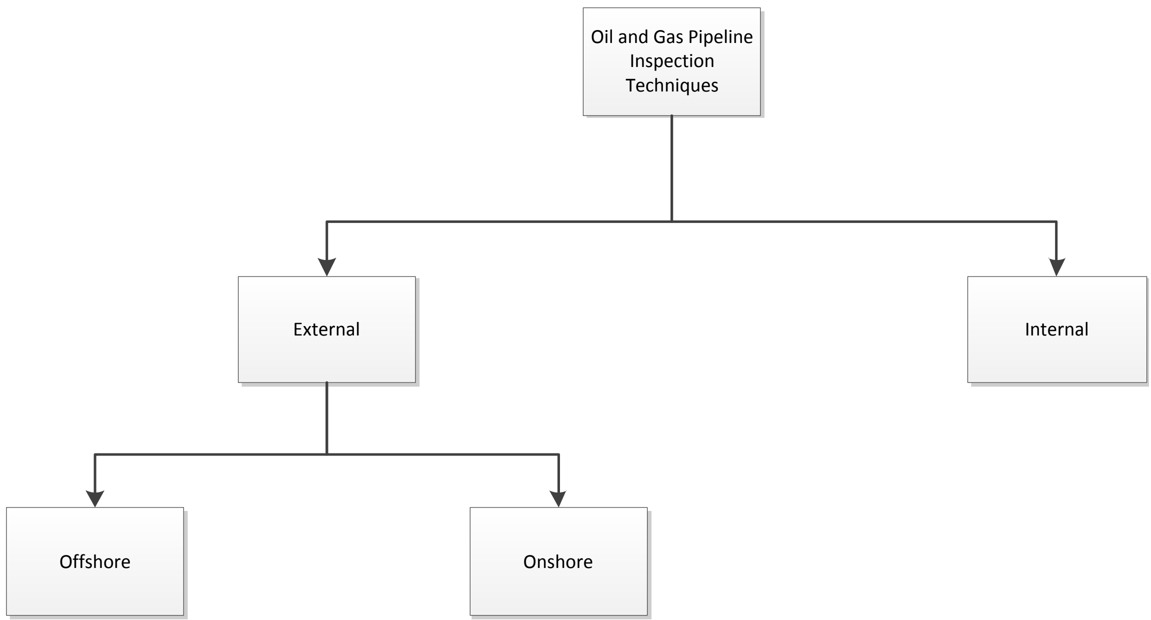


Figure 0-1 **Oil and Gas Pipeline Inspection Techniques**

External Inspection for Pipeline

The majority of aging pipelines cannot be internally inspected (unpiggable) due to the absence of pig launcher or receiver. That makes external inspection the only way to assess these pipelines (Ali, 2011). External inspection is also used for offshore pipelines to observe external data such as sea bed activity.

External Inspection for Offshore Pipeline

Remote Operated Vehicle R.O.V.

ROV is an underwater robot that allows vehicle operators to remain a safe place while the vehicle works in the hazardous environment below. ROV is a vehicle connected to the control van and the operator on the surface by an umbilical cable which carries the power and control signals to the vehicle. This cable also conveys the sensory data back to the operator topside. ROV system is also comprised of; a handling system to control dynamic cables, a launch system and associated power supplies (Remotely Operated Vehicle Comittee of the Marine Technologie Socitey, 2011). The cost of ROV per hour including the operation ship is 80$ (Husein, 2011).

ROV can detect several types of defects for pipelines such as (Ali, 2011):

- Cathodic protection.
- Visual external condition.
- Free span existence.
- Dents existence.
- Detect leak.
- Sea bed profile.

ROV is a non-expensive and safe inspection techniques but it does not give any information about corrosion or remaining wall thickness.

Figure 0-2 ROV (Remotely Operated Vehicle Comittee of the Marine Technologie Socitey, 2011)

The Autonomous Underwater Vehicle AUV

AUV is similar to ROV but it not attached with cable to the vessel, which gives AUV the advantage to run freely around the pipeline guided with integrated GPS. It is comprised of a battery and it is usually equipped with a sonar camera and a data storage system. It is a safe inspection technique it does not require system shut down (Teledyne Gavia).

AUV can detect the following pipeline conditions:

- Cathodic protection.
- Visual external condition.
- Free span existence.
- Dents existence.
- Leak detection.
- Sea bed profile

Figure 0-3 shows the composition of an AUV (Teledyne Gavia)

Divers

Divers are the oldest inspection method for pipelines, they are the best way to inspect pipeline externally. Divers are a very expensive. There is a need to perform a number of safety procedures to ensure the safety of the diver. Temporary shutdown is mandatory before using divers (Ali, 2011). Divers use two underwater inspection techniques, as follow:

General Visual Inspection (GVI)

This is the most common inspection technique and gives a general impression about the pipeline, then a set of important points are chosen to do detailed inspection.

Close View Inspection (CVI)

Which is a detailed inspection done for the chosen points selected on the GVI. Divers use equipment such as UT to measure the remaining wall thickness of the pipeline or CP meter to measure Cathodic protection (Dale, 2002).

Divers are an expensive inspection solution. A diver cost 200 $ per hour and more for deep water. Also diver productivity is low because of frequent breaks needed (Husein, 2011).

Divers can detect and measure all of the following characteristics:

- Cathodic protection
- Visual external condition.
- Free span existence.
- Dents existence.
- Leak detection.
- Remaining Wall thickness using UT.
- Geometrical measurements and ovality

External Inspection for Onshore Pipeline

External inspection for onshore pipelines is usually used for unpigable and above ground pipeline. It also used to verify anomalies detected by in line inspection. We will discuss in this section the different types of external inspection methods for onshore pipelines.

