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Data Analysis for Improved Risk Assessment in

Underground Pipelines

By

Francisco Anes-Arteche

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In the

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To my wife, Yuan and my parents and brothers

BRUNEL UNIVERSITY LONDON

Abstract

College of Engineering, Design and Physical Sciences

Engineering Doctorate

by Francisco Anes-Arteche

This thesis describes research relating to data analysis for improved risk assessment in buried pipelines. The kind of pipelines being considered includes onshore underground pipelines. External corrosion in buried pipelines is often complex to understand due to the diversity of factors affecting the corrosion process and in many cases, these pipelines operate in hostile environments. They may be less susceptible to failure and their failure may have different consequences in relation to aboveground pipelines. However, there is a limitation with respect what inspection techniques are efficient and therefore the assessment process is more difficult to be carried out.

One of the major integrity risks to aging pipelines is the degradation and failure of the protective coating, leading to external corrosion. A commonly used approach for the assessment of external corrosion risk of buried pipelines is based on measurements from indirect inspections which are used to assess the likelihood of external corrosion. The underlying assumption is that indirect measurements can provide data to reliably identify corrosion defects on the pipeline, and prioritise defects according to their risk to pipeline integrity.

One established method to determine the condition of the pipeline coating is to use an above-ground technique, such as DCVG, to locate the severity of the any coating defects, that may be present on a pipeline. Whilst the location aspect of this technique is very accurate and reliable, the severity may not correlate very well with the actual size of the

coating defect when examined after excavation. Therefore, there is a need to refine the coating defect sizing model to provide a better indication of the severity of coating defects. However, there is little available research carried out to investigate this in a systematic manner. A further area of uncertainty relates to the correlation between the indirect inspection measurements, and the severity of the corrosion found following excavation. The development and refinement of regression models to address this link is required to ensure better corrosion predictions and improved inspection plans.

The aim of the research described in this thesis is to analyse the external corrosion phenomenon in underground pipelines through the analysis of data from inspection reports and soil surveys. This aim has been achieved through specific studies at TWI, two of which are described in this thesis.

The contribution to knowledge of the research included in this thesis is the improvement on the understanding of pipeline coating condition and external corrosion phenomenon in underground pipelines through the analysis of data from inspection reports and soil survey. Also, the identification of key factors affecting external corrosion along the probability distribution function, including factors that affect the initiation of corrosion and factors which have more importance in cases of severe corrosion.

The novelty of the research herein presented relies in the application of quantile regression to pipeline data combined with soil properties which has never been applied before. The results improve the understanding of pipeline coating condition and external corrosion in underground pipelines. Also, it proposes suggestions for improving the interpretation of the NACE ECDA SP-0502 standard which may lead to significant savings in the pipeline industry.

Keywords: Quantile Regression, ECDA, DCVG, Pipeline Corrosion, Underground Pipeline, Data Analysis.

Acknowledgements

The research presented here was made possible by funding from the National Structural Integrity Research Centre (NSIRC) and TWI Ltd, for which I am grateful.

I am very grateful to my supervisors Professor Keming Yu, Drs Ujjwal Bharadwaj, Chi Lee and Bin Wang for their support and encouragement during my PhD. I would also like to express my gratitude to Shervin Maleki for his help and advice. Heartfelt thanks go to my family and my wife, Yuan, for standing by me every day both in good and bad times.

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List of abbreviations

AC	Alternating Current
AE	Acoustic Emission
ANN	Artificial Neural Network
ANSI	American National Standards Institute
ASA	American Standard Association
ASME	American Society of Mechanical Engineers
BBN	Bayesian Belief Network
BEM	Boundary Element Method
BGS	British Geological Survey
BS	British Standard
CEH	Centre for Ecology and Hydrology
CIPS	Close Interval Potential Survey
CP	Cathodic Protection
CTE	Coal Tar Enamel
DA	Direct Assessment
DC	Direct Current
DCVG	Direct Current Voltage Gradient
ECDA	External Corrosion Direct Assessment
ECT	Eddy Current Testing

EMAT	Electromagnetic Acoustic Transducer
FBE	Fusion Bonded Epoxy
ICCP	Impressed-Current Cathodic Protection
ICDA	Internal Corrosion Direct Assessment
ILI	In-Line Inspection
IR	Voltage across a resistance in accordance with Ohm's Law
MFL	Magnetic Flux Leakage
MIC	Microbiologically Influenced Corrosion
MLR	Multiple Linear Regression
NACE	National Association of Corrosion Engineers
NDT	Non-Destructive Testing
NSIRC	National Structural Integrity Research Centre
PHMSA	Pipeline and Hazardous Materials Safety Administration
PIM	Pipeline Integrity Management
SCC	Stress Corrosion Cracking
SCCDA	Stress Corrosion Cracking Direct Assessment
UT	Ultrasonic Testing

Chapter 1

Introduction

1.1 Theme

This thesis describes research relating to data analysis for improved risk assessment in buried pipelines. The type of pipelines being considered are onshore underground pipelines. The efficient interpretation of the data obtained during pipeline inspection is an important duty for pipeline owners and operators.

External corrosion in buried pipelines is often complex to understand due to the diversity of factors affecting the corrosion process and, in many cases, these pipelines operate in hostile environments. They may be less susceptible to failure and their failure may have different consequences in relation to aboveground pipelines. However, there is a limitation with respect to what inspection techniques are effective and therefore the assessment process is more difficult to be carried out.

Current inspection techniques provide useful data to predict external corrosion in a systematic manner. However, interpretation of this data is often a challenge for pipeline owners and operators. Moreover, the effects of soil parameters make this process even more difficult.

At times, data from inspection surveys has substantial uncertainty that needs to be quantified for its use. Sometimes the data provides a measurement of the underlying factors that influence external corrosion thus giving only an indirect estimate of the condition of the pipeline; this may be because direct measurements are not feasible, thus requiring the assessor to look for optimum ways to use whatever information is available. Also, the assumptions made in the original predictions need to be updated in light of actual experience so that more precise predictions can be made in future.

Analysis of data from pipeline inspection and soil surveys is described in this thesis and innovative approaches for data analyses and its interpretation to improve support decision-making in asset integrity management in the types of situations mentioned above. The approaches have been validated by using real industry data available.

1.2 Aim and objectives

The aim of the research described in this thesis is to improve the understanding of the external corrosion phenomenon in underground pipelines through the analysis of data from inspection reports and soil surveys.

This aim has been achieved through specific studies at TWI, two of which are described in this thesis. These two studies and their objectives are as below.

- The first study applies innovative regression approaches to data from non-piggable pipelines which apply External Corrosion Direct Assessment (ECDA), in particular indirect inspections such as Direct Corrosion Direct Assessment (DCVG) and direct inspections gathering data from pipeline coating degradation and external corrosion. Here, the objective is to understand the relationship between corrosion depth, coating defect area and the voltage drop %IR from DCVG survey.
- The second study applies innovative regression approaches to data from piggable pipelines with data from Magnetic Flux Leakage inspection and soil surveys. Here, the objective is to find correlation between pipeline external corrosion and other environmental factors such as soil properties.

1.3 Layout of the Thesis

The layout of the Thesis, Chapter 2 onwards, is illustrated in Figure 1-1.

Chapter 2 sets out the common corrosion and statistics theory attributes of the methodologies described in the sections that follow. It starts with introducing the terms and concepts used in this Thesis. There is a description of the importance and uses of underground pipelines; this is followed by a description of corrosion theory and its presence in buried pipelines.

It then discusses control and mitigation of external corrosion commonly used systems, and it is followed by a description of the current Pipeline Integrity Management (PIM) approaches and practices used in industry. To end up, a description of the statistical tools applied to PIM programs is addressed.

Chapters 3 and 4 describe two studies that are important to the research described in this Thesis.

- Chapter 3 describes parts of a study on corrosion in underground non-piggable pipelines. This study models the relationships between pipeline coating defect area, corrosion depth, direct current-voltage gradient (DCVG) measurements and factors capturing diverse environmental conditions through the novel application of regression models. This study sheds light on the challenges in drawing conclusions in the assessment of corrosion from DCVG inspection data and other types of data that form key inputs to ECDA. There are three papers referred to in Chapter 3.
    - "Challenges in the application of DCVG-survey to predict coating defect size on pipelines." is a paper on this study published in the journal of Materials and Corrosion in 2016.
    - "Correlation of pipeline corrosion and coating condition with ECDA survey results." is a paper on this study presented at the EUROCORR 2016 Conference, Montpellier, France.
    - "Correlation of pipeline corrosion and coating condition with ECDA survey results." is a paper on this study presented at the 2016 National Structural Integrity Research Centre (NSIRC) Conference, Cambridge, UK.
- Chapter 4 describe a study on corrosion in underground piggable pipelines. This study models the relationships between pipeline corrosion depth and factors capturing environmental conditions through application of regression models. This study also describes the impact of welds and defect orientation on corrosion. There are two papers referred to in Chapter 4.
    - "An analysis of factors influencing external corrosion based of soil, weld location and defect orientation data." Is a paper on this study submitted to the journal of Materials and Corrosion in 2017.
    - "Influence of soil properties on corrosion pitting in underground pipelines." Is a paper on this study presented at the 2016 National Structural Integrity Research Centre (NSIRC) Conference, Cambridge, UK.

Chapter 5 discusses the findings in the application of regression models to underground pipeline corrosion, inspection survey data and environmental conditions. The limitations of this research and the possibilities for further work are also discussed.

Chapter 6 describes the concluding remarks from Chapters 3, 4 and 5.

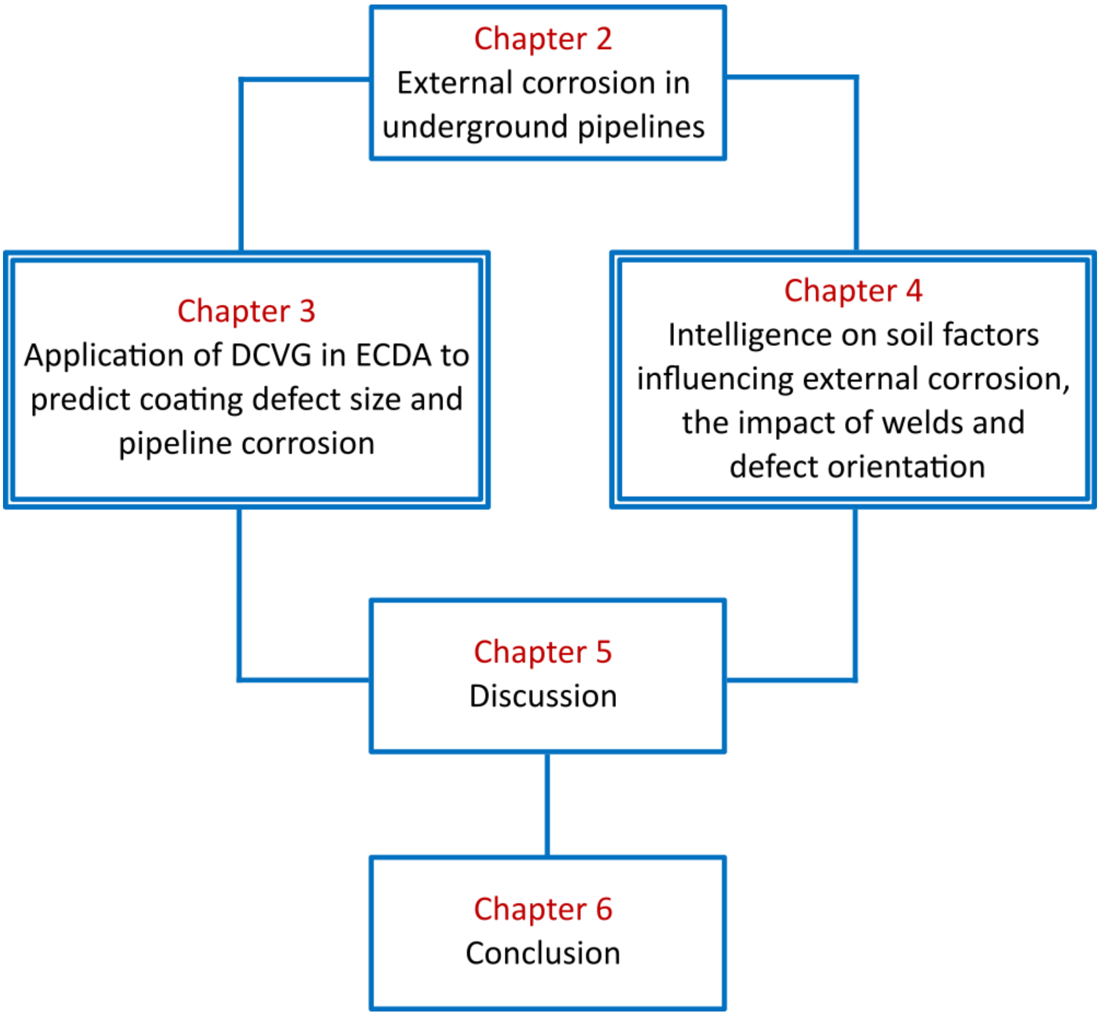

Figure 1-1 Structure of the Thesis

1.4 Contribution to new knowledge and novelty

The contribution to knowledge of the research included in this thesis is the improvement on the understanding of pipeline coating condition and external corrosion phenomenon in underground pipelines through the analysis of data from inspection reports and soil survey. Also, the identification of key factors affecting external corrosion along the probability distribution function, including factors that affect the initiation of corrosion and factors which have more importance in cases of severe corrosion.

The novelty of the research herein presented relies in the application of quantile regression to pipeline data combined with soil properties which has never been applied before. The results improve the understanding of pipeline coating condition and external corrosion in underground pipelines. Also, it proposes suggestions for improving the interpretation of the NACE ECDA SP-0502 standard which may lead to significant savings in the pipeline industry.

1.5 Other relevant studies

The research presented here is directly or indirectly influenced by

- Courses undertaken:
    - Probabilistic analysis – uncertainty modelling – statistics, probability and stochastic variables at TWI Ltd, Cambridge, August 2014.
    - Risk-Based Inspection (RBI) Course in accordance with API 580 recommended practice. CSWP Plant Inspector Levels 2/3 Module 3 at TWI Ltd, Cambridge, September 2014
    - Damage Mechanism Assessment Course for RBI and FFS based on API RP 571. CSWP Plant Inspector Levels 2/3 Module 2 at TWI Ltd, Cambridge, September 2014.
    - Applied Bayesian Methods, at London Taught Course Centre, London, January-February 2015.
- Conferences attended/presented at:
    - Seminar presentation at 'Reliability Training Seminar', 19 June 2014 at TWI Ltd, Cambridge. Presentation titled 'Data analysis and its interpretation in remaining life assessments'.
    - Symposium presentation at 'Departmental Postgraduate Student Research Symposium', 22 April 2015 at Brunel University London, London.

Presentation titled 'Correlation of underground corrosion and coating condition with ECDA survey results'.

  - Conference presentation at 'Condition Monitoring' conference, 16 June 2015 at Salford University, Manchester. Presentation titled 'Correlation of underground corrosion and coating condition with ECDA survey results'.
  - Conference presentation at 'NSIRC Annual Conference', 23 June 2015 at TWI Ltd, Cambridge. Presentation titled 'Correlation of underground corrosion and coating condition with ECDA survey results'.
  - Seminar presentation at the 'Young Members Committee (YMC)', 16 February 2016 at TWI Ltd, Cambridge. Presentation titled 'Challenges in the Application of DCVG Survey to Predict Corrosion in Pipelines'.
  - Conference presentation at 'NSIRC Annual Conference', 27 – 28 June 2016 at TWI Ltd, Cambridge. Presentation titled 'Influence of soil properties on corrosion pitting in underground pipelines'.
  - Conference presentation at the 'European Corrosion Congress (EUROCORR)' conference, 11 – 15 September 2016 at Montpellier, France. Presentation titled 'Correlation of Pipeline Corrosion and Coating Condition with ECDA Survey Results'.
- Awards and prizes:
  - Winner of the Best Speaker Presentation Award at 'NSIRC Annual Conference', 27 – 28 June 2016 at TWI Ltd, Cambridge. Presentation titled 'Influence of soil properties on corrosion pitting in underground pipelines'.
  - Winner of the Armourers and Brasiers TWI Award, 2016. Research title 'Correlation of Pipeline Corrosion and Coating Condition with ECDA Survey Results'.
- Supervision:
  - Doctor Keming Yu (Brunel University London), Doctor Ujjwal Bharadwaj (TWI Ltd), Doctor Chi Lee (TWI Ltd) and Doctor Bin Wang (Brunel University London).

1.6 Industrial hosts: NSIRC and TWI

TWI Ltd is the industrial host of this doctorate. TWI Ltd is an independent, membership-based, research, technology and consultancy organisation. TWI services include research and investigation for industrial member companies and public funding bodies. It also offers training and examination services in NDT, welding and inspection cross the world.

This research includes some of my work done within the Asset & Fracture Integrity Management section of the Integrity Management Group (IMG) at TWI Ltd, Cambridge, where I have been based. The Asset & Fracture Integrity Management section provides a variety of services which include: providing consultancy in the field of risk-based inspection (RBI), fitness for service (FFS), software development and system analysis using standard tools such as FMEA, FMECA, FTA and ETA.

The National Structural Integrity Research Centre (NSIRC) is a state-of-the-art postgraduate engineering facility established and managed by structural integrity specialist TWI Ltd. NSIRC unites academia and industry, working closely with lead academic partner Brunel University London and more than 20 other respected universities. The collaborating partners provide academic excellence to address the need for fundamental research, as well as high-quality, industry-relevant training for the next generation of structural integrity engineers.

Chapter 2

External corrosion in underground pipelines

2.1 Underground Pipelines

Pipelines are commonly used to transport hazardous liquids and gases. Comparing to competing modes such as road and rail, they are often seen as the most economical, safe and reliable model of transporting fluids [1]. Companies who are responsible for operating pipelines aim to ensure that pipelines are working under safe conditions within an acceptable risk of failure.

Nevertheless, companies often struggle to use integrity/reliability data in a meaningful way in order to determine the predicted remaining life of their underground pipelines: sometimes because inspections are not carried out or are deferred so up-to-date information is not always available, other times because expertise to analyse this data in order to take decisions based may not be available.

The history of the pipeline industry started about 200 years ago, and it has been notable important during the industrial revolution. The first use of iron pipes dates back to the 1830s; however, they were used for different purposes rather than the oil and gas industry.

With the creation of the first commercial oil well in Pennsylvania (1859) by Edwin Drake and the first wooden pipeline (1862) [2], there was a rapid development in the field of transport of oil and gas. The pipeline business expanded, as well as the quality of the metal used for pipes which changed from wrought iron to steel. But it is not until 1865 when William Snow defined the first specifications for laying underground pipelines.

However, it was in 1879 when the first crude oil pipeline was laid in Pennsylvania [3] with a length of 175 km and 6 inches of diameter. Between 1880 and 1905 many refineries were created near oil fields and the need of transporting crude oil increased.

In 1920, the total pipeline mileage grew to over 185,000 km in the USA and, in 1930 the first cross-country pipeline was commissioned connecting some important cities. The first production pipelines were built in the 1930s and with the World War II (1945), the construction and commissioning of these grew significantly.

New oil exploitations were found in South America, Canada, the Caspian Sea and the Middle East during the 1950s and 1960s, and since the oil production in the USA decreased compared with the demand, the pipeline industry developed [2]. Large diameter pipelines with diameters above 30 inches were made in the 1960s.

In 1968, the Alaskan Prudhoe Bay oil field was discovered, and two years later it started the construction of one of the largest pipelines in the world, the Trans-Alaska Pipeline. The construction period was 7 years, and once finished in 1977 it was able to transport 2 million barrels per day along 1280 kilometers of distance in an environment with temperatures below 0 °C.

Since the 1980s, the pipeline industry has been growing continuously, not only with the commission of new pipelines but also in the design aspects related to quality and reliability. Metals used in the manufacture of pipelines have undergone a constant development during the last two centuries.

But it is not until 1871 when Bessemer steel begins to displace wrought iron thanks to the creation of the steel manufacturing processes. Steel was acquiring more importance and was used to develop dresser couplings to join pieces of pipe end-to-end mechanically (1891) and steel welding processes (1900).

Since the 1920s, most of the oil and gas pipelines have been made of steel [4]. With the appearance of the first API Standard 5L in 1928, the design of pipelines was standardised [5][6][7]. Twenty years later the API Standard 5LX was introduced (1948), and some time after, in 1953, pipes grades X46 and X52 were introduced. The evolution of steel for pipeline uses was associated to the volume of oil and gas extracted during this period of time.

In 1959, The American Standard Association (ASA) issued the ASA B31.4 as a separate code for Oil Transportation Piping Systems [8].

The combination of API 5L and 5LX in the same standard (1983) could be applied to all grades of steel and led to a big change on pipeline design. All the design and manufacturing requirements were gathered in the same document. A new steel grade, API 5L X80, was introduced in 1985 and its main purpose was to be used for onshore pipelines.

Most modern underground steel pipelines are constructed from carbon steel. The most common materials specifications are: API 5L A25, A, B, X42, X46, X52, X56, X60, X65, X70, X80 and ASTM A 53, 106, 134, 135, 139, 333, 381, 671, 672 as dictated in ASME B31.8 and B31.4 [9], [10].

2.1.1 Pipeline failures

The use of pipelines for the transport of large quantities of natural gas, oil, and water to industry and to commercial and domestic consumers represent a reliable mode of transport of energy [11]. However, since the commissioning of the first pipeline, accidents have occurred. Pipeline ruptures and leaks can cause injuries and fatalities from explosions and fires, and can also cause high environmental impact [12].

In the USA 360 fatalities, 1368 injuries, and 10845 accidents have been recorded in the last 20 years (Figure 2-1) as reported by the Pipeline and Hazardous Materials Safety Administration (PHMSA), from which 8.8% were due to external corrosion (Figure 2-2)

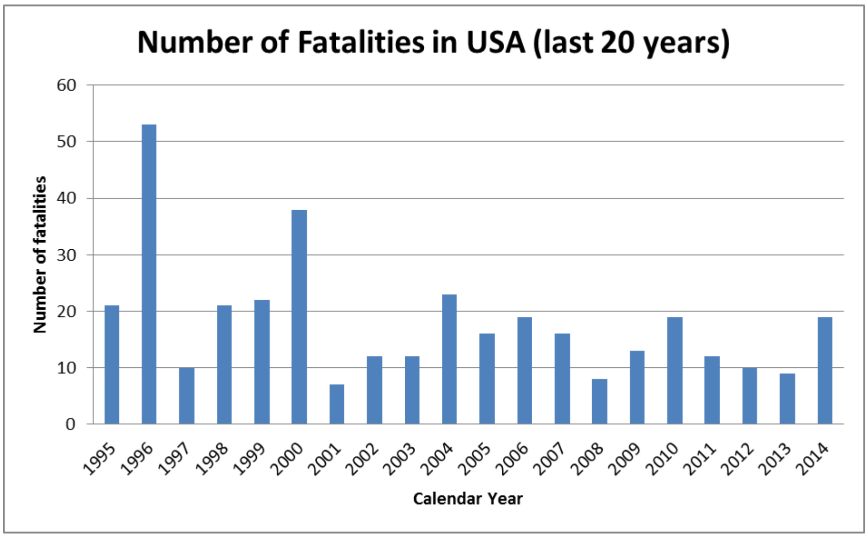

Figure 2-1. Number of fatalities in USA in the last 20 years.

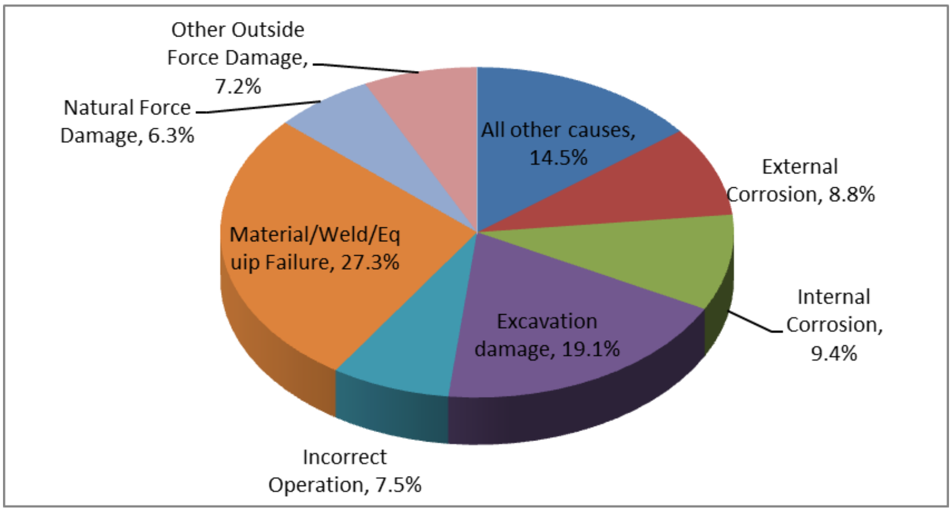

Figure 2-2. Distribution of pipeline accidents in the USA by cause.

The Columbia Gas Transmission Corporation pipeline rupture is an example. On December 2011, a buried 20-inch diameter interstate natural gas transmission pipeline, owned and operated by Columbia Gas Transmission Corporation, ruptured in a sparsely populated area, in Sissonville, West Virginia in the USA. About 20 feet of pipeline was separated and ejected from the underground pipeline and landed more than 40 feet from its original location (Figure 2-3).

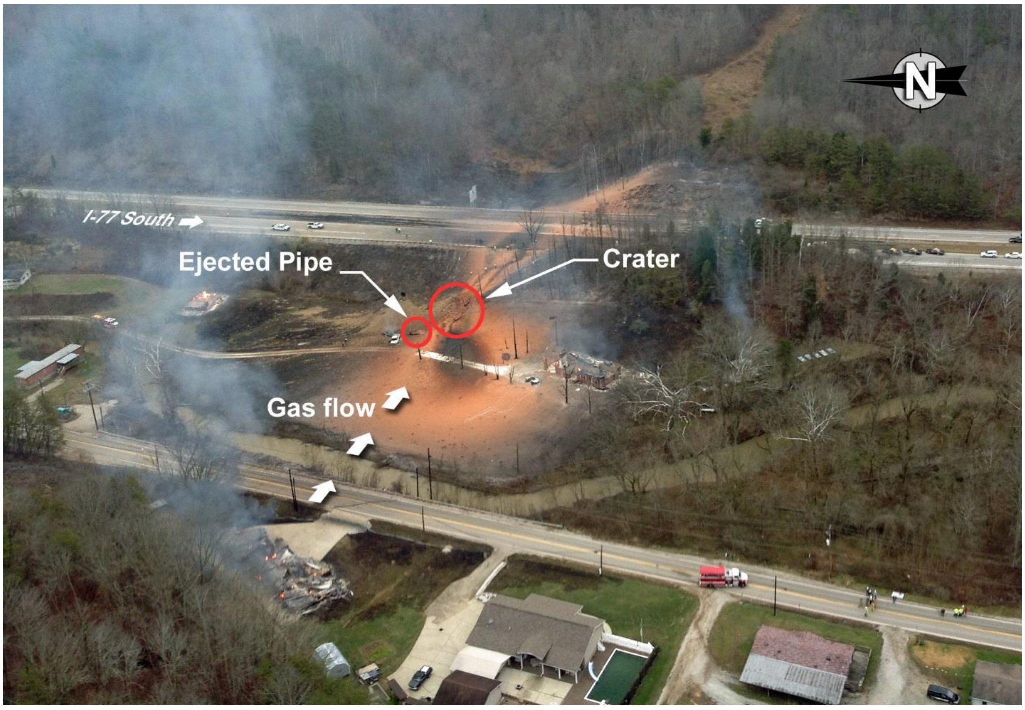

Figure 2-3. Columbia Gas Transmission Corporation pipeline rupture consequences [13]

The escaping high-pressure natural gas ignited immediately. The area of the fire damage was about 820 feet wide and extended nearly 1,000 feet along the pipeline right of way. Three houses were destroyed by the fire and several other houses were damaged. There were no fatalities or serious injuries. About 76 million standard cubic feet of natural gas was released and burned. The total cost of the pipeline repair was $2.9 million, the cost of the system upgrades to accommodate in-line inspection was $5.5 million, and the cost of gas loss was $285,000.

The National Transportation Safety Board determined that the probable cause of the pipeline rupture was (1) external corrosion of the pipeline wall due to a degradation of the coating and an ineffective cathodic protection and (2) the failure to detect corrosion because the pipeline was not inspected or tested after 1988 [13].

Therefore, preventing pipeline accidents is an important task. In order to reduce the number of accidents, the implementation of the correct pipeline integrity management system to new and already installed pipelines is required.

2.2 Corrosion Theory / Fundaments of Corrosion

Corrosion can be defined as a natural process in which a material is degraded due to a reaction with its environment. Metals corrode in presence of an environment where they are unstable, for example, steel is thermodynamically unstable in wet/moist oxygenated environments. However, the corrosion rate of some metals and alloys is considered to be slow enough that it can be considered as materials used in metallic structures [14].

Corrosion is an electrochemical process [15]. It follows the physical laws of thermodynamics and therefore can be measured and predicted. However, corrosion processes can be produced at specific and isolated areas due to the nature of the reactions at atomic levels, complicating the predictability of corrosion.

The effect of corrosion on a metallic surface can take many forms [14]. There are several morphological forms of corrosion. In the context of this study, it is useful to categorise them into two groups: corrosion affecting underground metallic structures and corrosion not affecting underground structures:

- Corrosion affecting underground metallic structures:
    - **General (uniform) corrosion**. It is characterised by the uniform material loss. The exposed metal surface area is entirely corroded. Atmospheric corrosion, galvanic corrosion, high-temperature corrosion, liquid-metal corrosion, molten-salt corrosion, biological corrosion and stray current corrosion are some types of general corrosion [14][16].
    - **Pitting (localized) corrosion**. It is characterised by localised loss of material. In extreme cases, it appears as a deep, small hole [17][18].
    - **Crevice corrosion**. It is a form of localised attack occurring at shielded areas on metal surfaces exposed to certain environments [17] [19][20][21] [22].
    - **Stress Corrosion Cracking (SCC).** It is characterised by one or more crack fronts which have developed due to a combination of corrosion and tensile stresses [23][24][25].
- Corrosion not affecting underground metallic structures externally:
    - **Intergranular corrosion**. It is characterised by attacking those sites where individual grains within a metallic material are in contact with each other [16][26][27].
    - **Erosion corrosion**. It is a degradation of the metal surface due to the movement of a corrodent over a surface. The mechanism is generally identified by localised corrosion, in particular, pitting [28][29][30][31].

For a corrosion event to occur, it is necessary the presence of four components: anode, cathode, electrolyte and a metallic connection between the anode and the cathode [32].

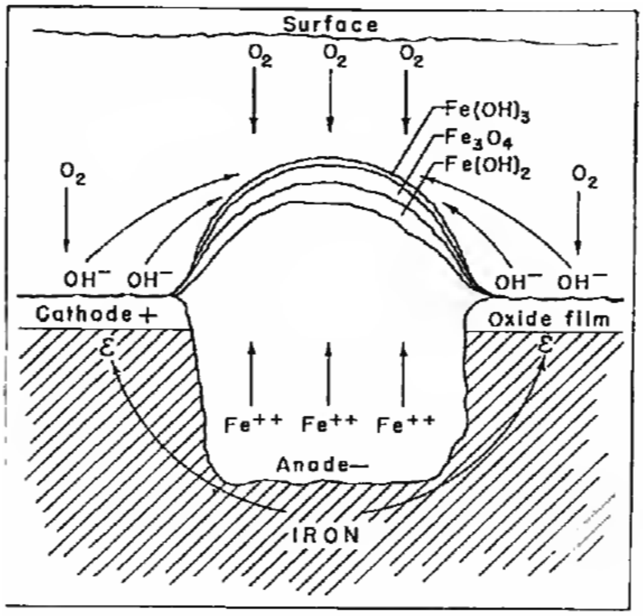

Figure 2-4. Diagram explaining the corrosion mechanism in presence of an anodic and cathodic reaction [32].

An electrolyte is homologous to a conductive solution, which contains cations and anions. The corrosion mechanism needs the presence of an anodic and cathodic reaction (Figure 2-4). Thus, metal oxidation appears through an anodic reaction and reduction is through a cathodic reaction [33].

2.3 Pipeline external corrosion (underground corrosion)

2.3.1 Electrochemical/Galvanic corrosion

The most common corrosion mechanism for metals in underground environments at moderate temperature is electrochemical corrosion [32].

Electrochemical corrosion appears when two points with a potential difference are electrically connected in a presence of an electrolyte. The electric current I flows from the anode through the electrolyte to the cathode, and then, through the metal from the cathode to the anode to complete de circuit [Figures 2-5 and 2-6].

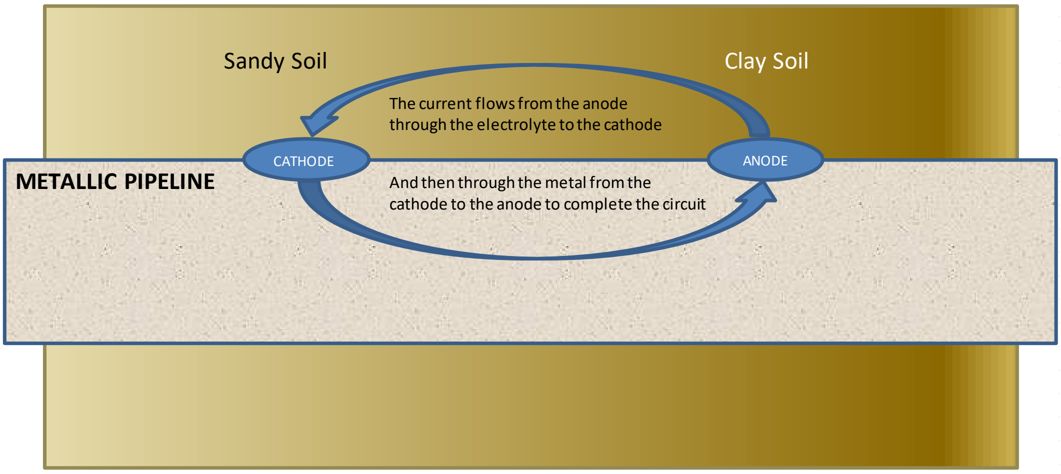

Figure 2-5. Diagram explain how the electric current flows from the anode to the cathode through the electrolyte (soil).

The anodic area is corroded by loss of metal ions to the electrolyte (Figure 2-5).

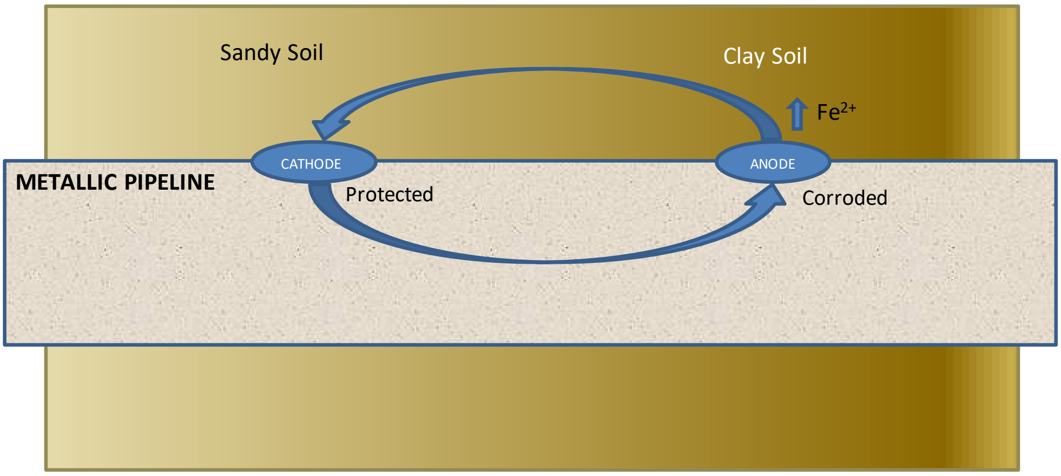

Figure 2-6. Diagram explaining how the electric current flows from the cathode to the anode through the metal to complete the circuit.

A differential corrosion cell is created by differences in soil properties. The arrows indicate the direction of the ionic and electronic current flows (Figure 2-6).

These reactions are known as anodic and cathodic reaction and are defined below for iron metal (Fe) immersed in water (H_2O) solution as an example [33].

$$Fe \rightarrow Fe^{2+} + 2e^{-} \qquad (Anodic \equiv Oxidation) \qquad (2.1)$$

$$H_2O + \frac{1}{2}O_2 + 2e^- \rightarrow 2OH^- \qquad \textit{(Cathodic} \equiv \textit{Reduction)} \qquad (2.2)$$

$$Fe^{2+} + 2OH^- \rightarrow Fe(OH)_2 \qquad \textit{(Overall} \equiv \textit{Redox)} \qquad (2.3)$$

where Fe = Iron metal; Fe^{2+} = Iron metal cation

H_2O = Water; OH^- = Hydroxide anion

$Fe(OH)_2$ = Ferrous hydroxide

The anodic reaction (oxidation) loses $2e^-$ iron electrons and the cathodic protection gains $2e^-$ electrons and hence, both anodic and cathodic reactions are coupled in a corrosion process. Thus, the equation (2.3) represents the overall reaction at equilibrium where the anodic and cathodic reaction rates are equal [33].

Since the anodic area has a more negative potential than the cathodic area, is the one that corrodes losing metal ions, whereas the cathodic area is protected from corrosion.

2.3.2 Factors affecting underground corrosion

The theory of the corrosion mechanisms is simple: corrosion appears when the metal loses ions at anodic areas. Nonetheless, the correlation between corrosion and potential difference of underground metals is complicated as a result of the many factors that affect (either singly or combined) the electrochemical reaction [32].

The amount of corrosion (or corrosion rate) and the nature of corrosion are determined by these factors. The importance and significance of factors and the correlation between themselves have been discussed in many papers and books cited in the list of references, in particular [34][35][36][37].

These corrosion studies have allowed a better understanding of the influence of individual factors but they do not often discuss the effect of a combined number of factors.

Romanoff [32] has grouped factors on four classes: (1) aeriation, (2) electrolyte, (3) electrical factors, and (4) miscellaneous which are addresses in depth below.

2.3.2.1 Aeriation factors

Aeriation factors are defined as the elements that influence the access of oxygen and moisture to the metal and therefore influence the corrosion mechanism. Oxides and hydroxides are formed by associating oxygen (from atmospheric sources or from oxidizing salts) and metal ions, enhancing corrosion.

Aeriation factors are dependent upon physical characteristics of the soil. Some examples are the particle size, particle size distribution, and apparent specific gravity [32]. Particle size and particle size distribution affect the continuity of the pore space and may create oxygen concentration cells. In the case of developing oxygen concentration cells, the area with the least oxygen concentration is anodic (where corrosion might meterialise).

Volume shrinkage is a phenomenon common in soils. Shrinkage appears when the soil dries out. It increases its volume when it is humid again [38][39]. Volume shrinkage is present particularly in clay soils rich in organic matter, and also in extreme weathers. This phenomenon is not only dangerous from a corrosion point of view (creation of oxygen cells) but as well because of the mechanical effects, the shrinking soil contributes to pulling the coating off the pipeline. During the soil expansion, the coating is deformed by compression.

2.3.2.2 Electrolyte factors

Electrolyte corrosion factors are those variables that influence the electrolyte, the flow of current along the electrolyte and the chemical reactions present within the aforementioned electrolyte.

In this section, the electrolyte factors are addressed and defined, as well as how they affect corrosion.

- Soil resistivity is the process of measuring how much the soil resists the flow of an electric current , which affects directly to the state of corrosion [40]. Due to the nature of soils, soil resistivity is a heterogeneous factor which is difficult to predict. Therefore, changes in soil resistivity are a problem which requires monitoring [41]. Since the resistivity is inversely proportional to the flow of electric current (Ohms

Law), the higher the soil resistivity, the lower the electron exchange and therefore the likelihood of finding corrosion.