Direct Current Voltage Gradient (DCVG)

DCVG is used mainly for detecting pipeline coating defects that cause external corrosion. The technique is based on measuring the voltage gradients in the soil above a cathodically protected pipeline. It is suitable for buried pipelines. It can be used across asphalt, concrete, desert and rocky terrain. It is also unaffected by stray currents, induction and static. DCVG is used for (Southern Cathodic Protection Company, 2007):

- Accurately locates coating defects.

- Estimates defects sizes.
- Identifies priorities for excavation.
- Provides data for CP adjustment/upgrading.
- Enables coating deterioration to be monitored.
- Confirms electrical continuity and can locate shorts.

Figure 0-4 DCVG inspection and tool (Southern Cathodic Protection Company, 2007)

Close Interval Pipe to Soil Potential CIPS

CIPS is a technique used for the detailed analysis of cathodic protection systems in underground pipelines. A continuous measurement of pipeline potentials is done regarding the copper/copper sulphate reference anode. The pipeline potentials are recorded with switched on and off potentials to eliminate IR errors in measurements caused by current flow (PROTAN, 2007).

Usually CIPS is done with DCVG by the same inspector who caries both equipment for the two tests because usually CP failure exists with coating failure .CIPS is used for (PROTAN, 2007):

- Identification of zones with inadequate cathodic protection levels
- Identification of zones with excessive cathodic protection levels

- Identification of zones with possible defects in coating quality

- Identification of zones affected by possible electrical interference

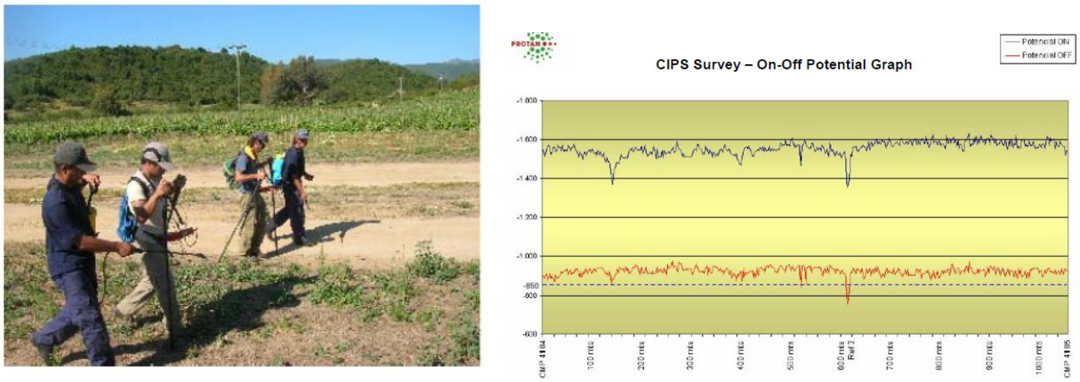


Figure 0-5 CIPS Performance and Results (PROTAN, 2007)

Soil Resistivity Test

The resistance to the earth of any earth electrode is influenced by the resistivity of the surrounding soil. Resistivity of soil depends mainly on the nature of soil and the moisture content. Soil resistivity may change with depth, temperature and also vary from place to place depending on the strata of soil and rock formation (Johnson, 2006) . Soil resistivity is one of the main factors that could cause external corrosion because the lower soil resistivity; the higher will be the corrosion. Low soil resistivity is a challenging problem for pipeline operators in the gulf especially Saudi Arabia because of the high corrosivety of soil at AlSabgha zone (Salah, 2011).

Wenner four pin method is the most widely used test to determine soil resistivity

(Farwest Corrosion Company, 2011). The test is performed by driving four electrodes into the ground along a straight line separated with equal distance as shown in figure 2.9. Soil resistivity can be calculated as a function from the voltage drop between the center pair of pins, with the current flowing between the two outside pins (Lightning and Surge Technologies).

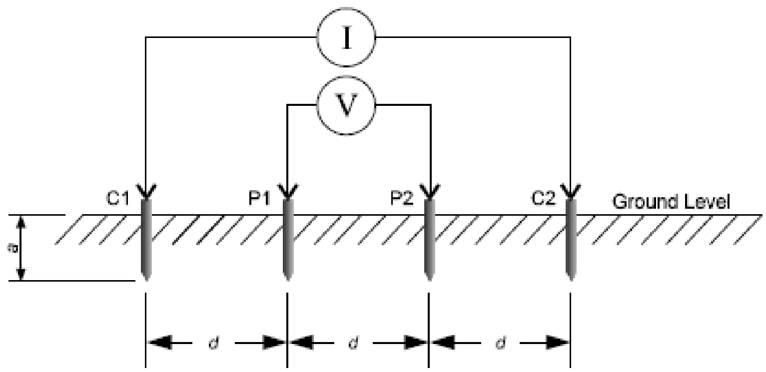


Figure 0-6 Wenner 4 Pin Test test (Lightning and Surge Technologies)

Ultrasound Inspection UT.

Ultra sound is the most common and reliable technique for detecting cracks and metal loss in pipeline because it is a direct measurement for wall thickness. UT is not interpretation of magnetic field distortion as in MFL. UT uses high frequency sound energy to do measurement. A UT inspection system consists of several units, such as pulsar /receiver which is an electronic unit that produce high voltage electrical pulses. The transducer generates high frequency ultrasonic energy; this sound energy propagates through in the form of waves. A discontinuity (such as a crack) in the wave path cause that a part of the energy will be reflected back from the flaw surface. The reflected wave signal is transformed into an electrical signal by the transducer and is displayed on the screen. This also indicates any metal loss due to corrosion (NDT Resource Center).

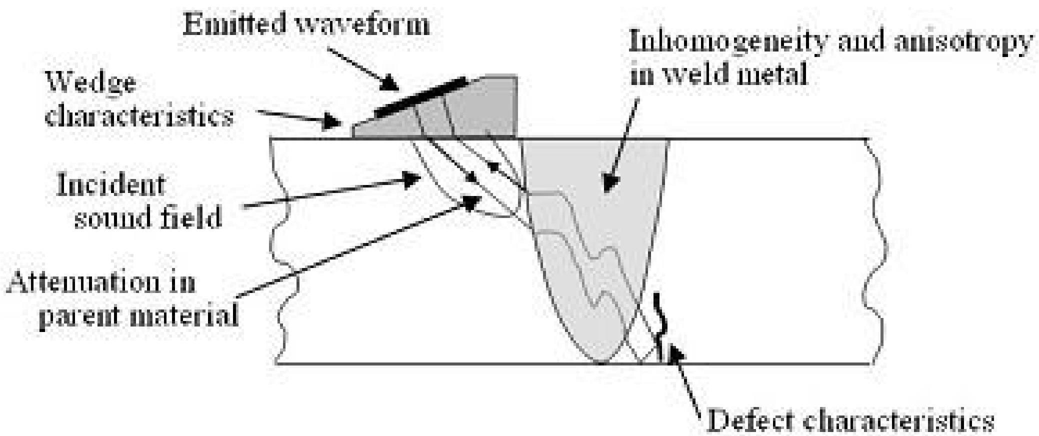


Figure 0-7 The Ultrasonic Technique (Komura, et al., 2009)

There are several forms of ultrasound devices depending on the position of transmitted waves.

Ultra sound inspection is used for:

- Measuring the remaining wall thickness
- Detecting corrosion
- Detecting cracks

Eddie Current Test.

Eddie current test (ET) is a Non Destructive Test (NDT) with electromagnetic technology. It can be used only on conducting materials. An energized coil is brought near the surface of steel pipeline that induce the eddy current in the specimen .The induced eddy current sets up a magnetic field in the specimen that tend to oppose the original magnetic field .The impedance in the coil is alerted when the eddy current is distorted by flaws or any material variation. Eddy current test is an external inspection method which makes it suitable for unpiggable pipeline (Bickerstaff, et al.).

Eddie current is used for the following:

- Cracks
- Laminar defects
- Assessing wall thicknesses

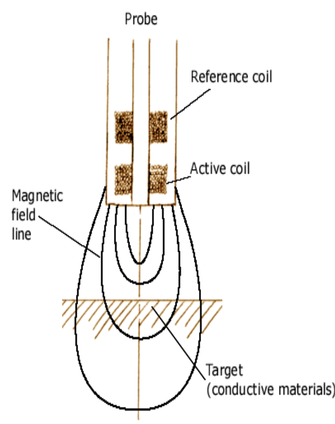


Figure 0-8 Eddy Current Technique (Efunda, 2011)

Acoustic Emission AE

In this technique one or more ultrasonic transducers are attached to the pipeline permanently. Then the sounds generated into the system using computer-based instruments are analyzed. There is no pigging needed in that method and the pipeline can be tested without taking it out of service or interrupting the product flow. It can be used in continuous monitoring with alarm systems .

AE is used for the following purposes (Bickerstaff, et al.):

- Crack growth
- Turbulence (including leakage)

- Material changes such as corrosion

In Line Inspection (ILI)

Inline inspection contains very accurate techniques for pipeline inspection but it is very expensive. In this section we will show the various In line Inspection ILI techniques.

Gauging Pig

Intelligent pigs such as ultrasonic pigs or MFL pigs are very expensive and they could be damaged or stuck if the internal condition of pipeline is not suitable. Gauging pig is usually used for pipelines with no previous pigging history or when there are doubts as to the internal pipeline condition. Gauging pig runs into the pipeline to ensure that other pigs can traverse the pipeline from the launcher to the receiver. Pipeline gauging detects any internal restriction and indicates if a pipeline needs more extensive cleaning pigs. Gauging is performed by fitting a pig with aluminum plate, sized to approximately 90% of internal pipeline diameter (Pig Tek Limited, 2010) .

The figure below shows gauging pig with damaged aluminum plate due to debris found in the pipeline.

Figure 0-9 A Gauging Pig After An Internal Run (Pig Tek Limited, 2010)

Calliper Pig

Calliper pigs are used to determine the geometric properties prior of using intelligent inspection pigs. Calliper pigs have an array of levers mounted on one of the pig cups. Levers are connected to recording device located on the pig body. The body is usually 60% of the pipeline diameter. The body is combined of flexible cups that allow the pig to pass constriction up to 15% of bore. Calliper pigs are very important to use in offshore pipeline (Guo, et al., 2005).

Cleaning Pig

A cleaning pig is used for cleaning the pipeline from solid and accumulated debris to increase the efficiency of operation they are also commonly used before intelligent piging in order to prevent other pig from being stuck. They use rotary wire wheel brushes (Guo, et al., 2005)

Magnetic Flux Leakage MFL

MFL could be used for oil and gas pipeline. The technology is based on creating a magnetic field between the tool (pig) and the pipe wall. Magnetic flux will leak out the pipe wall if there is any defect. The relative magnitude of the signal depends on the strength of permanent magnet, the wall thickness and the proximity of sensor device (Russell, et al.). MFL is used to detect internal and external corrosions. It works by magnetizing the pipe wall near saturation flux density that generates a steady magnetic field. If there are any corrosions, pits or cracks the field that will come out will indicate the amount of leakage of field and will be measured by sensors. The output data from the sensors is analysed by experts to calculate the amount of metal loss.