- Chloride ions accelerate corrosion in metals. Their presence in soils results in a reduction of the resistivity. Additionally, Vijh [42] demonstrated that the corrosion potentials of Cu, Ni, Sn, Pb, Fe, Al and Zn in chloride solutions can form corrosion films which affect negatively the integrity of pipelines [18].
- Oxidation reduction potential (redox potential) is the activity of the oxidizers and reducers in comparison to their concentration. During a redox reaction, the reducers lose electrons, while oxidizers accept electrons. Oxidizing conditions appear in the presence of high redox potentials which tend to increase the oxygen concentration.
- Sulphides are present in most of the soils, but it is only significant in conjunction with relevant redox potentials (<+100mV) [43]. However, sulphate levels are more critical where concrete structures are present. Iron is corroded by electrolytes that contain sulphates from the soil because the corrosion products formed at the anode and the cathode are both soluble [32].
- The soil acidity is indicated by the pH value, ranging from a pH of between 2.5 and 10. When the pH level is 5 or below, the corrosion rate is high and pitting is very likely to occur on steel structures. Whereas, a pH near neutral is favorable because it minimises the likelihood of damage due to corrosion [44]. In the range of 4 to 8.5, the corrosion rate of iron is relatively independent of the pH of the solution and it is governed by the rate at which oxygen reacts [43].
- The moisture content of soils is considered to be one of the most important factors affecting soil corrosivity. Water is one of the dominant elements needed for the process of electrochemical corrosion, including other components such as metal and oxygen. Typically, corrosion will not appear in the absence of water (if the soil entirely dry) [45]. Murray and Moran demonstrated that the corrosion rates in two different soil types were approximately equivalent at the same moisture levels [46]. It is important to be aware that moisture content directly affects the soil resistivity.

- The heterogeneity of the soil affects the formation of electrochemical cells. Big changes in soil composition help the formation of electrochemical cells in the electrolyte, thus, increasing the likelihood of corrosion.
- Temperature influences many parameters that are critical to pipeline corrosion such as biological activity, physical properties of the solution, thermodynamic and physical properties of corrosion scale, and chemical rates [47]. A reduction in temperature typically will reduce the microbiological activity, thus decreasing the probability of corrosion, but it could trigger other damage mechanisms such as stress corrosion cracking.

2.3.2.3 Electrical factors

Electrical factors specify the geometry of anodic areas including size, number, location and intensity of the current that circulates from the pipe to the soil. The dominant electrical factor in underground corrosion of metals is the variation in the potential between two different points on the pipeline metal surface [32]. Potential differences may appear because of the heterogeneity of the soil and the presence of microorganisms and may be boosted by low resistivity soils.

The relative size of the anode and cathode areas is a factor in determining the amount of corrosion damage. If the anode area is large and the cathode area is small, the current density may be negligible [16][32]. Whereas, if the anode area is small compared to the cathode area, the corrosion activity is localised (high current density) and severe local damage may occur.

Potential differences may be occur due to the presence of nearby adjacent underground pipelines. Sometimes new pipelines are laid in parallel to the old ones with both connected at pump stations. In this situation, typically the new pipeline remains anodic to the old one. Usually the currents are not intense enough to damage the new pipeline; however, it can prolong the life of the old one.

Stray current corrosion refers to corrosion damage resulting from current flow other than which is intended in the pipeline. Grounded electric power sources or equipment, electric railways not well insulated and nearby underground pipelines are good examples of stray currents. The principle of this sort of corrosion is based on large potential differences and the small size of the anodic area (where the current leaves the pipeline) [48].

2.3.2.4 Other factors

Soil biological activity has a big influence on pipeline corrosion. Microbes can modify the rate of oxygen reduction and the redox conditions [49], cause pH gradients and produce corrosive metabolites [47]. The role of microorganisms is either to assist in the formation of the electrolyte cell or to activate the anodic or cathodic reaction [50]. Soils rich in organic matter are more susceptible to microbiologically influenced corrosion (MIC) [51]; however, MIC is rarely linked to a single mechanism.

2.4 Control and mitigation of external corrosion

The occurrence of corrosion is inevitable. However, it is possible to control the rate at which pipelines corrode. Important maintenance costs for operation of pipelines are related to corrosion control and mitigation. The purpose of a good integrity management systems is to preserve the asset of the pipeline and to ensure safe operation without failures that threaten public safety [3].

The selection of materials for pipeline construction is limited when all the aspects of safety, structural integrity, operating life, and economic considerations are taken into account [52]. Carbon steel is the almost exclusive choice of pipeline designers.

The most effective methods to prevent and mitigate external corrosion in buried pipelines are to use a combination of a coating system together with a cathodic protection system [4]. Mitigation systems are defined and explained in detail in the following sections.

2.4.1. Coatings

Coatings are one of the corrosion control systems used for underground pipelines. They are used to isolate the pipeline from the soil thereby decreasing the corrosion activity. Coatings control corrosion by providing a barrier against oxygen and water and also by insulating the metal surface [53]. Another purpose of coatings is to isolate the anode and cathode area of the corrosion cells from each other.

In order to be effective, a coating must meet certain requirements:

- Corrosion resistance (chemical and water resistance).
- Broad range of service temperatures.
- Strong adhesion.
- Resistance to electricity (high dielectric strength).
- Resistance to cathodic disbondment.
- Resistance to bacteria and fungi.
- Impact and abrasion resistance.
- Easy application and repair.

The minimum requirement is that a coating should prevent corrosion for the design life of the pipeline; however, a more realistic objective is that the coating should prevent corrosion as long as the pipeline remains in service [54]. Most pipelines are operated well beyond their original design life.

The first pipelines were coated by coal tar or asphalt coatings on field, but since then, many improvements have been taken place. There are a wide number of coatings which are being used for underground pipelines for corrosion protection[54]. They can be classified as follows:

2.4.1.1 Coal tar based coatings

Coal tar based coatings have been applied since the 19th century, however, its first application to a pipeline was in 1914 [55]. Coal tar enamel (CTE) coatings have been used extensively.

CTE coatings possess high resistance to soil chemicals and bacteria. They don't suffer from cathodic shielding and cathodic disbondment is almost inexistent. Coal tar based coatings are insoluble in hydrocarbons. Furthermore, they are easy to repair.

However, CTE coatings have a series of limitation which makes them unsuitable for new pipelines. These coatings have comparatively poor mechanical strength and therefore, protected pipelines require higher cathodic protection current, increasing the cost of the cathodic protection. CTE coatings require early rehabilitation and are no longer environmentally desirable due to air-pollution fumes during application.

2.4.1.2 Polyethylene/PVC based tape coatings

Polyethylene coatings are thermoplastic polymers with an excellent chemical resistance; however, they can be dissolved at elevated temperatures in presence of hydrocarbons. They were first introduced into the pipeline oil and gas industry in the early 1950s [56] and they are applied to large diameter pipelines.

Cold applied tape systems, which nowadays are one of the most used coating systems in the USA, are used on pipelines carrying oil, gas and water. Their function is to prevent electrochemical corrosion from the underground soil, as well as a mechanical protection [57].

Polyethylene/PVC based coatings are cheap and easy to apply, either on site or in production sites, but they present a number of limitations: poor shear stress resistance which can induce to cathodic protection shielding and also, the adhesive part is subjected to biodegradation. Depending on the application and the predicted time in service they can be the appropriate coating choice.

2.4.1.3 Fusion bonded epoxy (FBE) powder coatings

FBE are versatile and high-performance organic coatings [58]. They are thermoset polymer coatings. Fusion bonded epoxy coatings have excellent corrosion resistance, adhesion to the metal and they are extremely resistant to soil stress, making them suitable for using near roads and train rails.

Often, FBE coatings are the best option to protect pipelines, however, it is important to mention that they are expensive during installation and during service time due to its nature as an hygroscopic material, leading to an increase in cathodic protection demand as pipeline ages.

There are two commonly used FBE coatings: single-layer and dual-layer.

2.4.1.3.1 Single-layer FBE coatings

Single-layer FBE coatings are easy to apply. They offer resistance to soil bacteria, marine organisms, and cathodic disbondment. Single-layer coatings have excellent electrical resistance, hence insulating electrically the pipeline from stray currents.

Nonetheless, single-layer FBE coatings have some limitations compared with other coatings. At high temperatures, they absorb moisture allowing permeation. When they are stored, before installation, there is a risk of damage due to UV radiation.

2.4.1.3.2 Dual-layer FBE coatings

Dual-layer fusion bonded epoxy coatings have some advantages over single-layer coatings. They can operate at higher temperatures, up to 110°C. Additionally, they present an excellent abrasion and impact resistance, which combined with their UV resistance, make them easy to handle.

These coatings are excellent for most of the situations, however, they are expensive and, in some cases, when the coating is very thick, they manifest poor flexibility compared with single-layer coatings.

Although many coatings are excellent barriers, all organic coatings are semipermeable to oxygen and water [53].

However, even if the pipeline is coated, constructed and laid according to best practice, coating defects, especially at field joints where the welds are coated in-situ during construction, will inevitably be present.

2.4.2 Cathodic Protection

Coating defects can result from soil activity or pipeline movement during service or during installation.

Cathodic protection (CP) systems ensure that any exposed uncoated region of the pipeline, which is in contact with the potentially corrosive soil environment, is protected from corrosion. They control the corrosion of the pipeline by forcing it to be the cathode of an electrochemical cell [58].

2.4.2.1 Sacrificial anode CP

Sacrificial anodes are active metals used to prevent a less active metal surface (pipeline) from corroding. They are manufactured of metal alloys with a more negative electrochemical potential (rest potential) than the metal to be protected. The sacrificial anode in consumed instead of the metal that is protecting [59][60].

The rest potential of the anode material must be sufficiently more negatively than the metal of the object to be protected , so that an adequate driving voltage can be maintained. Sacrificial anodes are generally made of Iron, Zinc, Aluminium or Magnesium, however, other metals and alloys are used as well. The cathodic protection of a steel pipeline with sacrificial anodes is illustrated in Figure 2-7 [61].

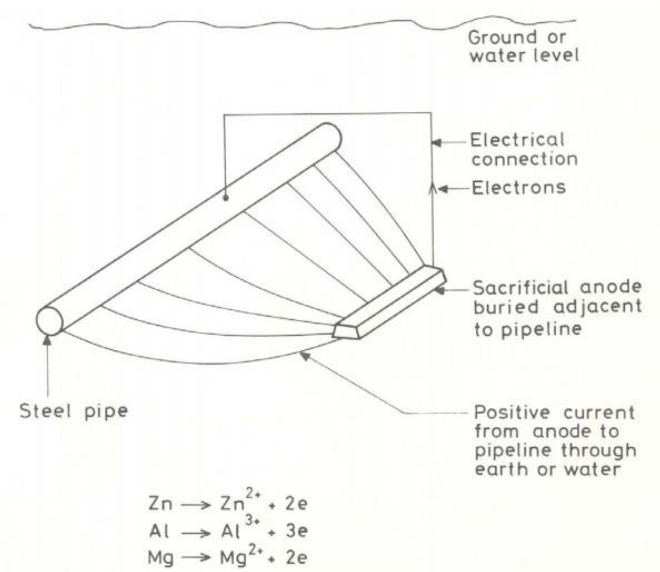

Figure 2-7. Cathodic protection of a steel pipeline using sacrificial anodes [61].

Several studies have allowed the improvement and optimizations in the use of sacrificial anodes for cathodic protection [62]. Boundary element methods (BEM) have been used to determine the potential and current density distributions along the electrodes without discretizing the electrolyte domain [63] allowing a better design of the overall system.

Cathodic protection using galvanic anodes is generally not very expensive and the maintenance, once installed, is very low. It doesn't need an alternating current (AC) electric supply and it does not interfere with neighbor structures [58]. However, in poorly conducting soils, the low driving voltage can limit the use of galvanic anodes. Increasing the current is only possible with the help of an additional external voltage.

2.4.2.2 Impressed-Current Cathodic Protection (ICCP)

Impressed-Current cathodic protection [64] has been used since the 1970s and it is a proven technique which is able to reduce ongoing corrosion and induce steel passivity [65].

The principle of ICCP is to apply and impressed current such as to induce negative steel polarization [66], driving the steel potential more cathodically than -850 mV, where the corrosion process is thermodynamically unlikely to occur and therefore making the pipeline immune to corrosion.

The configuration for protecting a buried pipeline is illustrated in Figure 2-8 [61].

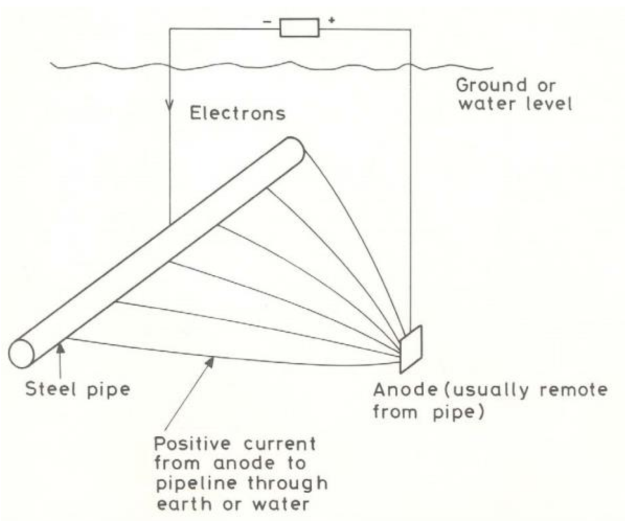

Figure 2-8. Cathodic protection of a steel pipeline using impressed-current CP [61].

The current needed for impressed-current cathodic protection is usually supplied from transformer-rectifier units. The buried pipeline receives current from a direct current (DC) power source via an auxiliary inert electrode buried in the ground. The pipeline becomes the cathode and the auxiliary electrode the anode.

There are many studies about cathodic protection modeling. Numerical methods and the application of the boundary element method have allowed optimising the impressed current performance [67][68]. However, many assumptions such as homogeneous resistivity, axisymmetric current density or flat earth have been made [48] and more accurate design model need to be developed.

2.5 Pipeline Integrity Management (PIM)

Pipeline Integrity Management systems are methodologies which apply the same process to all pipelines, enabling consistent decision making. They ensure that pipeline networks are safe, reliable, sustainable and optimised.

2.5.1 In-Line Inspection

In order to establish an effective management program, In-Line Inspection (ILI) is commonly used to assess the integrity of pipelines. In-Line Inspection is an inspection tool which applies various Non-Destructive Testing (NDT) methods for examining the condition of the pipeline walls. Depending on the pipeline, service and anticipated damage, different sensor technologies are applied, as for example, Magnetic Flux Leakage (MLFL), Eddy Current Testing (ECT), Ultrasonic Testing (UT), Electromagnetic Acoustic Transducer (EMAT) and Acoustic Emission (AE) [69]. All of these sensor technologies have in common that they need associated hardware devices that records information about the internal conditions of the pipeline, together they are called In-line inspection tool or smart pigs.

Often, pipelines are unpiggable, in particular, pipelines with small diameters, a high number of bends and connections and old pipelines. Therefore, it is not feasible to inspect them internally with conventional In-Line inspection tools.

Hossam et al [1] conducted a literature review and analysis of pipeline integrity management practices. Design practices were described and inspection techniques were studied in order to describe the integrity assessment techniques. Internal in-line inspection tools are often applied in industry to determine the state of underground pipelines, but since many pipeline facilities are not suited for in-line inspection tools, indirect practices such as “Direct Assessment” has been used as an alternative to pressure testing and internal inspection tools.

2.5.1 Standards and best practices

In order to mitigate and prevent failures and accidents, pipeline integrity management standards have been developed in the last decades with the aim of improving management practices. These standards provide requirements, specifications, guidelines or characteristics that can be used consistently to ensure the integrity of pipelines.

Many practices have been developed for the design and assessment of buried pipelines; some of the most commonly referred practices by industry include ANSI/ASME B31.4 [10], B31.8 [9], B31.8S [70], DNV-RP-F101 [71] and BS ISO15589 [66].

ANSI/ASME B31.4 and B31.8 prescribe requirements for the design, materials, construction, assembly, inspection and testing of piping transporting liquids, such as crude oil, between facilities.

ANSI/ASME B31.8S covers onshore pipeline (buried and not buried) systems constructed with ferrous materials and transporting gas. It provides the information needed for the pipeline operator to develop and implement an effective integrity management program utilizing proven industry practices and processes.

DNV-RP-F101 provides recommended practice for assessing pipelines with corrosion. It provides guidance to evaluate and calculate the remaining strength at locations where corrosion defects are found.

Cathodic protection is generally used in combination with a protective coating system to protect the external surfaces of steel pipelines from corrosion. BS ISO 15589 specifies requirements and gives recommendations for the pre-installation surveys, design, materials, equipment, installation, commissioning, operation, inspection, and maintenance of cathodic protection systems for buried on-land pipelines. This standard states "DCVG surveys can be used to locate and establish the relative size of defects in protective coatings on buried pipelines". There is an acceptance by the pipeline industry that DCVG provides an estimate of coating defect area.

2.5.3 Direct Assessment

When ILI is not applicable, all of the ANSI/ASME standards mentioned above have one thing in common, that they all point to the use of the Direct Assessment (DA) methodology. Direct Assessment is one of the first methodologies acknowledged globally as an approved pipeline integrity inspection protocol. It consists of a four step process incorporating; pre-assessment, indirect inspection, direct examination and post-assessment using a combination of non-intrusive inspection techniques. This methodology provides both a quantitative and qualitative status of the general condition of the pipelines.

Direct Assessment is an approach for assessing corrosion in buried pipelines and has been applied widely by pipeline operators since its implementation. ASME B31.8S defines Direct Assessment as "an integrity assessment method utilizing structured process through which the operator is able to integrate knowledge of the physical characteristics and operation history of a pipeline system or segment with the result of the inspection, examination, and evaluation, in order to determine the integrity" [70].

Direct Assessment considers three damage mechanisms or threats to the integrity of the pipelines in order to ensure the integrity of the pipeline and applies three different methodologies addressed below:

- External Corrosion Direct Assessment (ECDA) [72] for external corrosion threat. It is used for determining external corrosion threats on pipeline segments using facilities data, and current and historical field inspections and tests, with the physical characteristics of the pipeline. The focus of the ECDA approach is to identify locations where external corrosion defects may be formed.

- Internal Corrosion Direct Assessment (ICDA) [73] for internal corrosion threat. It is used for determining internal corrosion threats on pipelines segments that normally carry dry gas but may suffer from short-term upsets of wet gas or free water.
- Stress Corrosion Cracking Direct Assessment (SCCDA) [74] for stress corrosion cracking threat. It is used for determining the likely presence or absence of SCC on pipeline segments by evaluating the SCC threat integrating facilities data, current and historical field inspections, and tests with the physical characteristics of the pipeline. The focus of the SCCDA approach is to identify locations where SCC may exist.

In this PhD, part of the research will focus on External Corrosion Direct Assessment.

2.5.3.1 External Corrosion Direct Assessment (ECDA)

ECDA is a structured process with the objective of increasing the safety of pipelines. The aim of ECDA is to assess and mitigate the threat of external corrosion in buried pipelines constructed from ferrous metals. Although various aspects of this process have been applied by industry, it was only formalised as a standard practice by the National Association of Corrosion Engineers (NACE) in 2004.

The ECDA process is used during the whole pipeline life cycle, having particular importance its application for ageing pipelines. However, it is also used during the first years of service and in some cases just after commissioning.

The ECDA methodology uses a meticulous evaluation of data such as design, environmental, and operating conditions, previous corrosion and cathodic protection history. This data needs to be collected, prepared, aligned, segmented and classified prior to applying the ECDA process.

The combination of cathodic protection data with other environmental and inspection data provides a better knowledge of CP performance and external corrosion risk. It is recommended that the ECDA methodology should be carried out by qualified and experienced personnel.

The primary purpose of the ECDA methodology is preventing future external corrosion damage and its implementation is a four steps process:

- Pre-Assessment; which includes data collection, feasibility assessment, indirect inspection tool selection, and identification of ECDA regions.
- Indirect Inspection. "The objective is to identify and define the severity of coating faults, other anomalies, and areas at which corrosion activity may have occurred or may be occurring" [72].
- Direct Examination. "The objectives of Direct Examination Step are to determine which indications from the indirect inspections are most severe and collect data to assess corrosion activity" [72]. The direct examinations require prioritization b selecting priority categories in order to assess the highest risk areas. These categories are:
    - Immediate action required.
    - Schedules action required.
    - Suitable for monitoring.
- Post-Assessment. "The objectives of the Post-Assessment step are to define the reassessment intervals and assess the overall effectiveness of the ECDA process" [72].

The advantages of ECDA are that it is possible to identify areas where defects could appear in the future (other methodologies only detect areas where defects have already been formed).