Pipelines should be cleaned before using the MFL because sensors should be very close to the wall thickness and sensors could be damaged if pipeline is not cleaned. Calibre pig should also be used to check pipeline pigability and valves prior to MFL (Russell, et al.).

MFL is influenced by tool and sensor lift off, tool speed, line pressures, corrosion pits, and welds. In general the MFL has low sensitivity to external defects and poor sensitivity to cracks (Mergelas, et al., 2007)

Despite the fact that magnetic flux is less accurate than the Ultrasound pig, it is preferable to use in oil pipeline because of the simplicity of the interpretation of its result (Ali, 2011).

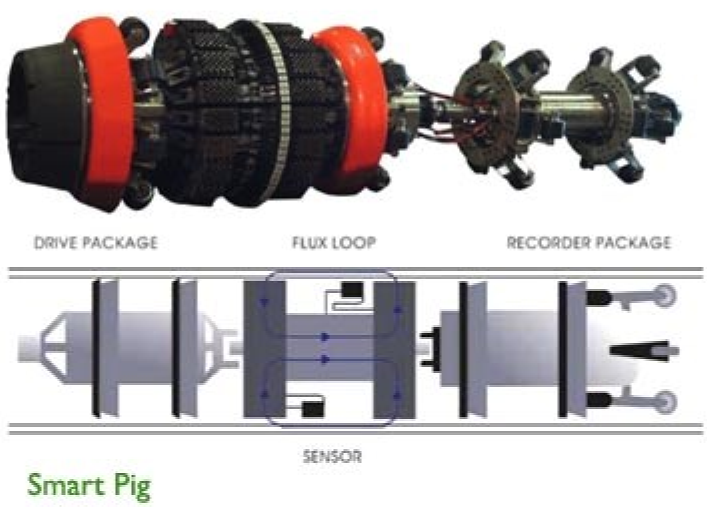


Figure 0-10 MFL Composition ((Pacicif L.A Marine Terminal, 2011)

MFL is used for the following (Bickerstaff, et al.):

- Detecting missing material, whether iron that has actually been removed or corrosion that - turns steel into non-ferromagnetic iron oxide.

- Detecting anomaly geometry or mechanical damage.

Ultrasonic Pig (U.T.)

Ultrasonic technology is used sometimes because MFL is not accurate enough to calculate the remaining the strength well enough, although Ultrasonic technology is more expensive and need liquid filled pipeline (Teitsma, 2004). Ultrasonic technology uses sound waves of short wave length with high frequency to detect flaws or measure wall thickness (Bickerstaff, et al.).

Ultrasonic technology can detect and measure stress corrosion cracking (SCC). As we mentioned before conventional Ultrasonic pig cannot inspect gas pipeline because it needs liquid coupling to get signal in and out the wall. To overcome this problem ultrasound pig could be injected into pipeline in a liquid slug (Teitsma, 2004).

UT is used for the following (Bickerstaff, et al.)**:**

- Internal/External metal loss
- Longitudinal channelling
- Blisters/Inclusions
- Deformations
- Flanges
- Laminations (sloping & hydrogen induced)
- Cracking
- Weld characteristics
- Wall thickness variations

- Usable on bends, tees, and valves

Invista Inspection

This is an ultra sound in line inspection tool designed for unpiggable pipeline. It is used now by several pipeline operators in gulf such as ARAMCO and Qatar Petroleum (Ali, 2011). Usually unpigable pipelines have small diameters, sharp elbows and reduced port valves. To overcome this problem Quest Company has designed InVista pig with small diameter (3 inches) and high flexibility. InVista uses ultrasonic sensors to detect wall thickness loss and cracking with high accuracy (Quest Integrity Group, 2011).

Figure 0-11 Invista Tool Dealing With Sharp Elbow (Quest Integrity Group, 2011)

Electromagnetic Acoustic Transducer EMAT

EMAT pigs were developed to detect and measure cracks specially Stress Corrosion Cracking SCC. EMATS pigs generates Ultrasound waves but without contacting the pipeline surface to do so. EMAT consists of a coil in a magnetic field placed at the internal surface of the pipe wall. This coil induces alternating current in the pipeline wall, causing Lorentz forces (forces acting on moving charges in magnetic fields), which generate ultrasound. It works by the same technique of ultrasonic except the way of generating ultrasound waves. One of the main advantages of this technique that it does not need a gas coupling to inspect gas pipelines and it gives results more accurate than

MFL results. That makes it usable at gas pipeline (Teitsma, 2004).

EMAT is used for the following**:.**

- Internal/External metal loss
- Longitudinal channelling
- Blisters/Inclusions
- Deformations
- Laminations (sloping & hydrogen induced) Cracking
- Weld characteristics
- Wall thickness variations

Elastic Wave Vehicle

Elastic wave vehicle was developed in 1993. It uses liquid filled wheel to inject ultrasound into the pipeline wall in the circumferential direction. EWV can detect cracks larger than 25% of the pipeline wall thickness and greater than 2” long. It also has good results in detecting coating disbondment. It is also effective in detecting stress corrosion cracking. However it generates many false positives that need too much verification digs (Teitsma, 2004).

EWV is used for the following **:**

- Stress corrosion cracks SCC.
- coating disbandment.

Remote Field Eddy Current REFC

This technique is suitable for unpiggable pipeline because its entire component can be made much smaller than the pipeline to be inspected. In this technique the current transmitted by the exciter coil is received by the sensor coil which can determine any defect represented by any change in the field propagation. The main disadvantages of the REFC are; the high power consumptions and the low speed of inspection (2 Mph or less. (Teitsma, 2004)

APPENDIX C

SPSS RESULT FOR ANN MODELS

ANN MODEL FOR 2 OUTPUTS

Notes

Output Created		26-Apr-2012 18:25:26
Comments		
Input	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	180
Missing Value Handling	Definition of Missing	User- and system-missing values are treated as missing.
	Cases Used	Statistics are based on cases with valid data for all variables used by the procedure.
Weight Handling		not applicable
Syntax		MLP output (MLEVEL=N) BY service landuse facility WITH age diainch /RESCALE COVARIATE=STANDARDIZED /PARTITION TRAINING=8 TESTING=2 HOLDOUT=0 /ARCHITECTURE AUTOMATIC=NO HIDDENLAYERS=1 (NUMUNITS=26) HIDDENFUNCTION=TANH OUTPUTFUNCTION=IDENTITY /CRITERIA TRAINING=BATCH OPTIMIZATION=GRADIENTDESCENT LEARNINGINITIAL= 0.05 MOMENTUM= 0.9 INTERVALCENTER=0 INTERVALOFFSET=0.5 MEMSIZE=1000 /PRINT CPS NETWORKINFO SUMMARY CLASSIFICATION IMPORTANCE /PLOT ROC /OUTFILE MODEL='C:\Users\Bassem\Desktop\ann 2out fin in shaa alla.xml' /STOPPINGRULES ERRORSTEPS= 20 (DATA=AUTO) TRAININGTIMER=ON (MAXTIME=15) MAXEPOCHS=AUTO ERRORCHANGE=1.0E-4 ERRORRATIO=0.0010 /MISSING USERMISSING=EXCLUDE .
Resources	Processor Time	00 00:00:01.295
	Elapsed Time	00 00:00:01.473
Files Saved	Model File	C:\Users\Bassem\Desktop\ann 2out fin in shaa alla.xml

[DataSet1]

Case Processing Summary

		N	Percent
Sample	Training	150	83.3%
	Testing	30	16.7%
Valid		180	100.0%
Excluded		0	
Total		180	

Network Information

Input Layer	Factors	1	service
		2	land use
		3	facility
	Covariates	1	age
		2	dia/inch
	Number of Units[a]		10
	Rescaling Method for Covariates		Standardized
Hidden Layer(s)	Number of Hidden Layers		1
	Number of Units in Hidden Layer 1[a]		26
	Activation Function		Hyperbolic tangent
Output Layer	Dependent Variables	1	output
	Number of Units		2
	Activation Function		Identity
	Error Function		Sum of Squares

a. Excluding the bias unit

Model Summary

Training	Sum of Squares Error	21.511
	Percent Incorrect Predictions	20.7%
	Stopping Rule Used	20 consecutive step (s) with no decrease in error
	Training Time	00:00:00.248
Testing	Sum of Squares Error	5.463
	Percent Incorrect Predictions	26.7%

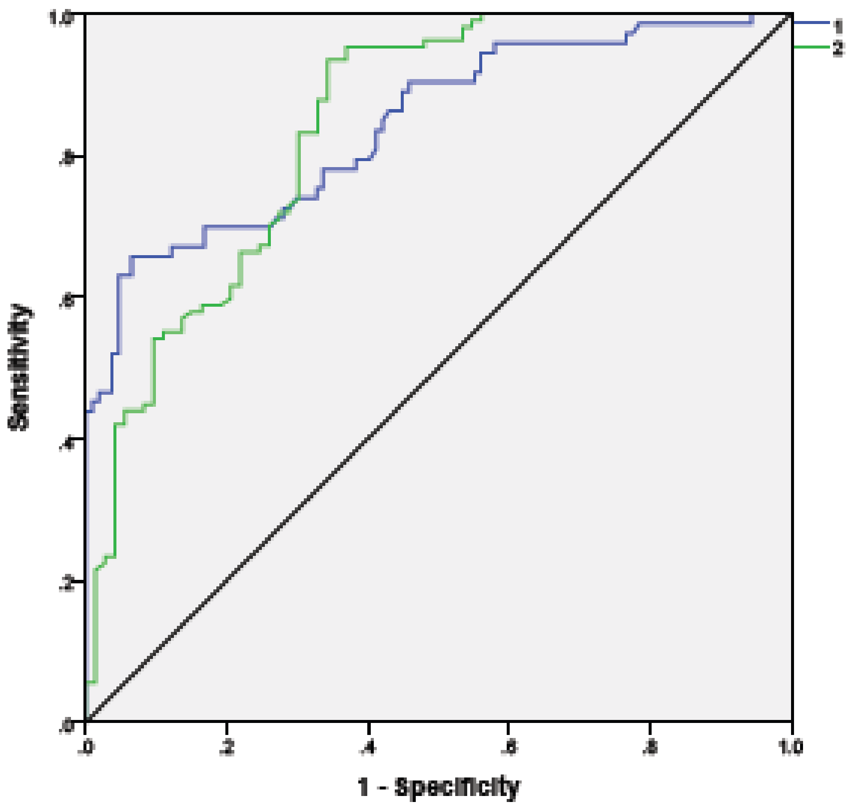
Dependent Variable: output

a. Error computations are based on the testing sample.