However, not all pipelines can be assessed with the ECDA methodology, and it is especially challenging to apply to poorly coated or bare pipelines. The first time ECDA is applied, the results have a certain degree of accuracy which is correlated to the accuracy of the gathered data. Repeated application of the ECDA methodology on the same pipelines will improve the accuracy of the predictions. ECDA is best applied as a continuous improvement process (Figure 2-9).

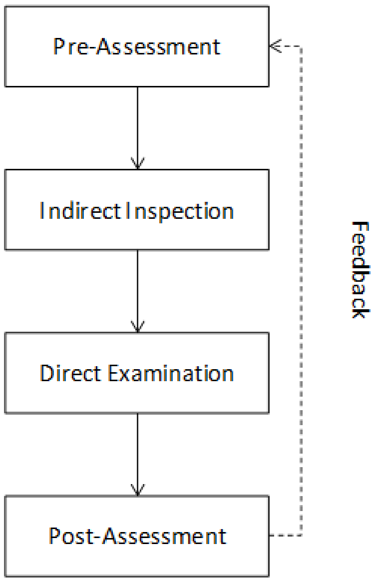

Figure 2-9. External Corrosion Direct Assessment procedure.

The ECDA methodology requires a large amount of data (which are not always available), multiple complex decisions based on criteria, a record of anomalies and changes in the system, multifarious calculations, and monitoring assessment intervals. In order to perform these activities, considerable human, financial and time resources are required.

2.5.3.2 Indirect Inspections (Survey Techniques)

As specified in NACE SP0502, a minimum of 2 indirect techniques are needed in order to assess the integrity of a pipeline. Direct Current Voltage Gradient (DCVG) and Close Interval Potential Survey (CIPS) are the most common techniques used in ECDA assessments.

2.5.3.2.1 Direct Current Voltage Gradient

Direct Current Gradient Survey is an indirect inspection tool discovered by John Mulvany in the early 80s. It is used to assess the effectiveness of corrosion protection (coating) on buried steel pipelines by using the pipeline CP system (impressed current) operating at its normal output. "DCVG surveys are used to delineate and determine the relative severity of indications" [75]. Since there is no direct continuous electrical connection to the pipeline, a severity classification of indications is determined by calculating the %IR (voltage drop) at each indication.

DCVG survey procedure can be divided into two steps, detection of the location of indications and determination of the indication severity. During the first step, the surveyor walks along the pipeline with two probes in contact with the soil. If a pulse is detected on the meter net scale, the direction of the meter needle points towards the electrode that is closest to the indication. As the indication is approached, the pulse magnitude increases, and when the indication is passed, the direction of the needle reverses (Figure 2-10)

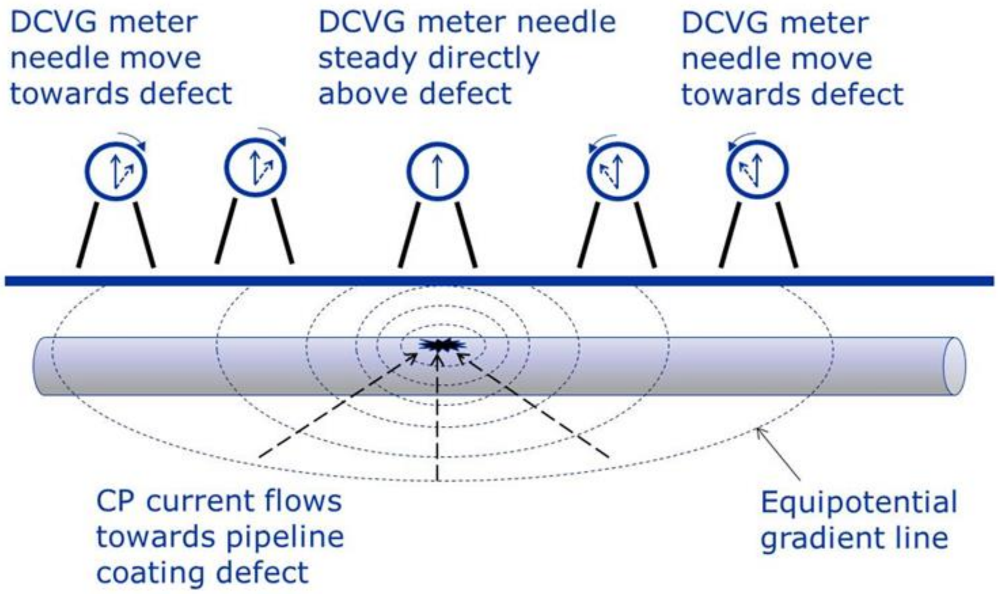

Figure 2-10. Direct Current Gradient Voltage survey measurement procedure.

During the second step, the voltage gradient is measured from the epicenter of the indication to remote earth. Before performing DCVG, the DCVG magnitude needs to be measured at each test post and recorded (pipe to remote earth P/RE). In order to calculate the pipeline DCVG magnitude, a straight line attenuation formula is used [75] (Figure 2-11).

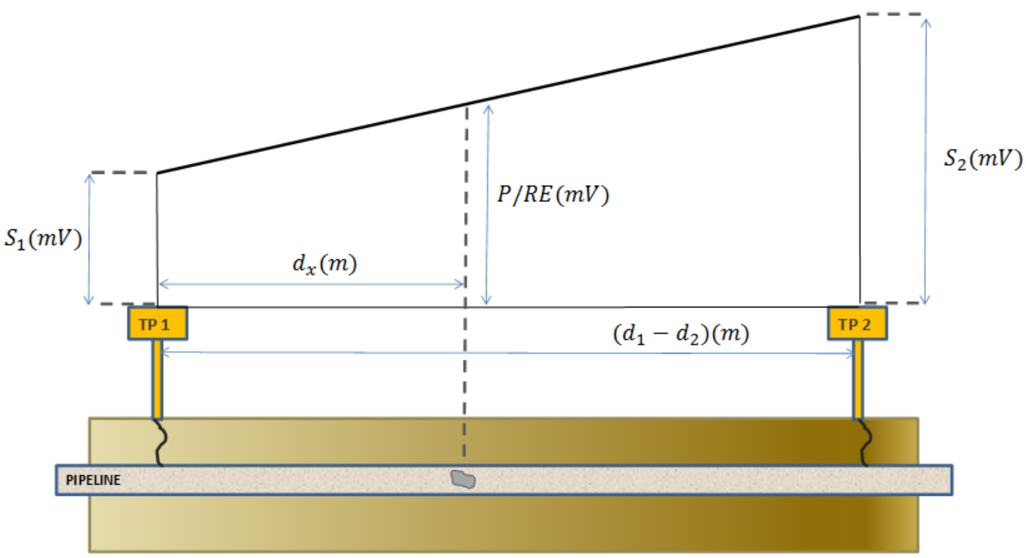

Figure 2-11. Pipe to remote earth P/RE calculated during DCVG inspection.

$$Coating\ fault\ P/RE = S_1 + \frac{dx(S_2 - S_1)}{(d_2 - d_1)} \tag{2.4}$$

Where:

P/RE = Pipe to remote earth DCVG signal magnitude (mV).

S_1 = DCVG signal amplitude to remote earth at Test Post 1 (mV).

S_2 = DCVG signal amplitude to remote earth at Test Post 2 (mV).

d_1 = Distance measurement of Test Post 1 (m).

d_2 = Distance measurement of Test Post 2 (m).

dx = Distance measurement of indication from Test Post 1 (m).

Once the epicenter of the indication has been detected, a series of perpendicular stepped readings are measured moving towards remote earth (Figure 2-12). The summation of the reading is the voltage gradient from indication epicenter to remote earth (OL/RE).

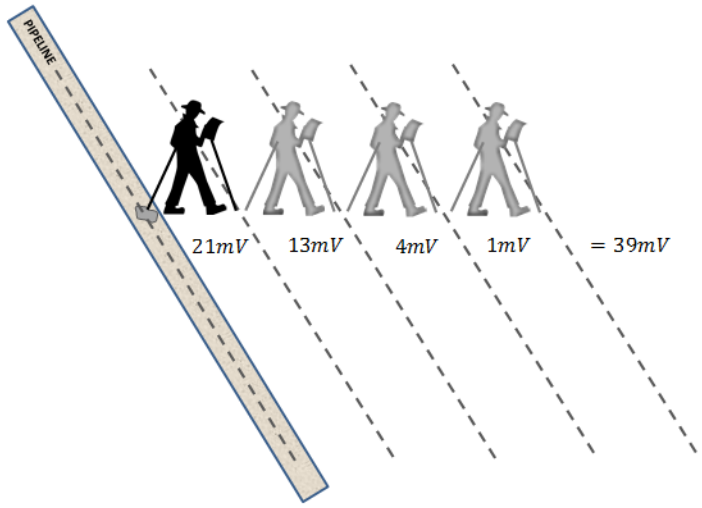

Figure 2-12. Perpendicular stepped readings measured as part of DCVG survey.

The coating indication severity (%IR) is estimated as a difference between the potential difference from indication epicenter to remote earth (OL/RE) and the total calculated potential shift on the pipeline ar the indication location. It is expressed as a percentage.

$$\%IR = \frac{OL/RE \times 100}{P/RE} \tag{2.5}$$

The indications %IR severity value are used to classify the indications [72] based on the operator criteria.

2.5.3.2.2 Close Interval Potential Survey

Close Interval Potential Survey (CIPS) is a pipe to soil gradient survey. It is performed in order assess the effectiveness of the cathodic protection system used on underground pipelines [76]. It is often used in the ECDA methodology.

CIPS measures the voltage difference between a buried pipeline and the surrounding soil. The operator establishes an electrical connection to the pipeline by means of a wire. The pipeline potentials are measured by an operator walking along the length of the pipeline at intervals of about 1 meter.

2.5.3.2.3 Soil resistivity measurement

Soil resistivity measurements quantify the electrical properties of the soil. It provides an indication of the ability of the soil to conduct electricity.

It is difficult to standardize how the soil resistivity affects aboveground techniques. The voltage gradient is a product of the resistance of the soil and the electrical current moving between the pipe surface and the soil. As a consequence, films formed from corrosion products and the cathodic protection can affect the resistivity.

To use the correct value of soil resistivity in the standardization of the voltage gradient, it is necessary to measure the resistance between the pipe surface and the soil. This is the reason why often, expert judgment is required in order to prioritize anomalies based on soil resistivity.

Generally, it is measured using the Four-Pin method (Wenner) [77], the Soil Box method or the Single-Probe method detailed in NACE SP0502.

2.5.3.3 Prioritization

Prioritization is the process of estimating the need to perform a direct examination at each indirect inspection indication based on current corrosion activity plus the extent and severity of prior corrosion [72]. During the ECDA methodology, the operator establishes the criteria for prioritizing the need to carry out direct examinations. NACE SP0502 does not establish time requirements for scheduling remediation and other actions. However, it defines three priority categories as follows:

- Immediate action required: includes indications that the pipeline operator considers as likely to have ongoing corrosion activity and that when coupled with prior corrosion pose an immediate threat to the pipeline under normal operating conditions.
- Scheduled action required: includes indications that the pipeline operator considers may have ongoing corrosion activity but that when coupled with prior corrosion do not pose an immediate threat to the pipeline under normal operating conditions.
- Suitable for monitoring: includes indications that the pipeline operator considers inactive or as having the lowest likelihood of ongoing or prior corrosion activity.

The pipeline operator shall consider the physical characteristics of each ECDA region under year-round conditions, the region's history of prior corrosion, the direct inspection tool used, and the criteria used for identification and classification of indications.

When ECDA is applied for the first time, the pipeline operator should endeavor to make prioritization criteria as stringent as practicable.

Numerous studies have addressed the prioritization process [78][79][80]. Criteria to prioritize ECDA indications have been improved by taking environmental and construction-related factors [81], however, all of the prioritization criteria used before rely on the DCVG indication as an important critical factor. In this research, environmental factors are integrated into corrosion prediction models.

2.6 Statistical tools applied to pipeline integrity management

Pipeline operators place significant emphasis on assuring the integrity of pipelines by applying pipeline integrity management programs. In order to apply an effective pipeline integrity management program, an understanding of the current and likely future condition of pipelines is required. Statistical analysis has been and it is widely used in PIM programs in order to gain an understanding about the corrosion phenomenon. The most common and applied statistical tools are addressed in the following sections.

2.6.1 Regression analysis

Regression analysis is a statistical process for estimating the affinity between variables [82][83][84]. It is used to ascertain the causal effect of one variable upon another. Regression analysis assembles data on the underlying variables of interest and employs regression to estimate the quantitative effect of the causal variables upon the variable that they influence [85]. It evaluates the statistical significance of the estimated relationships, or in order words, the degree of confidence that the true relationship is close to the estimated one.

Regression analysis has been widely applied by the pipeline industry to develop predictive models [86][87]. Least square regressions (OLS) has been used for decades to find correlations between soil and pipeline variables, however, soil modeling contains many underlying factors and due to its heterogeneity, it is in general difficult in obtaining good estimates.

Quantile regression is a statistical technique used to estimate and draw inference on conditional quantile functions [88][89]. It can provide a complete statistical analysis of the stochastic relationships among random variables. Quantile regression has been applied successfully in economics and medicine to predict behaviors and trends; however, it has not been implemented yet to pipeline integrity management.

In this research, quantile regression will be used to find correlations between variables in order to provide useful relationships for external corrosion prediction.

2.6.2 Artificial Neural Networks

Artificial Neural Networks (ANNs) are computational models inspired by the structure of biological neural networks [90]. They obtain information out of given sets of data. Artificial Neural Networks can approximate any continuous function with a desired accuracy and are especially useful for classification problems and for function approximation.

ANNs have been extensively used in PIM programs to solve a wide variety of problems such as leaks detection [91][92], modeling [93] and external corrosion detection amongst others. Castañeda and Urdiqui [94] built an experimental prototype, comprising a buried pipeline, with the purpose of calibrating a transmission line model and an ANN algorithm for locating and assessing the severity of external corrosion damage. The factors considered were soil resistivity, defect (holiday) location and different levels of CP. This methodology accurately assesses the level of CP and locates the position of holidays, however, it is a laboratory physical model and it has not been proved in real scenarios. In the field, the soil properties are heterogeneous and the presence of stray currents is inevitable, and therefore laboratory models are not able to reproduce all the behavior of real pipelines.

Artificial Neural Networks training requires a huge amount of data (which often is not available) in order to make sure that the results are statistically precise [95]. This makes it difficult to apply ANNs to field data due to the lack of resources that most operators face every day, but they are useful to apply for laboratory models in order to understand better the behavior of factors under ideal conditions.

2.6.3 Bayesian inference

Bayesian inference is the process of updating probabilities for a hypothesis of events based on evidence known about the situation at hand [96][97]. Bayesian inference has been applied to Pipeline Integrity Management programs [98][99]. Bayesian analysis provides a way of combining prior information with available data by incorporating past information about a parameter and forming a prior distribution. When new observations are gathered, the posterior distribution becomes the new prior following Bayes' theorem.

Bayesian analysis has allowed the estimation of the statistical distributions of the density and size of external corrosion defects from corrosion data samples taken at excavation sites along the inspected pipeline [100].

There exists some general guidance for selecting priors [101]. However, there is no corrosion guideline in the literature for the selection of Bayesian priors and if it is determined wrongly, it can produce inaccurate results [102]. It requires a deep knowledge in pipeline corrosion to determine the prior distribution.

For this research, Bayesian inference methods are deemed unsuitable due to the lack of knowledge about external corrosion under the present specific environmental conditions. In future, assessments and once a new investigation is gathered, it may be possible to apply Bayesian inference methods using the findings of this research as the prior distribution.

2.6.4 Bayesian belief network

Bayesian belief network (BBN) models are graphical models of a probabilistic dependency model [103] that connects cause (independent variables) and consequence (dependent variables) through directed arrows pointing from the cause to the consequence. The arrows represent causal relationships between the variables. These causal relationships are usually probability distributions that are also called priors. An overly simplistic example of the Bayesian network is shown in Figure 2-13.

Figure 2-13. A simplistic example of a Bayesian belief network.

Where, A is the cause node and B is the consequence node. A can be in several possible states or assume different values (a_1, a_2,... a_n) and B can be in several possible states or assume different numeric values (b_1, b_2,... b_n). The causal relationship or the arrow represents the conditional probabilities for B to be in a given state (b_1, b_2... or b_n) where A is in a fixed state.

This Bayesian network model can be used to determine the probability distributions on the forward and the backwards directions, i.e. given the state of A, one can compute the probability of B in a certain state and vice versa using Equation 2.6.

$$P(A = a_i | B = b_j) = \frac{P(B = b_j | A = a_i) \cdot P(A = a_i)}{P(B = b_j)} \tag{2.6}$$

Where:

$P(A = a_i | B = b_j)$ = Probability of observing A given that B is true.

$P(B = b_j | A = a_i)$ = Probability of observing B given that A is true.

$P(A = a_i)$ = Probability of observing A

$P(B = b_j)$ = Probability of observing B

Once the mechanism or cause-consequence relationship for a process is known, a Bayesian network can be developed. The conditional probability distributions or priors can be obtained through analysis of the literature data, field data, or through discussions with experts in the subject matter.

Bayesian belief networks have been used recently in PIM for addressing and preventing threats such as internal corrosion [104], external corrosion [105][106] and stress corrosion cracking [107]. These models have been used to develop recommendations for further pipeline inspections.

An advantage of Bayesian belief network models is that, if initially the probability density functions are not known or the confidence in the prior is low, the distributions can be updated from the observed data by using Bayesian inference. The observed data can be given as a weightage depending on the confidence on the priors.

A Bayesian network is as useful as its prior belief is reliable. This, added to the need of large amounts of data, makes BBN a good statistical tool to implement when the required resources are available.

Furthermore, using Bayesian learning is computationally expensive. Because of these reasons, whilst acknowledging that Bayesian belief networks show promise in certain situations, given the data that is available, this research implements other techniques that are more appropriate.

2.7 Gaps in the assessment of external corrosion

This thesis will support the need for the effective management of the integrity of aging pipelines. This will be accomplished by investigating the accuracy and validity of the results of a commonly used above-ground pipeline integrity management methodology, External Corrosion Direct Assessment, for identifying and addressing the risk of pipeline corrosion.

One of the major integrity risks to aging pipelines is the degradation and failure of the protective coating, leading to external corrosion. A commonly used approach for the assessment of external corrosion risk of buried, land pipelines is based on the NACE RP502 standard [72]. This approach initially assesses the likelihood of external corrosion occurring on a pipeline from indirect measurements which may include, amongst others; the conditions of the pipeline coating, effectiveness of the cathodic protection and corrosiveness of the soil. Since the initial assessment is based on indirect measurements, a further validation process is required, involving excavations and inspection of the pipeline and coating at selected locations. Based on the correlations of the actual observations on the condition of the pipeline and coatings at these locations, refinement may be made to the risk assessment model. The accuracy of the approach is therefore very dependent on the quality and accuracy of these indirect measurements and the number of excavations carried out to verify the measurements. The underlying assumption is that indirect measurements can provide data to reliably identify corrosion defects on the pipeline, and prioritise defects according to their risk to pipeline integrity.

One established method to determine the condition of the pipeline coating is to use an above-ground technique, such as DCVG, to locate and estimate the severity of the any coating defects, expressed as a percentage drop in the IR value, %IR, that may be present on a pipeline. Whilst the location aspect of this technique is very accurate and reliable, the severity, which is inferred from the %IR value, may not correlate very well with the actual size of the coating defect when examined after excavation. Therefore, there is a need to refine the coating defect sizing model to provide a better indication of the severity (and/or size) of coating defects.

The inconsistencies in the correlation may be due to a number of factors, but there is little research carried out to investigate this in a systematic manner. This may be due to the fact that excavations on a pipeline are often very expensive to carry out and/or relevant data was not collected when the pipe and pipe coating were examined.

A further area of uncertainty relates to the correlation between the indirect inspection measurements, and the severity of the corrosion found following excavation. The development and refinement of risk models to address this link is required in order to ensure the ECDA methodology can be safely applied.

Chapter 3

Application of DCVG to predict coating defects on pipelines

3.1 Introduction

Corrosion is frequently the cause of pipeline failure which can result in disasters causing damage and fatalities. In order to maintain the integrity of non-piggable lines, NACE's external corrosion direct assessment (ECDA) methodology is widely applied to assess external corrosion that can occur at coating defects on underground pipelines [108].

Research presented in this chapter is from a validation exercise carried out on the results of ECDA assessment using subsequent excavation data.