Classification

Sample	Observed	Predicted 1	Predicted 2	Predicted Percent Correct
Training	1	32	26	55.2%
	2	5	87	94.6%
	Overall Percent	24.7%	75.3%	79.3%
Testing	1	7	8	46.7%
	2	0	15	100.0%
	Overall Percent	23.3%	76.7%	73.3%

Dependent Variable: output



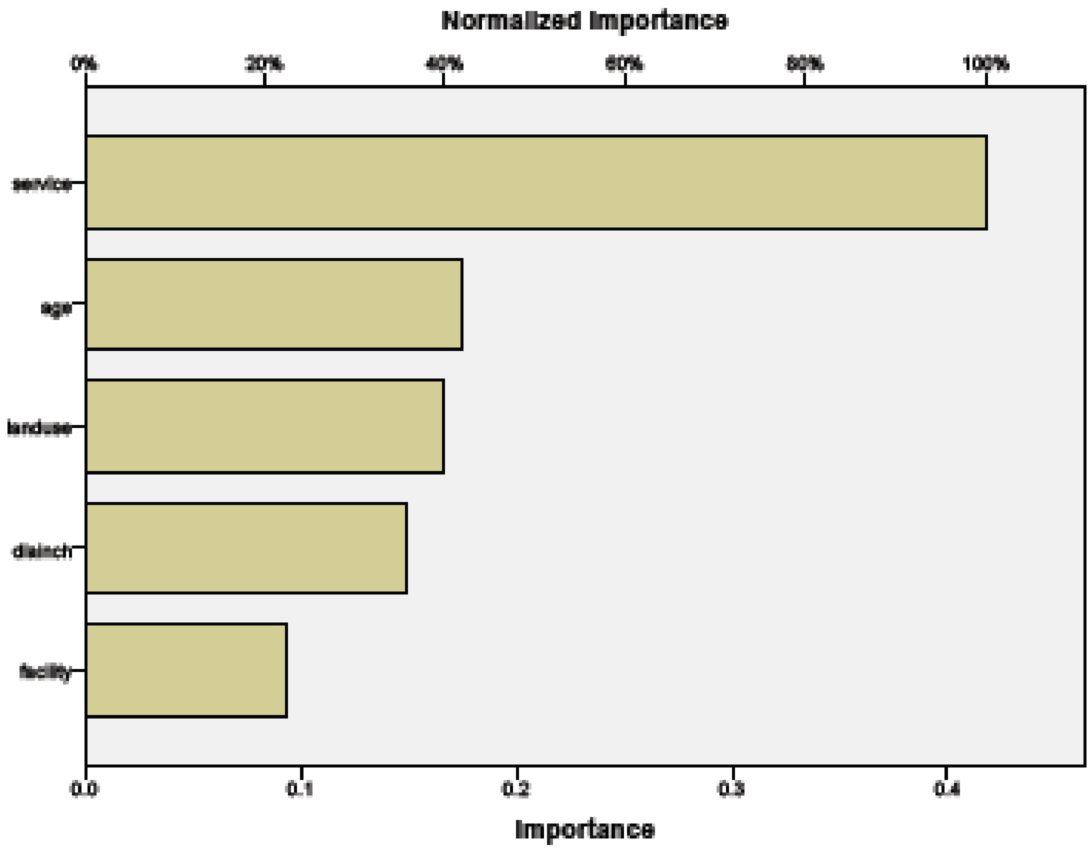
Dependent Variable: output

Area Under the Curve

		Area
output	1	.842
	2	.842

Independent Variable Importance

	Importance	Normalized Importance
service	.418	100.0%
land use	.166	39.8%
facility	.093	22.2%
age	.174	41.8%
dia/inch	.149	35.7%



ANN MODEL FOR 3 OUTPUTS

Notes

Output Created		19-Apr-2012 13:29:14
Comments		
Input	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	232
Missing Value Handling	Definition of Missing	User- and system-missing values are treated as missing.
	Cases Used	Statistics are based on cases with valid data for all variables used by the procedure.
Weight Handling		not applicable
Syntax		MLP output (MLEVEL=N) BY service facility landuse WITH disinch age /RESCALE COVARIATE=STANDARDIZED /PARTITION TRAINING=8 TESTING=2 HOLDOUT=0 /ARCHITECTURE AUTOMATIC=NO HIDDENLAYERS=1 (NUMUNITS=35) HIDDENFUNCTION=TANH OUTPUTFUNCTION=IDENTITY /CRITERIA TRAINING=BATCH OPTIMIZATION=GRADIENTDESCENT LEARNINGINITIAL= 0.05 MOMENTUM= 0.9 INTERVALCENTER=0 INTERVALOFFSET=0.5 MEMSIZE=1000 /PRINT CPS NETWORKINFO SUMMARY CLASSIFICATION IMPORTANCE /PLOT NETWORK ROC PREDICTED /OUTFILE MODEL='C:\Users\Bassem\Desktop\3Out gradiant ann.xml' /STOPPINGRULES ERRORSTEPS= 10 (DATA=AUTO) TRAININGTIMER=ON (MAXTIME=3) MAXEPOCHS=1000 ERRORCHANGE=1.0E-4 ERRORRATIO=0.0010 /MISSING USERMISSING=EXCLUDE .
Resources	Processor Time	00:00:00:02.886
	Elapsed Time	00:00:00:05.474
Files Saved	Model File	C:\Users\Bassem\Desktop\3Out gradiant ann.xml

Case Processing Summary

		N	Percent
Sample	Training	190	81.9%
	Testing	42	18.1%
Valid		232	100.0%
Excluded		0	
Total		232	

Network Information

Input Layer	Factors	1	service
		2	facility
		3	land use
	Covariates	1	dia/inch
		2	age
	Number of Units[a]		10
	Rescaling Method for Covariates		Standardized
Hidden Layer(s)	Number of Hidden Layers		1
	Number of Units in Hidden Layer 1[a]		35
	Activation Function		Hyperbolic tangent
Output Layer	Dependent Variables	1	output
	Number of Units		3
	Activation Function		Identity
	Error Function		Sum of Squares

a. Excluding the bias unit

Model Summary

Training	Sum of Squares Error	47.459
	Percent Incorrect Predictions	35.3%
	Stopping Rule Used	10 consecutive step (s) with no decrease in error
	Training Time	00:00:00.400
Testing	Sum of Squares Error	9.222
	Percent Incorrect Predictions	26.2%

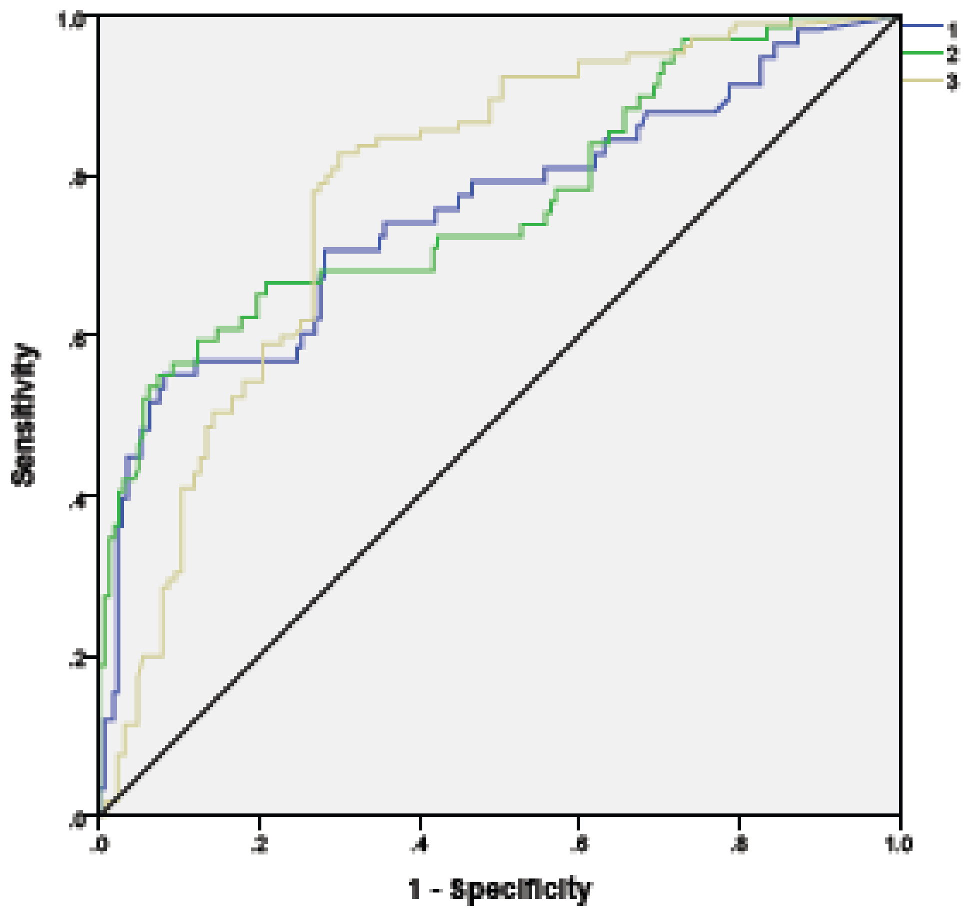
Dependent Variable: output

a. Error computations are based on the testing sample.

Classification

		Predicted			
Sample	Observed	1	2	3	Percent Correct
Training	1	26	2	22	52.0%
	2	5	26	26	45.6%
	3	9	3	71	85.5%
	Overall Percent	21.1%	16.3%	62.6%	64.7%
Testing	1	5	0	3	62.5%
	2	2	5	5	41.7%
	3	1	0	21	95.5%
	Overall Percent	19.0%	11.9%	69.0%	73.8%