3.2 Background

All underground pipelines are affected by corrosion when the levels of cathodic protection (CP) are inadequate and the protective coating is damaged, in particular in ageing pipelines. A commonly used approach for the assessment of eternal corrosion risk of buried, land pipelines is based on the NACE SP0502 standard [108], often referred to as external corrosion direct assessment (ECDA).

Work reported in this chapter builds on an integrity assessment carried out by TWI on pipelines. This chapter presents the results from the application of this assessment that included ECDA. In this approach, which has been described in more detail in Section3.4, initially, an assessment of the likelihood of external corrosion occurring on a pipeline was made from indirect measurements to prioritise further action. This formed the basis for a more comprehensive inspection that involved excavation at selected sites.

Based on the correlation between actual observations (from pipeline excavations) regarding the condition of the pipeline and coating with prior data (indirect inspections), this chapter improves the understanding and interpretation of data used in ECDA in order to make more reliable predictions [108][75][109].

Existing approaches often assume that indirect measurements can provide data to reliably identify corrosion defects on the pipeline, so that excavation location can be prioritised. One established indirect method to determine the condition of the pipeline coating is to use an above-ground technique, such as Direct Current Voltage Gradient (DCVG), to locate and estimate the severity of any coating defects that may be present on the pipeline [75]. Whilst the location aspect of this technique is very accurate and reliable, the severity , which is inferred from the %IR value, may not correlate very well with the actual size of the coating defect when is examined after excavations [109]. Therefore, there is a need to exercise caution using %IR value to provide an indication of the severity (and/or size) of coating defects.

3.3 Scope

Correlate data from the pre-assessment and indirect inspections with data from direct examination in order to improve prediction of corrosion on buried pipelines.

3.4 Description of the data

For the purposes of this chapter, data from Pre-Assessment, Indirect Inspection and Direct Examination (the first three steps of ECDA as specified by NACE) was gathered and analysed. The type of data gathered is described in the sub-sections below and the analyses carried out are shown in the sections that follow.

3.4.1 Pre-Assessment data

Pre-Assessment data available included pipeline design specifications, operational data and time in service. These data were gathered from design and installation reports.

There was a total of nine pipelines, covering 300km, with diameters ranging from 26” to 42”. The material used was API 5L-X60 and X52. Operational pressures varied from 8 to 17 bar. The operational temperatures ranged from 40 to 60 °C. The flow rates varied from 400 to 1520 m^3/h. The pipelines inspected in this research were commissioned between 1972 and 1992. The time in service was calculated from the time since commissioning of the line. The coating applied to protect them was either cold wrap tape or coal tar.

3.4.2 Indirect Inspection data

During the Indirect Inspection phase of the integrity management project, DCVG was performed along the entire length of the pipelines using the pipeline CP system (impressed current) operating at its normal output. For each coating defect identified, the OL/RE (over-the-line to remote earth voltage) was measured. Then, as per NACE TM0109 [75], the P/RE (calculated pipe to remote earth potential at indication) was calculated using a linear interpolation between the pipe to remote earth voltage at the two closest test stations.

In this way, IR drop was calculated for each location at which coating damage had been detected with DCVG. Voltage drop (or %IR) is an indicative value of the amount of current travelling through the soil to protect the coating defect and takes values from 0 to 100%.

3.4.3 Direct Examination data

In the third phase of the ECDA methodology, a series of measurements were taken and coating defects were examined after excavation, this was done not only at defect locations where DCVG data showed high severity, but also at some locations where the severity was not indicated as high. This was done with a view to test the predictions using indirect against actual excavated (direct) data.

Two kinds of data were gathered: environmental and pipe related data. Table 3-1 shows the nature of this data. It must be noted that for the regression analyses carried out, both quantitative data and categorical data (qualitative measurement or descriptive data) were used.

Soil resistivity data was measured using the four pins method detailed in NACE SP0502 [108] at representative soil depths of 0.75, 1.5 and 3 meters. The values used for the analyses are the closest measurements to the depth of the pipeline.

Backfill properties were not easy to quantify. They were classified as three different groups: sandy, clay and clay with a mix of gravel/rock/stones due to the different properties. The geometry of the backfill refers to the shape that the soil particles have. They were divided into round and angular geometries: round where soil particles have rounded edges and angular where the soil particles have sharp edges.

For each excavation location, the presence or absence of water was noted; however, in some excavation reports, this data was missing. When water was present, the pH value was also measured.

Coating defect areas were calculated from the excavation reports in which only length and width were annotated. However, photographs of each individual defect were taken. Using these, it was possible to estimate the real defect area. Only sections of the pipeline without coating were considered; disbonded defects were not considered in the analysis. The corrosion depth measurements were carried out using ultrasonic testing equipment.

The amount of deposits under coating was also measured. It is assigned a value from 0 to 100% and it was calculated by dividing the coating defect area with deposits by the total coating defect area.

Factor	**Type of data**	**Range of values**
Soil resistivity (Environmental)	Quantitative	Values from 75 to 43,332 Ωcm
Backfill type (Environmental)	Categorical	See Table 3-4
Backfill geometry (Environmental)	Categorical	See Table 3-4
Presence of water (Environmental)	Categorical	See Table 3-4
pH of water (Environmental)	Quantitative	Values from 6 to 14 when applicable
Coating defect area (Pipe related)	Quantitative	Values from 0 to 21,550 cm^2
Corrosion depth (Pipe related)	Quantitative	Values from 0 to 6.6mm

Deposits under coating (Pipe related)	Quantitative	Values from 0 to 100%

Table 3-1. Types of data used in regression analyses.

3.4.4 Exploratory analysis

An exploratory analysis has been performed using data gathered in sections 3.4.1 to 3.4.3 to get a better understanding of the data (Table 3-2). The sample size is 200.

Variable	**Range**	**Type**	**Mean**	**Variance**	**Standard deviation**
Coating defect area (cm^2)	0 - 21,550	Quantitative	15,470	$6.67 \cdot 10^8$	25,824
Corrosion depth (mm)	0 – 6.60	Quantitative	1.26	2.07	1.44
Time in service (years) (w)	24 - 44	Quantitative	35.20	52.35	7.23
Soil Resistivity (Ω-cm) (x)	75 - 43,332	Quantitative	2,775	$2.34 \cdot 10^7$	4,845
Voltage drop (%IR) (y)	2.29 - 100	Quantitative	38.21	614.94	24.80
Deposits under coating (cm^2) (z)	0 - 100	Quantitative	40.97	1020.41	31.94
Water pH	-	Categorical	-	-	-
Presence of water	-	Categorical	-	-	-
Backfill type	-	Categorical	-	-	-

Backfill geometry	-	Categorical	-	-	-
Coating type	-	Categorical	-	-	-

Table 3-2. Exploratory analysis using data from sections 3.4.1 to 3.4.3.

The correlation between response variable (coating defect area) and each of the independent variables is presented in Table 3-3. Correlation analysis is used as a preliminary analysis to explore the relationships between the dependent variables and each of the independent variables.

	Corrosion depth	**Years (w)**	**Resist. (x)**	**%IR (y)**	**Depts. (z)**	**w^2**	**x^2**	**y^2**	**z^2**	**wx**	**wy**	**wz**	**xy**	**xz**	**yz**
Coating defect area	-0.12	-0.24	-0.03	0.36	-0.04	-0.24	-0.03	0.34	0.02	-0.03	0.26	-0.06	0.04	0.09	0.15

Table 3-3. Correlation between coating defect area and quantitative independent variables.

The results show that, %IR is the variable with the highest correlation with coating defect area.

A prior analysis on the correlation between independent variables indicates that there is no multi-collinearity issue on the independent variables.

3.5 Correlation between DCVG (%IR) and corrosion depth

During the Indirect Inspection phase of the ECDA methodology, DCVG was carried out and during the Direct Examination, external corrosion depth of the pipe wall was measured. Linear regression has been applied to the data in order to observe the existence or absence if correlation between the data.

It was found that there is no straightforward relation between corrosion depth (wall thickness lost) and the voltage drop (%IR) calculated during DCVG (Figure3-1). A total of 43% of the points corresponded to regions where there was no corrosion activity and therefore the corrosion depth was zero.

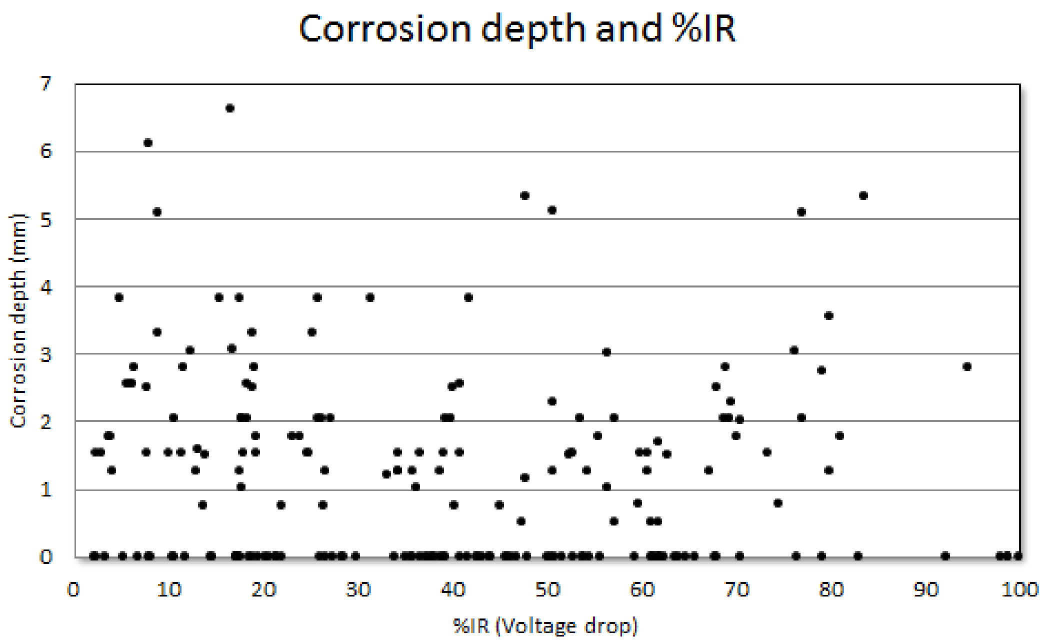

Figure 3-1. Corrosion depth and %IR diagram.

3.6 Correlation between DCVG (%IR) and coating defect size

Relationship between %IR and coating defect area is important. BS ISO 15589 states "DCVG surveys can be used to locate and establish the relative size of defects in protective coatings on buried pipelines" [66] so there is an acceptance by the pipeline industry that %IR provides an estimate of the size of coating defects. By "relative" it is understood that, voltage drop is proportional to the coating defect area, however, this has not been quantified.

With a good understanding of how the voltage drop measured during DCVG is related with the coating defect area, it is possible to improve the accuracy in the prediction of coating defect area and consequently identify the high risk areas. This relationship has been investigated using the data described in Section 3.4.3; the analyses are described in the following sections.

3.6.1 Linear regression model

Linear regression is first used to model the relationship between %IR and coating defect area with the aim of finding the relation between %IR and coating defect area. The advantage of applying linear regression are its simplicity and interpretability. Also, it provides a good initial understanding of the behaviour between these two parameters.

A linear regression model employs the least squares estimator to fit a single explanatory variable x to the dependent variable y. The target is to find the equation (Equation 3.1) of the straight line that would give the best fit for the data points.

$$y = \beta_0 + \beta_1 x + \varepsilon \tag{3.1}$$

In our case, y is coating defect area in cm^2, x is %IR, β_1 is the slope or regressor coefficient, β_0 is the intercept and ε is the model error.

The linear regression attempts to illustrate the correlation between voltage drop (%IR) and coating defect area (Figure 3-2). Although a strong trend has not been observed, increase of the coating defect area (exposed pipe area) generally correlated to an increase in the %IR drop, especially at values above 30%.

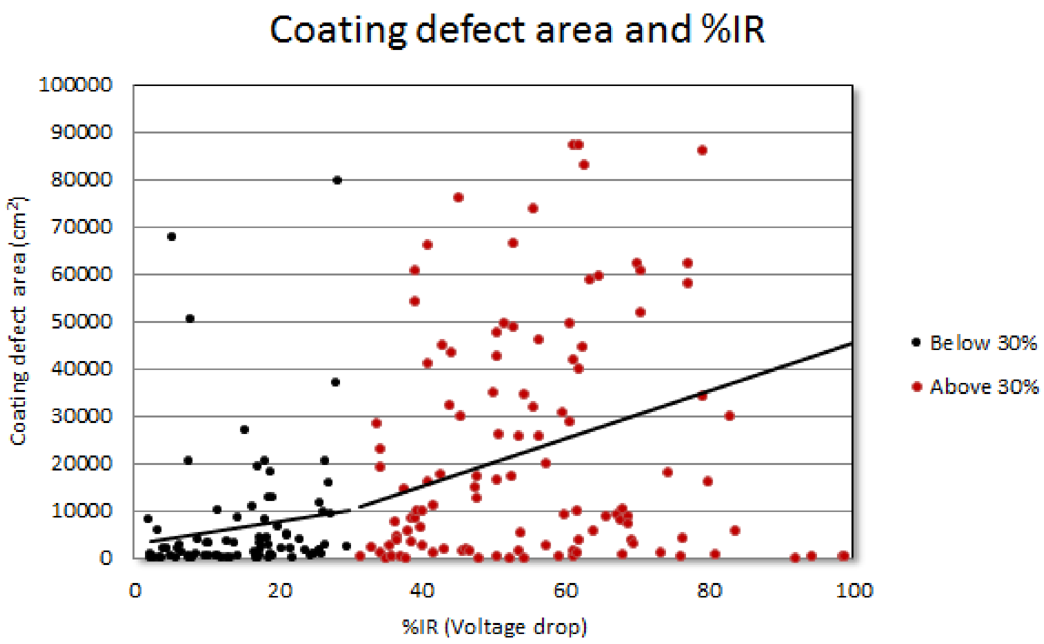

Figure 3-2. Coating defect area and %IR diagram.

The equation modelled in Figure 3-2 corresponds with the following expression:

$$y = 238.92x + 3088, \quad if \quad IR \leq 30\% \qquad R^2 = 0.0183 \qquad (3.2)$$

$$y = 504.59x - 5000, \quad if \quad IR > 30\% \qquad R^2 = 0.0235 \qquad (3.3)$$

The low R^2 value indicates that the regression model does not fit well with the data. Some of the possible reasons are explained in Section 3.8.

Only defects where the exposed pipeline is in direct contact with the soil (bare sections of the pipeline) have been taken into consideration. Regions with disbonded coating have been omitted due to the poor correlation with the voltage drop caused by CP shielding.

The simple linear model is unsuitable for multiple independent variables requiring a more complex regression method such as multiple linear regression.

3.6.2 Multiple linear regression model

Multiple linear regression (MLR) can be used to fit a predictive model to an observed data set in order to quantify the strength of the relationship between the dependent variable and the independent variables. The assumptions considered in order to apply MLR are as follows:

- Variables have weak exogeneity , meaning they are free of error.
- Linearity.
- There is no correlation between the predictor variables.

For the analysis, it is therefore assumed that the variables are free of error, the relationships are linear and there is no correlation between themselves.

In order to model the coating defect area, MLR has been implemented using R Studio software, taking in consideration variables described in Table 3-2 by using Equation (3.1).

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n + \varepsilon \qquad (3.4)$$

Because some of these factors are categorical (qualitative), dummy variables are included to be used in the regression model. Table 3-4 illustrates the factors included in the regression model with dummy variables.

When using dummy variables, at least one category needs to be omitted, which becomes the reference category against which the effects of other categories are assessed.

Nine independent variables were introduced in the mathematical model, including %IR. The eight new variables, representing other factors (shown in Table 3-2) not considered in the simple regression model, were introduced to obtain their individual influence on the coating defect area.

Factors with dummy variables	**States**
	>7.5
pH of water from excavation	<7.5
	Unknown

Presence of water	Yes No
Type of backfill	Sand Clay Clay with mix of gravel/rock/stone
Geometry of backfill	Round Angular
Type of coating	Cold wrap Coal tar

Table 3-4. Factors with dummy variables and their states.

MLR provides better predictive capability than simple linear regression, and provides an estimate of the relative importance of each variable. However, MLR is very sensitive to outliers. Thus, to understand better the relationship between variables a more robust mathematical model, described below, is considered.

Multiple linear regression has been performed in order to estimate the average of coating defect area. The following expression predicts the area of coating defect for the nine given parameter addressed in Section 3.4.

$$\text{Average Coating Defect Area }(\text{cm}^2) = 4.60 \cdot 10^4 - 1.18 \cdot 10^3\alpha + 4.68 \cdot 10^3\text{A1} - 2.58 \cdot 10^3\text{A2} + 1.91 \cdot 10^{-1}\beta + 3.35 \cdot 10^2\gamma + 4.42 \cdot 10^3\text{B1} + 9.16 \cdot 10^3\text{C1} - 1.35 \cdot 10^{-3}\text{C2} - 7.58 \cdot 10^3\text{D1} - 1.52 \cdot 10^3\text{E1} + 1.56 \cdot 10^2\delta \quad (3.5)$$

where α is the time in service, β is soil resistivity at site location, γ is %IR drop, δ is the amount of deposits under coating (%).A1 → If 1, pH>7.5; A2 → If 1, pH<7.5; B1 → If 1 , there is presence of water at site location; C1 → If 1, sand backfill at site location; C2 → If

1, clay backfill at site location; D1 → If 1, backfill have round geometry; E1 → If 1, coating is cold wrap.

Each of the coefficients in Equation 3.5 has a "p-value" associated (Table 3-5). The "p-value" is the probability of finding the observed results when the null hypothesis is true. If the "p-value" is less than 0.05, then, given variable has significantly different results from zero meaning that the statistic is reliable and therefore this factor has a strong correlation with the dependent variable. The "p-value" < 0.05 implies that a 5% significance level is used.

Variable	Estimate	Std. error	t-Value	p-value	Interpretation
Intercept	$4.60 \cdot 10^{4}$	$2.78 \cdot 10^{4}$	1.651	0.10071	Near significant differences
α	$-1.18 \cdot 10^{3}$	$6.67 \cdot 10^{2}$	-1.769	0.07876	Near significant differences
β	$1.91 \cdot 10^{-1}$	$3.83 \cdot 10^{-1}$	0.500	0.61767	No significant differences
γ	$3.35 \cdot 10^{2}$	$7.86 \cdot 10^{1}$	4.263	3.4·10-5	Significant Differences
δ	$1.56 \cdot 10^{2}$	$6.85 \cdot 10^{1}$	2.280	0.02392	Significant Differences
A1	$4.68 \cdot 10^{3}$	$1.03 \cdot 10^{4}$	0.455	0.64993	No significant differences
A2	$-2.58 \cdot 10^{3}$	$9.56 \cdot 10^{3}$	-0.270	0.78735	No significant differences
B1	$4.42 \cdot 10^{3}$	$6.09 \cdot 10^{3}$	0.726	0.46873	No significant differences
C1	$9.16 \cdot 10^{3}$	$1.13 \cdot 10^{4}$	0.811	0.41883	No significant differences
C2	$-1.35 \cdot 10^{-3}$	$5.06 \cdot 10^{2}$	-2.671	0.00833	Significant Differences
D1	$-7.58 \cdot 10^{3}$	$8.39 \cdot 10^{3}$	-0.904	0.36740	No significant differences
E1	$-1.52 \cdot 10^{3}$	$1.14 \cdot 10^{4}$	-0.134	0.89386	No significant differences

Table 3-5. Multiple linear regression coefficients.

Equation 3.5 and Table 3-5 indicate a significant positive association between voltage drop (%IR) and coating defect area. An increase of one unit in %IR, the predicted coating area increases 335 cm^2. Voltage drop is limited to 100%, therefore the maximum coating defect for the predictive model is 33,500 cm^2.

A coating defect size of 33,500 cm^2, means that the pipeline does not have any coating (bare pipe) and therefore, even if the coating defect size takes higher values, the interpretation would be the same.

Based on the assumption that $p = 0.05$, some of the factors have been addresses as having "near significant differences". The independent variable α (time in service) is not significant for $p = 0.05$, but becomes significant if the p-value is increased to 0.1. This means that α has some degree of correlation with the dependent variable, however, not as strong as variables with $p < 0.05$.

Also, from this regression model it can be determined that only 21.53% of the variation is explained by the regression and the rest is due to error (R-square = 21.53%).

3.6.3 Multiple non-linear regression model

Multiple non-linear regression model can be used to fit a predictive model to an observed data set in order to quantify the strength of the relationship between the dependent variable and the independent variable. To perform multiple non-linear regression, the data used fulfils the following criteria:

- Variables have weak exogeneity, therefore the explanatory variables are not correlated with the error.
- There is no correlation between the predictor variables.

In order to model the coating defect area, quadratic polynomial regression was implemented using R Studio (R Core Team, 2013) taking in consideration the variables described in Table 3-1 by using Equation 3.6.

$$Average\ Coating\ Defect\ Area\ (cm^2) = a + \beta_1 w + \beta_2 x + \beta_3 y + \beta_4 z + \beta_5 w^2 + \beta_6 x^2 + \beta_7 y^2 + \beta_8 z^2 + \beta_9 wx + \beta_{10} wy + \beta_{11} wz + \beta_{12} xy + \beta_{13} xz + \beta_{14} yz + \beta_{15} A1 + \beta_{16} A2 + \beta_{17} B1 + \beta_{18} C1 + \beta_{19} C2 + \beta_{20} D1 + \beta_{21} E1 + \varepsilon \qquad (3.6)$$

Some variables ($A1, A2, B1, C1, C2, D1, E1$) have not been used in quadratic terms because they are dummy variables (take either 0 or 1 as value) and squaring these variables is not meaningful.

The value a is the intercept and ε is the model error. Where factor were categorical (qualitative), these were substituted by dummy variables in the regression model. Table 3-6 illustrates the factors included in the regression model with dummy variables.

Factors with dummy variables	**States**	**Dummy Variables**
	>7.5	A1
pH of water from excavation	<7.5	A2
	Unknown	Not applicable
Presence of water	Yes	B1
	No	Not applicable
	Sand	C1
Type of backfill	Clay	C2
	Clay with mix of gravel/rock/stone	Not applicable
Geometry of backfill	Round	D1
	Angular	Not applicable
Type of coating	Cold wrap	E1

Coal tar	Not applicable

Table 3-6. States of factors with dummy variables.

When using dummy variables, at least one category needs to be omitted, which becomes the reference category against which the effects of other categories are assessed.

Nine independent variables were introduced in the mathematical model including %IR. They were introduced to obtain their individual strength of correlation with the coating defect area.

Multiple non-linear regression has been performed in order to estimate the average of coating defect area. The following expression predicts the area of coating defect for the nine given parameters addressed in Section3.4.

$$Average\ Coating\ Defect\ Area\ (cm^2) = -8.47 \cdot 10^4 + 7.15 \cdot 10^3 w - 2.11 \cdot 10^0 x + 1.21 \cdot 10^3 y - 3.67 \cdot 10^2 z - 1.18 \cdot 10^2 w^2 + 2.92 \cdot 10^{-5} \cdot x^2 - 1.70 \cdot 10^{-1} \cdot y^2 + 3.29 \cdot 10^0 \cdot z^2 + 1.68 \cdot 10^{-2} wx - 2.62 \cdot 10^1 wy - 4.23 \cdot 10^{-1} wz - 7.35 \cdot 10^{-3} xy + 3.76 \cdot 10^{-2} xz + 2.30 \cdot 10^0 yz - 8.93 \cdot 10^2 A1 - 1.65 \cdot 10^3 A2 + 3.78 \cdot 10^3 B1 + 1.31 \cdot 10^4 C1 - 1.37 \cdot 10^4 C2 - 5.88 \cdot 10^3 D1 - 1.85 \cdot 10^3 E1 \quad (3.7)$$

where w is the time in service, x is soil resistivity at site location, y is %IR drop, z is the amount of deposits under coating (%).$A1$ → If 1, pH>7.5; $A2$ → If 1, pH<7.5; $B1$ → If 1 , there is presence of water at site location; $C1$ → If 1, sand backfill at site location; $C2$ → If 1, clay backfill at site location; $D1$ → If 1, backfill have round geometry; $E1$ → If 1, coating is cold wrap.

Each of the coefficients in Equation 3.7 has a “p-value” associated (Table 3-7). If the “p-value” is less than 0.05, then, given variable has significantly different results from zero meaning that the statistic is reliable and therefore this factor has a str`ong correlation with the dependent variable. The “p-value” < 0.05 implies that a 5% significance level is used.

Variable	Estimate	Std. Error	t value	p value	Interpretation
Intercept	$-8.47 \cdot 10^{4}$	$9.76 \cdot 10^{4}$	-0.868	0.38669	No significant differences
w	$7.15 \cdot 10^{3}$	$6.26 \cdot 10^{3}$	1.142	0.25532	No significant differences
x	$-2.11 \cdot 10^{0}$	$5.07 \cdot 10^{0}$	-0.416	0.67775	No significant differences
y	$1.21 \cdot 10^{3}$	$5.66 \cdot 10^{2}$	2.131	0.03466	Significant differences
z	$-3.67 \cdot 10^{2}$	$6.15 \cdot 10^{2}$	-0.597	0.55134	No significant differences
w^2	$-1.18 \cdot 10^{2}$	$9.98 \cdot 10^{1}$	-1.182	0.23903	No significant differences
x^2	$2.93 \cdot 10^{-5}$	$4.59 \cdot 10^{-5}$	0.638	0.5245	No significant differences
y^2	$-1.70 \cdot 10^{-1}$	$3.11 \cdot 10^{0}$	-0.055	0.95643	No significant differences
z^2	$3.29 \cdot 10^{0}$	$2.65 \cdot 10^{0}$	1.24	0.21701	No significant differences
wx	$1.68 \cdot 10^{-2}$	$1.09 \cdot 10^{-1}$	0.153	0.87831	No significant differences
wy	$-2.62 \cdot 10^{1}$	$1.27 \cdot 10^{1}$	-2.06	0.04109	Significant differences
wz	$-4.23 \cdot 10^{-1}$	$1.74 \cdot 10^{1}$	-0.024	0.98063	No significant differences
xy	$-7.35 \cdot 10^{-3}$	$3.52 \cdot 10^{-2}$	-0.209	0.83492	No significant differences
xz	$3.76 \cdot 10^{-2}$	$1.70 \cdot 10^{-2}$	2.214	0.02828	Significant differences
yz	$2.30 \cdot 10^{0}$	$2.76 \cdot 10^{0}$	0.835	0.40487	No significant differences
A1	$-8.93 \cdot 10^{2}$	$1.12 \cdot 10^{4}$	-0.08	0.93634	No significant differences

A2	$-1.65 \cdot 10^3$	$9.66 \cdot 10^3$	-0.17	0.86497	No significant differences
B1	$3.78 \cdot 10^3$	$6.15 \cdot 10^3$	0.615	0.53943	No significant differences
C1	$1.31 \cdot 10^4$	$1.16 \cdot 10^4$	1.129	0.26064	No significant differences
C2	$-1.37 \cdot 10^4$	$5.23 \cdot 10^3$	-2.613	0.00986	Significant differences
D1	$-5.88 \cdot 10^3$	$8.76 \cdot 10^3$	-0.671	0.50323	No significant differences
E1	$-1.85 \cdot 10^3$	$1.33 \cdot 10^4$	-0.139	0.88978	No significant differences

Table 3-7. Multiple non-linear regression coefficients and parameters.

Equation 3.7 and Table 3-7 indicate a significant positive association between voltage drops (%IR) and coating defect area.

This model can be used to predict the average coating defect area under the presence of environmental factors. However, it is important to be aware that it will only be accurate for sets of pipelines with similar conditions.

Figure 3-3 shows the predicted coating defect area, calculated using equation3.7, plotted against the real coating defect area, obtained from the real measurements.

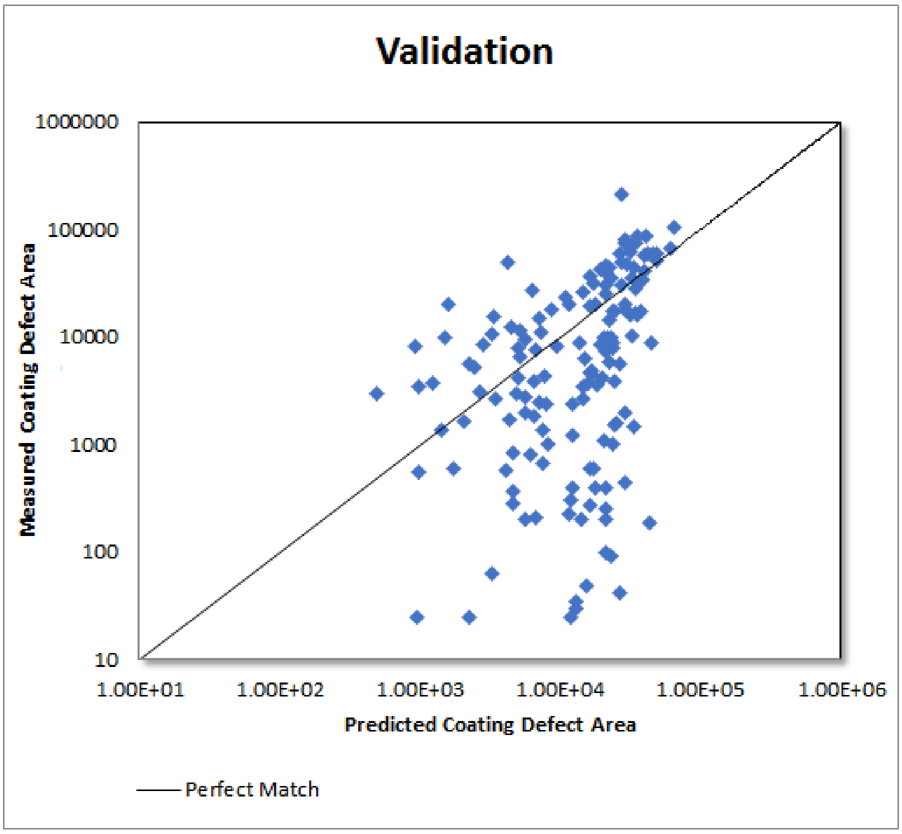

Figure 3-3. Predicted coating defect area and measured coating defect area.

The diagonal line represents the ideal case and it has a slope equal to 1. If a defect falls near this line, it means that the predicted coating defect area is close to the measured coating defect area. The results of this model improve the prediction compared to the multiple linear regression model from Section 3.6.3.

From this regression model, it can be determined that only 29.79% of the variation is explained by the regression and the rest is due to error (R-square = 29.79%).

3.6.4 Quantile regression model

The probability density function of the coating defect area is not symmetric; it has a positive skewness (Figure 3-4), leading us to use more complex models such as quantile regression, because we aim to assess how a factor or factors could cause larger or smaller coating defects. In such situation, mean-based regression models such as described above are not effective in finding solutions. Instead, the use of quantile regression may be more appropriate to identify the effect of key factors (%IR) for large and small coating defects.

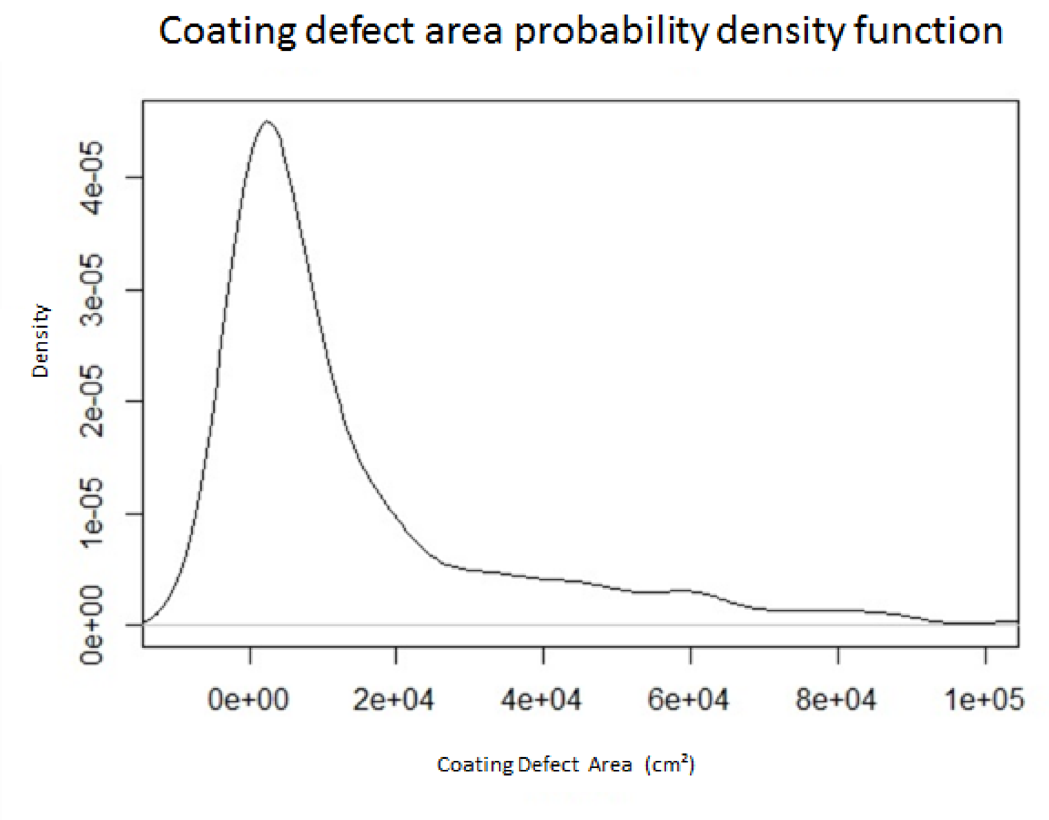

Figure 3-4. Probability density function for coating defect area variable.

Quantiles describe the distribution of the dependent variable in terms of quantile [110]. While the median is a special quantile to measure the middle location, extreme quantiles describe the tails of the distribution. MLR models the relationship between one or more independent variables and the conditional quantiles of the dependent variable rather than the conditional mean of aforementioned variable [89][111].

From basics statistics, it is known that any real valued random variable, Y, is characterized by its distribution function,

$$F(y) = Prob(Y \leq y) \tag{3.8}$$

The τ-quantile of $F(y)$ is usually defined as the inverse of $F(y)$, i.e., $F^{-1}(\tau)$. Correspondingly, the τ-empirical quantile of the sample $\{Y_1, \dots, Y_N\}$ can be computed by the following minimization problem *[112]*:

$$\hat{q}_\tau = argmin_z \sum_{i=1}^{n} [\tau \cdot I(Y_i > z) + (1 - \tau) \cdot I(Y_i < z)] \cdot |Y_i - z| \tag{3.9}$$

where I is an indicator function. While a conditional distribution of Y given independent variables X_s is concerned and replaced, quantile regression is defined correspondingly. The parameter z is the value which minimizes the function.

Quantile regression was computed using R Studio software. The variables included were the same as described in Section 3.4. This quantile regression gives a more comprehensive view of the effect of the independent variables on the dependent variable (coating defect area) and will help to determine the factor combinations affecting to high or low coating defects.

With quantile regression, we can study the effects of the %IR drop on coating defect area for low and high %IR drop. Although it is possible to do this with a normal distribution, it will not differentiate between those locations with low %IR drop and those with high %IR drop.

The advantages of applying quantile regression are the flexibility for modelling data with heterogeneous conditional distributions and more robustness relative to the use of linear regression. Also, quantile regression has richer characterisation and the description of the data can show different effects of the independent variables on the dependent variable across the spectrum of the independent variable.

The calculated quantile regression estimates multiple rates of change (slopes) from the minimum to the maximum response, providing a more complete picture of the relationships between variables, which is an improvement over the regression models shown earlier.

Equations for some of the most relevant quantiles are presented in Equations 3.10 to 3.12. The 0.5 quantile is important because it is the median of the distribution.

$$Coating\ defect\ area(0.5\ quantile) = 4.77 \cdot 10^4 - 1.19 \cdot 10^3\alpha + 3.00 \cdot 10^{-2}\beta + 1.08 \cdot 10^2\gamma + 7.89 \cdot 10^1\delta + 1.49 \cdot 10^3A1 - 1.39 \cdot 10^3A2 + 4.42 \cdot 10^3B1 + 1.26 \cdot 10^4C1 - 5.43 \cdot 10^3C2 - 4.31 \cdot 10^3D1 - 1.70 \cdot 10^2E1 \tag{3.10}$$

The 0.05 quantile (5th quantile) represents the coating defect area for the 5% of the defects on the left of the probability density function (small coating defects).

$$Coating\ defect\ area(0.05\ quantile) = 2.09 \cdot 10^3 - 5.26 \cdot 10^1 \alpha + 7.41 \cdot 10^{-3} \beta + 4.10\ \cdot 10^0 \gamma + 1.11 \cdot 10^{-1} \delta - 3.73 \cdot 10^1 A1 + 2.71 \cdot 10^3 A2 + 1.52 \cdot 10^2 B1 + 2.72 \cdot 10^3 C1 - 1.57 \cdot 10^2 C2 - 2.10 \cdot 10^2 D1 - 9.36 \cdot 10^2 E1 \quad (3.11)$$

The 0.95 quantile (95th quantile) represents the coating defect area for the 95% of the defects on the left of the probability density function (large coating defects).

$$Coating\ defect\ area(0.95\ quantile) = 4.96 \cdot 10^4 - 1.23 \cdot 10^3 \alpha + 6.69 \cdot 10^{-1} \beta + 8.61\ \cdot 10^2 \gamma + 3.35 \cdot 10^2 \delta - 2.07 \cdot 10^4 A1 - 2.71 \cdot 10^4 A2 + 1.94 \cdot 10^4 B1 + 2.45 \cdot 10^3 C1 - 1.85 \cdot 10^4 C2 - 3.29 \cdot 10^3 D1 - 1.32 \cdot 10^2 E1 \quad (3.12)$$

In Figure 3-5, the quantiles of the dependent variable are on the horizontal axis and the coefficient magnitudes on the vertical axis. The MLR coefficient is plotted as a horizontal red line with the confidence intervals as two horizontal lines around the coefficient line (red dotted line). The MLR coefficients do not vary by quantiles.

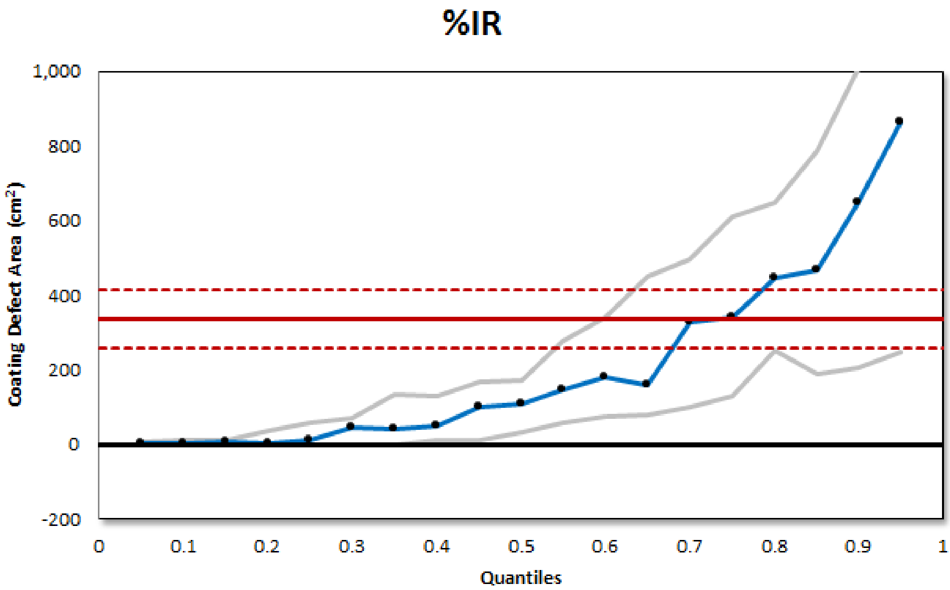

Figure 3-5. Representation of the quantile coefficients for the %IR on coating defect size.

The quantile regression coefficients are plotted as lines varying across the quantiles (black dots) with confidence intervals above and below them (grey lines). If the quantile coefficient is outside the MLR confidence interval, then we have significant differences between the quantile and MLR coefficients.

The quantile coefficients for the %IR (independent variables) on coating defect size (dependent variable) are significantly different from the MLR coefficients. Moreover the effect of %IR drop increases for locations with higher coating defect size (higher quantiles).