Dependent Variable: output



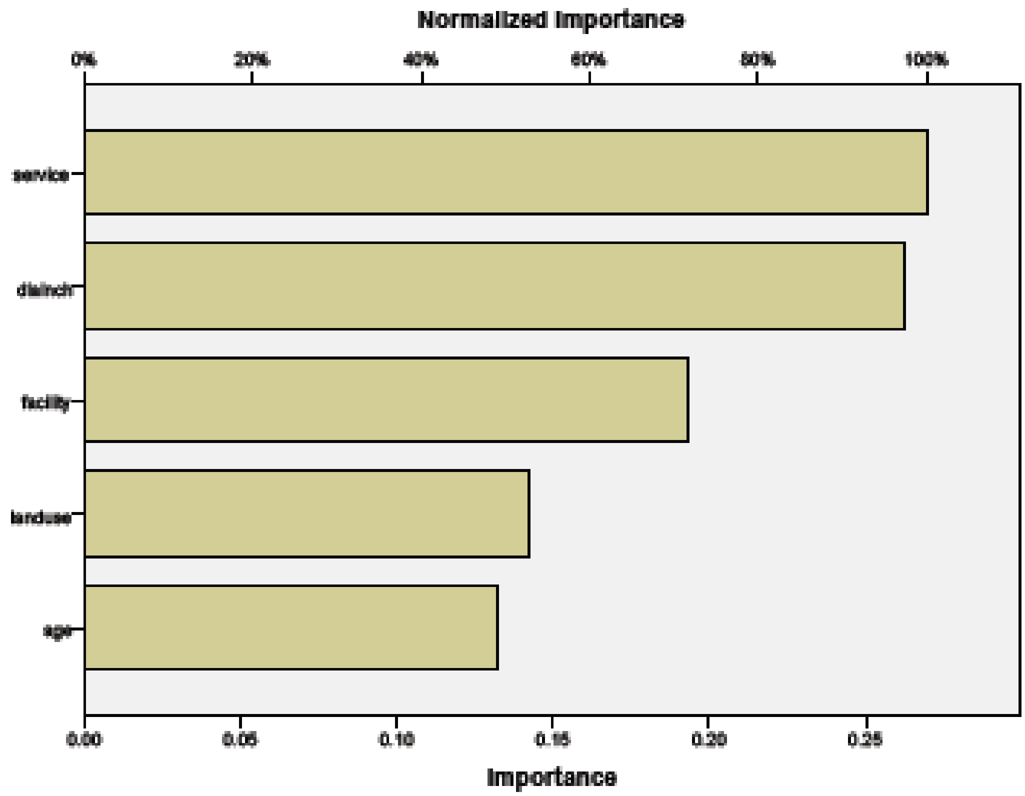
Dependent Variable: output

Area Under the Curve

		Area
output	1	.754
	2	.767
	3	.782

Independent Variable Importance

	Importance	Normalized Importance
service	.270	100.0%
facility	.193	71.7%
land use	.142	52.8%
dia/inch	.263	97.4%
age	.132	48.9%


Normalized Importance
0%
20%
40%
60%
80%
100%
service
dialnch
facility
landuse
age
0.00
0.05
0.10
0.15
0.20
0.25
Importance

APPENDIX D

SPSS RESULT FOR MNL MODEL

Case Processing Summary

		N	Marginal Percentage
output	1	58	25.0%
	2	69	29.7%
	3	105	45.3%
service	1	64	27.6%
	2	142	61.2%
	3	26	11.2%
facility	1	213	91.8%
	2	19	8.2%
land use	1	153	65.9%
	2	12	5.2%
	3	67	28.9%
Valid		232	100.0%
Missing		0	
Total		232	
Subpopulation		210[a]	

a. The dependent variable has only one value observed in 207 (98.6%) subpopulations.

Model Fitting Information

	Model Fitting Criteria	Likelihood Ratio Tests		
Model	-2 Log Likelihood	Chi-Square	Df	Sig.
Intercept Only	489.091			
Final	387.592	101.499	14	.000

Pseudo R-Square

Cox and Snell	.354
Nagelkerke	.402
McFadden	.205

Likelihood Ratio Tests

Effect	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	387.592[a]	.000	0	.
age	389.872	2.279	2	.320
diainch	399.623	12.031	2	.002
service	436.608	49.016	4	.000
facility	404.405	16.813	2	.000
landuse	398.546	10.954	4	.027

The chi-square statistic is the difference in -2 log-likelihoods between the final model and a reduced model. The reduced model is formed by omitting an effect from the final model. The null hypothesis is that all parameters of that effect are 0.

a. This reduced model is equivalent to the final model because omitting the effect does not increase the degrees of freedom.

Parameter Estimates

output[a]	B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B)	
							Lower Bound	Upper Bound
Intercept	2.005	1.495	1.798	1	.180			
Age	-.008	.015	.313	1	.576	.992	.963	1.021
diainch	.097	.032	9.249	1	.002	1.102	1.035	1.173
[service=1]	-1.453	1.326	1.201	1	.273	.234	.017	3.144
[service=2]	-1.493	1.277	1.366	1	.242	.225	.018	2.746
[service=3]	0[b]	.	.	0	.	.	.	.
[facility=1]	-2.351	.703	11.169	1	.001	.095	.024	.378
[facility=2]	0[b]	.	.	0	.	.	.	.
[landuse=1]	-.193	.444	.190	1	.663	.824	.345	1.968
[landuse=2]	.044	.798	.003	1	.956	1.045	.219	4.993
[landuse=3]	0[b]	.	.	0	.	.	.	.
Intercept	3.949	1.438	7.543	1	.006			
Age	.016	.014	1.292	1	.256	1.016	.988	1.046
diainch	.008	.033	.057	1	.812	1.008	.944	1.076
[service=1]	-3.358	1.103	9.263	1	.002	.035	.004	.303
[service=2]	-4.500	1.076	17.485	1	.000	.011	.001	.092
[service=3]	0[b]	.	.	0	.	.	.	.
[facility=1]	-.307	.908	.115	1	.735	.735	.124	4.359
[facility=2]	0[b]	.	.	0	.	.	.	.
[landuse=1]	-1.213	.411	8.717	1	.003	.297	.133	.665
[landuse=2]	-1.823	1.122	2.637	1	.104	.162	.018	1.458
[landuse=3]	0[b]	.	.	0	.	.	.	.

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a. The reference category is: 3.

b. This parameter is set to zero because it is redundant.

Classification

Observed	Predicted			
	1	2	3	Percent Correct
1	25	4	29	43.1%
2	5	33	31	47.8%
3	6	6	93	88.6%
Overall Percentage	15.5%	18.5%	65.9%	65.1%