For the 5th quantile, which represents the small coating defects, an increase of one unit in the %IR value, increases 4.10 cm^2 the coating defect area (Figure 3-6). Whereas for the 95th quantile, which represents the large coating defects, an increase of one unit in the %IR value, increases 861 cm^2 the coating defect area (around 200 times more than for the 5th quantile). The MLR coefficients cross with the quantile coefficients at the 75th quantile.

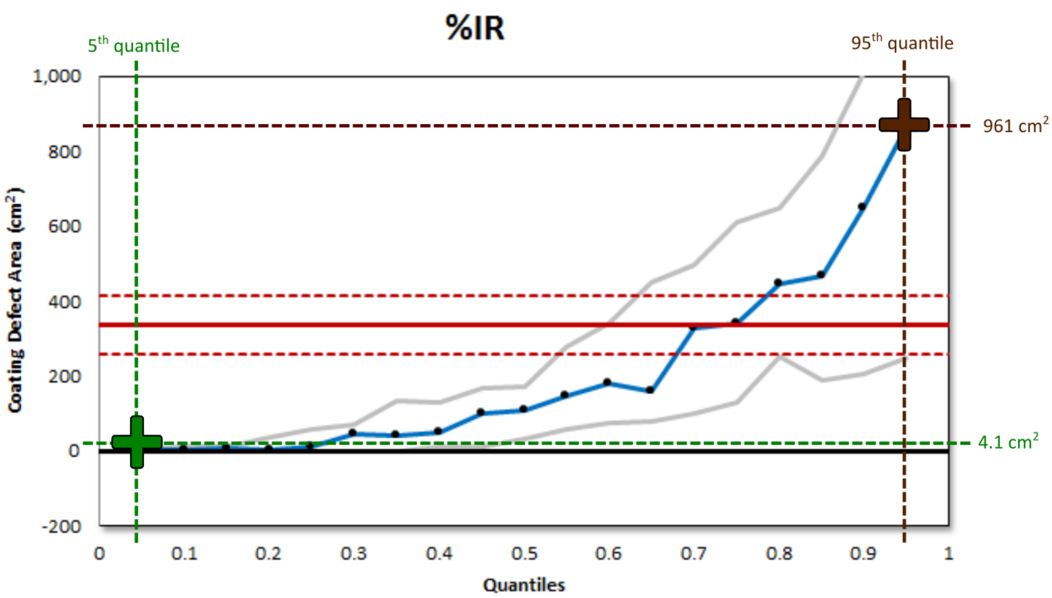

Figure 3-6. Representation of the 5th and 95th quantile coefficients for the %IR drop on coating defect size.

The analyses show that DCVG readings are more sensitive to large coating defect areas than small to medium coating defect areas.

3.7 Correlation between coating defect area and corrosion depth

When performing ECDA, the %IR value plays an important role in determining the severity classification of an indication. The pipeline operator defines and applies criteria for classifying the severity of each indication. Small indications (%IR) were classified as minor severity, while large indications were classified as severe (Table 3 of NACE SP0502 [113]).

The severity indication allows an estimation of the extent of the coating defect area. When a section of a pipeline is exposed after coating breakdown, corrosion activity might occur with certain areas having high corrosion depths that may compromise the integrity of the pipeline. It is not a straightforward process to predict the corrosion depth using indirect inspections. For this case, 200 locations were examined directly and corrosion depth was measured as detailed in Section 3.4.3. Results as discussed below.

There is no straightforward relation between corrosion depth and voltage drop (%IR). This is illustrated in Figure 3-1, which shows the correlation between voltage drop (IR%) and corrosion depth for the case study considered. A significant portion of the points correspond to regions where there was no corrosion activity and therefore the corrosion depth is zero.

Figure 3-1 shows that %IR is not a good parameter in order to quantify corrosion depth. External corrosion is strongly dependent on environmental factors and therefore they should be taken in consideration. That is the reason why it is not possible to rely on %IR as a factor to determine the extent of corrosion damage.

Figure 3-7 models the relationship between coating defect area and corrosion depth (peak depth). The cumulative corrosion feature line shows the corrosion feature count starting from the biggest and progressing to the smallest in terms of calculated area. As studied before by *Argent* el al. [114] and demonstrated here, the changing slope of this line shows that most of the coating defects are relatively small in area, and this number is decreasing with the increment of exposed area.

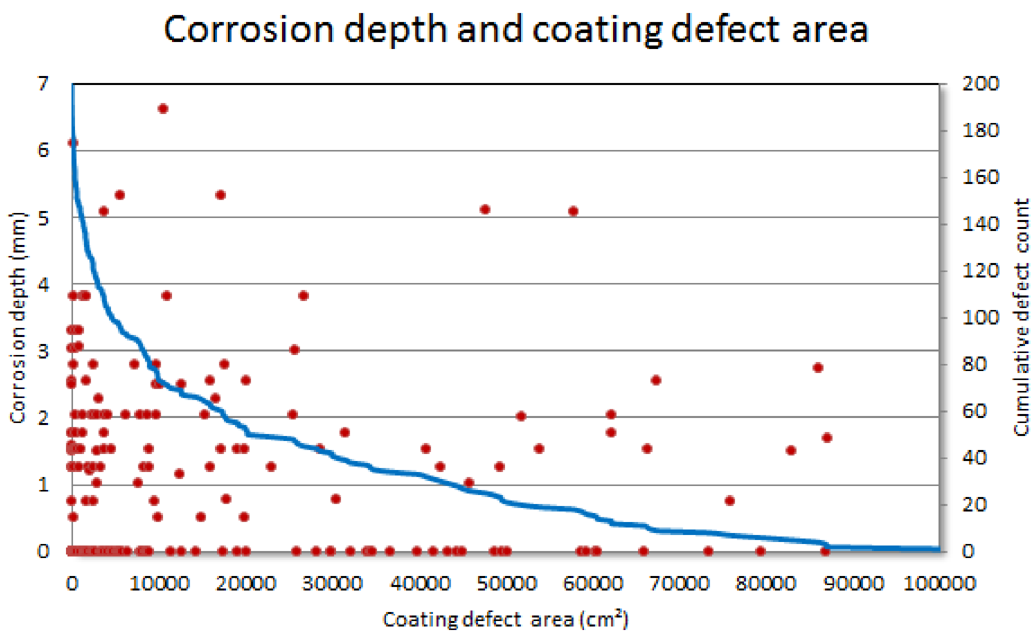

Figure 3-7. Relationship between coating defect area and corrosion depth.

Regression models have been applied in order to determine the strength of correlation for the cited variables including zero inflated models (binomial and Poison) in order to draw conclusions. The reason of using binomial and Poison models is due to the large amount of points with a corrosion depth equal to zero. However, the regressors obtained with zero inflated models did not show any direct relation between the coating defect area and the corrosion depth.

3.8 Causes of anomalies in DCVG readings

Analysing the outliers of the Figure 3-2 (points far from the trend line) by using individual inspection reports corresponding to such data, it was found that the DCVG readings have been potentially influenced by features such as:

- Sections of the pipeline with scales correspond with lower voltage drops (Figure 3-7). Scale deposits in the pipeline surface effectively isolate the pipeline electrically reducing the measured coating defect area. This is a problem because DCVG will give a smaller measure for sections of the pipeline with a severe coating damage, thus invalidating the damage prediction.

Figure 3-8. Example of scale covering exposed and corroded area of a pipeline.

- Reliability of the DCVG reading may be compromised in locations where old cable connections (cad welds) are present (Figure 3-9)

Figure 3-9. Example of an uncoated cad/thermite weld sacrificial anode connection.

- Accurate measurements are not always possible at crossings with roads and watercourses due to local changes in the soil/ground conditions (Figures 3-10 and 3-11).

Figure 3-10. Example of a pipeline crossing a watercourse.

Figure 3-11. Example of a pipeline crossing a road.

- The presence of nearby underground pipelines, in particular those with coating defects, reduce the accuracy of DCVG. The voltage signal is often interfered by the cathodic protection system of the nearby pipelines (Figure 3-12).

Figure 3-12. Example of pipelines crossing very close to each other.

- The soil resistivity affects the %IR value for non-homogeneous soils along the pipeline. When performing DCVG, the pipe to remote earth potential at the indication (P/RE) is calculated by using a linear function of the voltage between the two nearest test stations [75] (Figure 3-13).

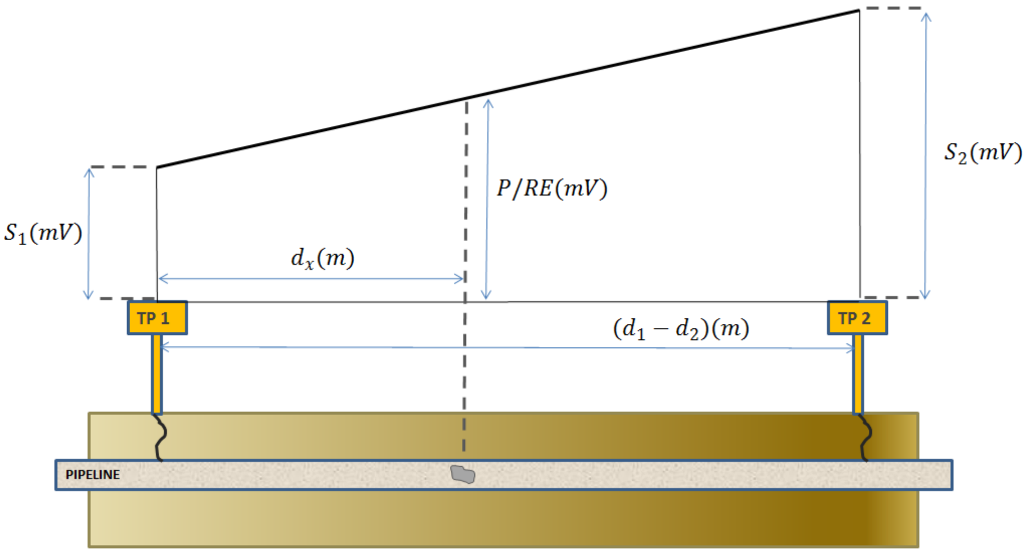

Figure 3-13. Assumption of linearity for the calculation of the earth potential at the indication (P/RE).

It is therefore assumed to be an homogeneous soil between the two test stations. However, soils are heterogeneous and the soil resistivity affects the %IR value. For the same coating defect area, %IR can be higher when soil resistivity has high values, whereas %IR can be lower when the local soil resistivity has low values. This is consistent with other work showing that a high resistivity could cause small defect to yield a large %IR, for example as in Ref. [115]. The electrochemical process of cathodic protection causes the environment around the pipeline to become alkaline, in particular at the surface of the defect being protected [116]. The increase in the pH value can result in a change in the soil resistivity near the defect and therefore increases the heterogeneity of the soil.

- Influence of AC-high voltage lines nearby buried pipelines releasing stray currents to the ground: stray currents have important influence in long distance pipelines, in particular for those running in parallel or across high voltage AC lines (Figure 3-14). During DCVG measurements, currents from AC-high voltage lines affect the voltage gradient from defect indication epicentre to remote earth (OL/RE) [75]. This effect could lead to inaccurate DCVG measurements with the level of influence depending on the intensity and direction of the AC current released. The presence of stray currents makes a DCVG survey difficult to interpret as there may be AC current flowing on or off the pipeline.

Figure 3-14. Example of pipeline close to AC power lines.

- Orientation of the coating defect indication: when a coating anomaly is located in the bottom part of the pipeline the voltage signal is attenuated. This factor has not been included in the analysis due to limited availability of such data; it has been included a study in defect orientation in Chapter 4.
- If there is physical contact between pipeline and metallic support of an aboveground pipeline, the voltage gradient measurements are affected (Figure 3-15).

Figure 3-15. Example of pipeline close to pipe supports.

- Depth of cover affects DCVG signal (Figure 3-16). DCVG indications decrease as depth of cover increases [115][116][78].

Figure 3-16. Example of pipeline exposed due to soil erosion.

Some errors in the data could be attributed to excavation and direct examinations:

- During Direct Examination, coating defect area is measured. In many cases, the coating is just disbonded and during the excavation activity it breaks off (Figure 3-17). Therefore, the measured defect area is larger than the area in contact with the soil before excavating. This is very common, especially for the bottom part of pipelines with coal tar coatings.

Figure 3-17. Example of disbonded coating next to damaged coating.

This study has identified some factors that can potentially cause poor linear correlation between DCVG data and defect area. There could be other factors at play, and, indeed, the factors could be different if the same pipeline system is in a different operating environment.

Chapter 4

Analysis of factors influencing external corrosion

4.1 Introduction

External corrosion is a common problem in underground pipelines, in particular in ageing pipelines. To prevent and control external corrosion, pipeline operators use mitigation systems, such as coatings and cathodic protection. When the protective coating is failing and the cathodic protection levels are low, in conjunction with a corrosive environment, corrosion appears.

4.2 Background

Pipeline coating degradation is inevitable and it is affected by the surrounding environmental conditions. Furthermore, cathodic protection levels can experience a reduction between inspection intervals. Therefore, in order to prioritise inspection and repair activities, and understanding of how environmental and other factors affect external corrosion is required.

Previous research in this area has included soil corrosivity rankings which are used to determine the risk of corrosion in different sections of pipelines. However, not much work has been carried out to provide a better understanding of the relationships between soil parameters and the corrosion defects, in particular at early, medium and late stages of corrosion.

This chapter studies the external corrosion phenomenon by analysing data from a case study. The type of data available is in the form of in-line inspection data (more than 60,000 corrosion defect readings), soil data and weld locations. Advanced statistical techniques were used to assess how different environmental variables and weld location affect the corrosion process during different stages of corrosion.

This chapter shows how useful information as to whether corrosion is occurring due to systematic factors causing more corrosion at weld locations or whether the corrosion is happening due to environmental factors or there is a combination of such factors. Additionally, this chapter draws some inferences from data related to the orientation of defects.

4.3 Scope

Correlate data from in-line inspection and soil surveys by using regression analysis in order to improve the understanding of external corrosion in underground pipelines. Particularly interest is placed on the use of the advanced Quantile Regression model to study the effect of diverse environmental (soil) factors on the external corrosion depth for low and high soil factor values.

4.4 Description of the data

Data used in this study belonged to three different bodies: in-line inspection (ILI) pipeline data obtained from a pipeline company, Centre for Ecology & Hydrology and British Geological Survey.

4.4.1 Pipeline data

Pipeline external corrosion data has been obtained from in-line inspection using the Magnetic Flux Leakage (MFL) technique. MFL is a magnetic method of non-destructive testing which has been widely used in in-line inspection tools for surveys of underground pipeline [117].

The Magnetic Flux Leakage in-line inspection tool can differentiate between internal and external metal loss by using two types of sensors. The first type measures the overall flux leakage from the whole cross section of the steel, and the second measures the leakage from just the first half millimetre of the internal steel surface closest to the sensor. So if both sensors pick up a reading, then it is internal metal loss, but if only the first sensor registers, then it must be external.

Whilst more types of data are typically available from an MFL inspection, this study focusses only on data on external corrosion depth at GPS location, defect orientation and distance to upstream weld (Table 4-1).

Factor	Type of data	Range of values
Corrosion depth (Pipeline data)	Quantitative	Values from 0.07 to 6.39 mm

Defect orientation (Pipeline data)	Qualitative	Values from 0:00 to 11:59
Distance to upstream weld (Pipeline data)	Quantitative	Values from 0 to 12m

Table 4-1. Pipeline data.

Corrosion depth as reported by the ILI has a specification accuracy of ±10% with 80% confidence. Reported ILI depth data has not been validated through field measurements.

The pipelines included in the study are coated with a factory-applied coal tar or asphalt-enamel coating.

The majority of the pipelines included in this case study have been in service for more than 30 years. Precise commissioning dates have been difficult to define with certainty.

4.4.2 Centre for Ecology and Hydrology data

The Centre for Ecology and Hydrology (CEH) is the UK's Centre of Excellence for integrated research in hydrology and terrestrial ecosystems. A series of soil data of 1km x 1km squares covering the UK were collected and analysed in 2007 by the CEH. See [118] and [119] for more details about how the data was collected and analysed.

Data from the CEH which was used in the analysis is summarised in Table 4-2. A total of 4 parameters were extracted from the respective soil databases and soil maps: carbon concentration, soil pH, moisture and bulk density.

Factor	**Type of data**	**Range of values**
Carbon concentration (CEH)	Quantitative	Values from 19 to 513g/kg

Soil pH (CEH)	Quantitative	Values from 4.4 to 8.2
Moisture (CEH)	Quantitative	Values from 22 to 80%
Bulk density (CEH)	Quantitative	Values from 0.17 to 1.21g/cm^3

Table 4-2. Centre for Ecology and Hydrology data

The carbon concentration was determined with a loss-on-ignition technique in which the soil sample was dried at 105°C for 16 hours and then combusted at 375°C for another 16 hours. To obtain the pH, 10g of field moist soil was used with 25ml de-ionised water giving a ratio of soil to water of 1:2.5 by weight [118][119].

Soil moisture was measured by performing weight readings throughout the soil. The moisture loss on each of the steps of the carbon concentration calculation was also used to calculate the moisture. Bulk density refers to the dry weight of soil per unit of volume of soil.

Samples for soil carbon concentration, soil pH, moisture and bulk density measurements were collected using a 15cm by 5cm plastic core following the filed protocol described in more detail in [119].

Carbon concentration was estimated by multiplying loss on ignition by a factor of 0.55 and it is assumed to be organic carbon.

4.4.3 British Geological Survey data

The British Geological Survey (BGS) collects data from the UK landmass in order to advance geoscientific knowledge. Data from BGS used in this research was extracted from a map which covers England and Wales showing interpolated values of topsoil sulphur and chlorine concentrations (mg/kg) at a 1km grid resolution.

The data from the BGS used in this chapter is summarised in Table 4-3. In the data, the concentration of both sulphur and chlorine were determined using wavelength disperse X-ray fluorescence spectrometry [120].

Factor	Type of data	Range of values
Sulphur concentration (BGS)	Quantitative	Values from 59 to 1,978mg/kg
Chlorine concentration (BGS)	Quantitative	Values from 504 to 1,736mg/kg

Table 4-3. British Geological Survey data.

Even though the sulphur and chlorine concentrations may not directly be related to the corrosion mechanism, they have been considered in this study as they reflect the ion concentration. Thus, in this study the assumption is that sulphur and chlorine concentrations are proportional to sulphide and chloride ion concentrations.

4.4.4 Data processing and management

The data from Sections 4.4.1 to 4.4.3 have been processed from their original databases.

- Pipeline data was originally in a comma separated value (csv) format. Each of the corrosion defect was associated to a GPS coordinate. These GPS coordinates were used to map each to the corrosion defects with soil properties.
- Centre for Ecology and Hydrology data was originally in a grid format. A series of soil data of 1km x 1km squares covering the UK which were also associated to GPS coordinates. Each of the squares in the grid were having different soil properties.

- British Geological Survey data was originally point data at a 1km grid resolution. Each of these values was associated to GPS coordinates.

The first step was to map each of the corrosion defects from the pipeline data to the data in the grid format. QGIS software was used to map these two types of data. The result was a csv format file with all the defects GPS coordinates and their associated soil properties (from the Centre for Ecology and Hydrology).

The second step was to interpolate the point data at a 1km grid resolution to each of the corrosion defect GPS coordinates. The result of this tedious activity was a csv format file with all the defects GPS coordinates and their associated soil properties (from the British Geological Survey).

The third and last step was to integrate the two previous steps into a single database by linking them using the common GPS coordinates. This data processing and management has allowed the data to be in a suitable format for further analysis.

4.5 Trends in corrosion defect orientation stablished from measurements

In buried pipelines, the pipeline coatings are subjected to stresses from the surrounding soil as a consequence of the weight of the top soil. Also, soil movements and changes in the operating pressure cause pipeline movement. Vibrations coming from nearby roads, train lines and cycles of expansion/contraction caused from changes in temperature and soil moisture content can all affect the soil stress distribution [121].

Soil stresses distribution around buried pipelines has been studied by many researchers and it has been found that normal and tangential soil stresses are present around underground pipelines [122]. Normal stresses are present in the top and bottom part of the pipeline, whereas tangential stresses have more importance at 3 and 9 o'clock positions. This explains why it is common to find coating breakdown near 6 and 12 o'clock positions and coating wrinkling near 3 and 9 o'clock.

In this study, the orientation of corrosion defects has been defined by selecting the centre point of the corrosion defect. It is assumed that the corrosion defect has been initiated in the centre point of the identified defect and that the corrosion propagation has extended equally from this point.

4.6 Corrosion at weld joints

In the case study analysed in this chapter (data from section 4.4), the pipelines were constructed from standard, double random lengths, with a nominal distance of 12 meters between weld joints.

Weld joints are areas of the pipeline where two metallic parts are joined together. They are not manufactured in the factory, but in the field. The coating installed over this area (field joint coating) is also installed in the field and therefore, it tends not to be as consistent as the coatings applied for the rest of the pipeline.

Analysis of corrosion at weld joints, where susceptibility to corrosion due to this factor is expected more, is necessary to establish whether there is a systematic failure caused by factors such as quality of coating that applies to all weld joints. Susceptibility to corrosion at welds is expected due to diverse factors such as high residual stresses, improper choice of filled metal, final surface finish, moisture contamination and the possible creation of oxide films and scales.

To take remedial action, pipeline operators would like to know if corrosion is occurring due to systematic factors or due to environmental factors such as those discussed later. Thus, the information as to whether there has been a systematic failure at weld joint positions or not is of value to the pipeline operators.

4.7 Correlation between corrosion depth and environmental (soil) factors

The relationship between maximum corrosion depth and soil factors is important. It is well known that parameters such as pH and moisture content have a significant effect in external corrosion. However, it is still not clear the level of importance of each of these environmental factors. Multiple regression and quantile regression models were used for the analysis of the available data and results of this analysis are reported in Section 4.8.

4.7.1 Multiple regression

The relationship between corrosion depth and environmental factors was analysed by using multiple regression. Multiple regression is used to study the relationship between one dependent variable (corrosion depth) and several independent or predictor variables (soil factors).

Multiple regression was implemented using R software by using factors from Table 4-2 and Table 4-3 as independent factors by using equation 4.1.

$$y = \alpha + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \beta_6 x_6 + \varepsilon \qquad (4.1)$$

Six variables were introduced in the mathematical model.

Multiple regression provides an estimate of the relative importance of each variable. However, it is very sensitive to outliers and therefore, in order to understand better the relationship between these soil factors and corrosion depth, a more consistent statistical model, described in Section 4.7.2, was applied.

4.7.2 Generalised extreme values and quantile regression

The histogram of all the corrosion depth defects is shown in Figure 4-1. Corrosion depth data has been fitted to a generalised extreme values (GEV) density function which has been proven to be one of the best fitted models for corrosion defects, and has been also applied by other researchers such as Velazquez et al. for statistical modelling of pitting [123].

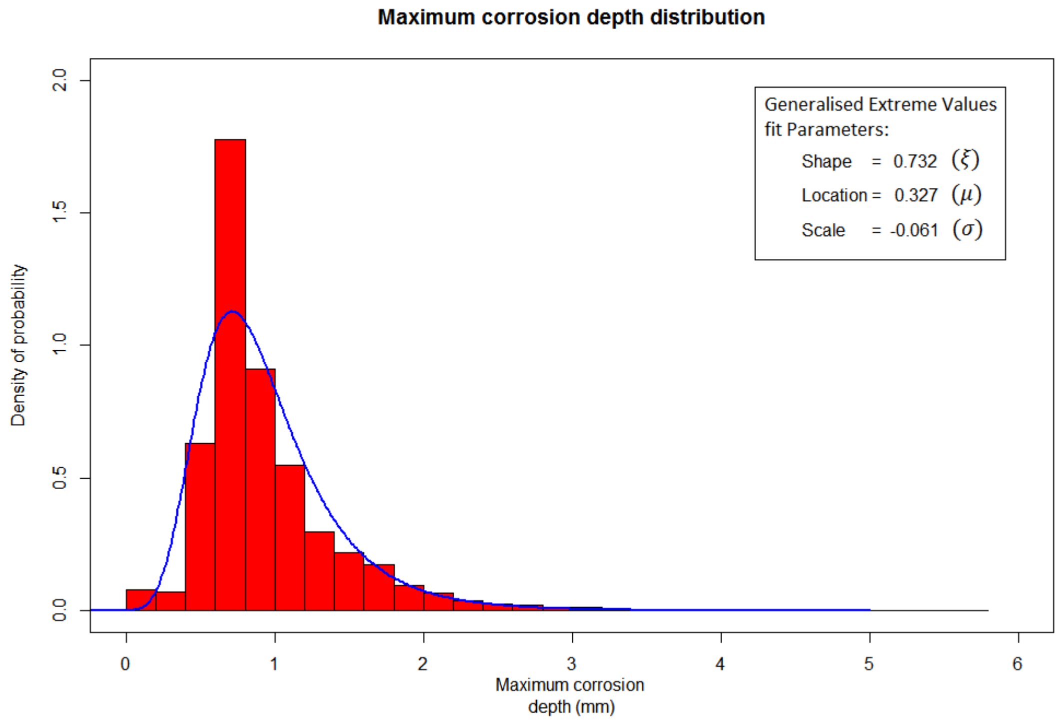

Figure 4-1. Corrosion depth probability density function using data from Table 4-1 (line 1).

The GEV distribution is defined in equation 4.2:

$$\mathrm{GEV}(x; \mu, \sigma, \xi) = \exp\left\{-\left[1 + \xi\left(\frac{x-\mu}{\sigma}\right)\right]^{-1/\xi}\right\} \tag{4.2}$$

where ξ, μ and σ are the shape, location and scale parameters of the GEV distribution, respectively.

The probability density function of the maximum corrosion depth is not symmetrical; it has a positive skewness (Figure 4-1). In this situation, mean-based regression models such as multiple regression are not effective since they average results for the overall density function. This indicates that multiple regression may not the most appropriate model to investigate the relationships between corrosion depth and soil factors.

To understand the effect of soil parameters on corrosion depth, it is more appropriate to analyse the evolution of the corrosion along the whole spectrum of the density function. This means to understand the effect of each soil parameters at different stages of corrosion, or in other words, how a factor or factors could have a stronger influence on defects with larger or smaller corrosion depths. The characteristic positive skewness observed for maximum corrosion depth leads us to use more complex models such as quantile regression. Quantile regression was used to identify the effect of key factors (soil factors) on the defects with the range of corrosion depths.

Quantile regression was computed using R software by following the procedure detailed in [124] to study the effects of soil factors on corrosion depth for low and high amounts of each independent variable (for example, pH). The independent variables included are shown in Table 4-2 and Table 4-3; the dependent variable was corrosion depth. This analysis gave a more complete view of the effect of each independent variable on the maximum corrosion depth and indicated which factors had a greater influence on the whole range of corrosion depths. The results of this analysis are discussed in Section 4.8.3.2.

4.8 Analysis

The analysis of the dataset carried out in this paper focused on the following main relationships between (i) number of defects and their orientation along the circumference of the pipeline; (ii) defect depth and the location of such defects from weld locations; and (iii) defect depth and certain environmental factors shown in Table 4-2 and Table 4-3.

4.8.1 Relationship between number of defects and their orientation

The orientation of defects on a pipeline has been the topic of many studies [125]. It has been demonstrated that the bottom of pipelines often suffers a higher density of defects compared with the top part of pipelines. This is explained by an increased risk of exposure to moisture/water especially during wet weather seasons where the ground water levels may be higher.

Variations in the oxygen content and chemical composition of the soil from top to bottom of the pipe can act as concentration cells that promote corrosion [125].

A total of more than 60,000 reported corrosion defects were included in the analysis for this study. The locations of the defects were divided into intervals of 15° around the pipelines, in a clock-like manner, in order to study the effect of orientation on pipeline corrosion. This provided a distribution of the defects in 24 regions around pipeline's circumference, as shown in Figure 4-2.

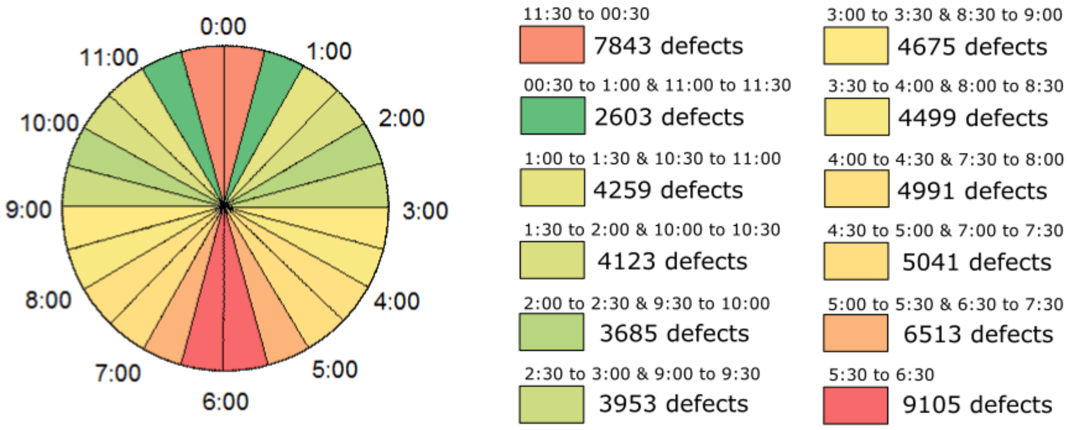

Figure 4-2. Distribution of defects in 24 regions around pipeline's circumference.

The results show that the density of defects was largely symmetrical with respect to the vertical axis. Since the results were symmetrical, in order to simplify reporting results, corrosion defects were reported for half of the pipe, ie for only 12 regions, which was equivalent to analysing half of the pipeline but considering all the available data.

Figure 4-3 shows a plot of the number of defects around the 12 regions of the pipeline. This shows clearly a greater density of defect at the top and bottom of the pipelines (centred around the 12 and 6 o'clock positions). It also shows a gradual increase of corrosion defects from 00:30 to 6:00 and from 11:30 to 6:00 positions.

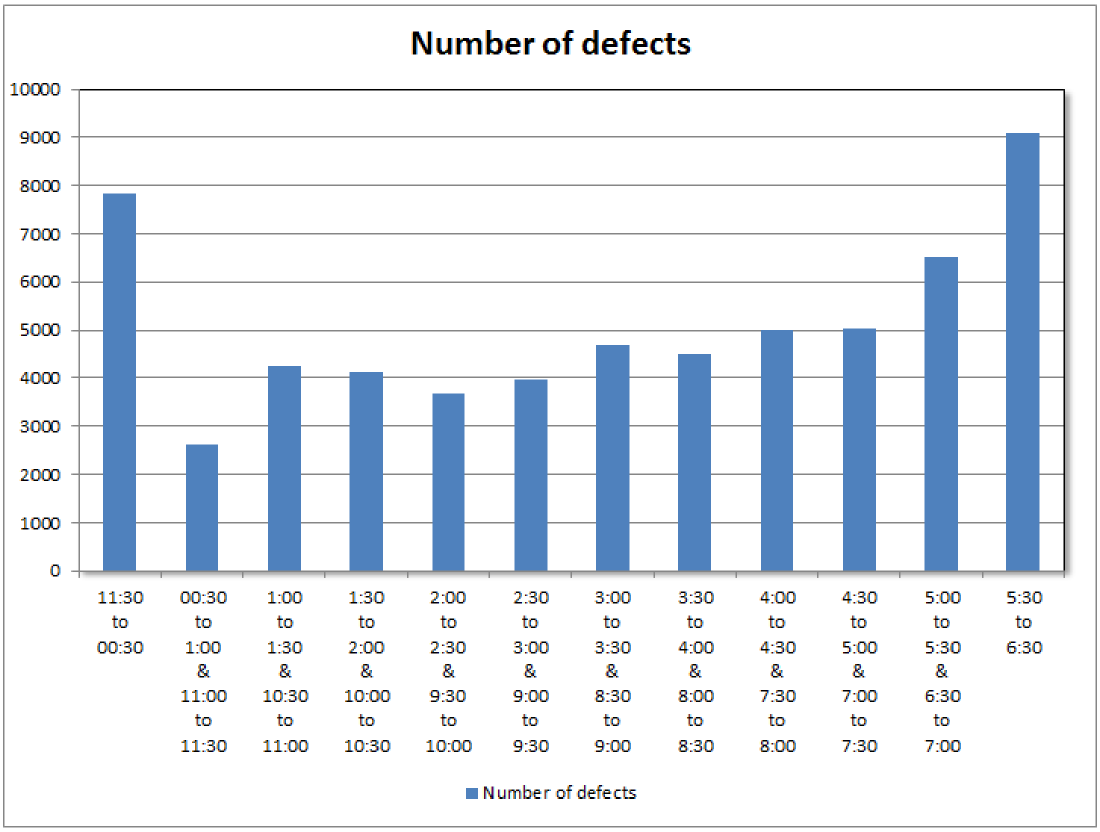

Figure 4-3. Number of defects around the 12 regions of the pipeline.

4.8.2 Corrosion at weld joints

Results reported in this section show the effect of the distance between corrosion defects and upstream welds (Figure 4-4). For pipelines suffering from corrosion at welded areas, it is expected that there are a higher number of corrosion defects closer to the welds than far from them. Moreover, these defects will be expected to be more critical, in terms of depth, than other defects far from welds.

An independence chi-square test has been performed for distance to upstream weld and defect depth. Chi-square tests whether one variable is independent from another one. In other words, it tests whether or not a statistically significant relationship exists between distance to upstream weld and defect depth.

By performing chi-square test a value of $p = 0.00003$ is obtained, which is lower than 0.05. Since, the result of the chi-square test is less than 0.05, it means that there is enough evidence to conclude that distance to upstream weld and defect depth are in fact different, therefore it proves their independence.

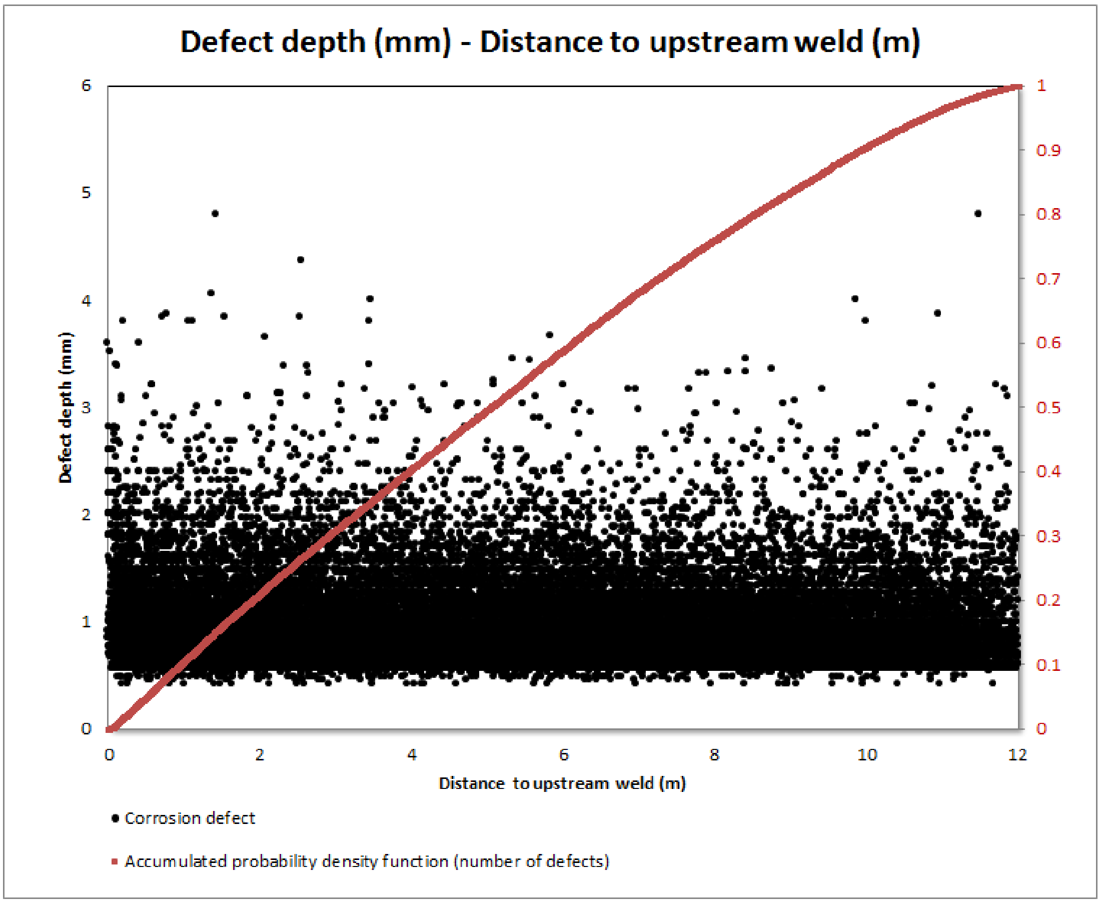

Figure 4-4. Depth of corrosion defects and distance to upstream weld.

In Figure 4-4, each point represents the depth of a corrosion defects plotted against the distance to the upstream weld. The red line represents the accumulated probability density function for the number of defects which is nearly a straight line. This means that the likelihood of finding a corrosion defect is independent on the distance to welds, and therefore, distance to upstream weld does not have any effect to external corrosion for this case study. In other words, we can confirm that in the welded areas where there is a field joint coating, the probability of finding a defect is roughly the same as for the rest of the pipe.

4.8.3 Environmental (soil) factors

4.8.3.1 Correlation between external corrosion (defect depth) and environmental factors: multiple regression and validation

Multiple Regression was performed in order to estimate the average of corrosion defect depth. The results from Multiple Regression are expressed in equation 4.3. This equation predicts the corrosion depth for the six given parameters addressed in Sections 4.4.2 and 4.4.3.

$$Average\ Corrosion\ Defect\ Depth\ (mm) = 3.12 \cdot 10^{-1} - 5.63 \cdot 10^{-4}x_1 - 3.29 \cdot 10^{-2}x_2 + 1.42 \cdot 10^{-2}x_3 + 2.32 \cdot 10^{-1}x_4 + 4.01 \cdot 10^{-4}x_5 - 4.53 \cdot 10^{-4}x_6 \quad (4.3)$$

Where:

x_1 = Carbon Concentration (g/kg).

x_2 = Soil pH.

x_3 = Moisture (%).

x_4 = Bulk density (g/cm^3).

x_5 = Sulphur concentration (mg/kg).

x_6 = Chlorine concentration (mg/kg).

Each of the coefficients in Equation 4.3 has a "p-value" associated (Table 4-4). The "p-value" is the probability of finding the observed results when the null hypothesis is true. If the "p-value" is less than 0.05, then, given variable has significantly different results from zero meaning that the statistic is reliable and therefore this factor has a strong correlation with the dependent variable. The "p-value" < 0.05 implies that a 5% significance level is used.

Variable	Estimate	Std. error	t-Value	p-value	Interpretation
Intercept	$3.12 \cdot 10^{-1}$	9.28·10-2	3.356	0.000792	Significant Differences

x_1	$-5.63 \cdot 10^{-4}$	$1.69 \cdot 10^{-4}$	-3.317	0.000911	Significant Differences
x_2	$-3.29 \cdot 10^{-2}$	$7.70 \cdot 10^{-3}$	-4.271	$1.95 \cdot 10^{-5}$	Significant Differences
x_3	$1.42 \cdot 10^{-2}$	$1.60 \cdot 10^{-3}$	8.817	$<2 \cdot 10^{-16}$	Significant Differences
x_4	$2.32 \cdot 10^{-1}$	$3.549 \cdot 10^{-2}$	6.541	$6.19 \cdot 10^{-11}$	Significant Differences
x_5	$4.01 \cdot 10^{-4}$	$1.621 \cdot 10^{-5}$	24.728	$<2 \cdot 10^{-16}$	Significant Differences
x_6	$-4.53 \cdot 10^{-4}$	$3.171 \cdot 10^{-5}$	-14.291	$<2 \cdot 10^{-16}$	Significant Differences

Table 4-4. Multiple linear regression coefficients.

In order to evaluate the accuracy of equation 4.3, a validation exercise was carried out. The calculated and the predicted corrosion depths (using equation 4.3) were plotted against the real measurements for all defects considered in this study.

Figure 4-5 shows the predicted corrosion depth, calculated using equation 4.3, plotted against the real corrosion depth, obtained from the real measurements (explained in Section 4.4.1).

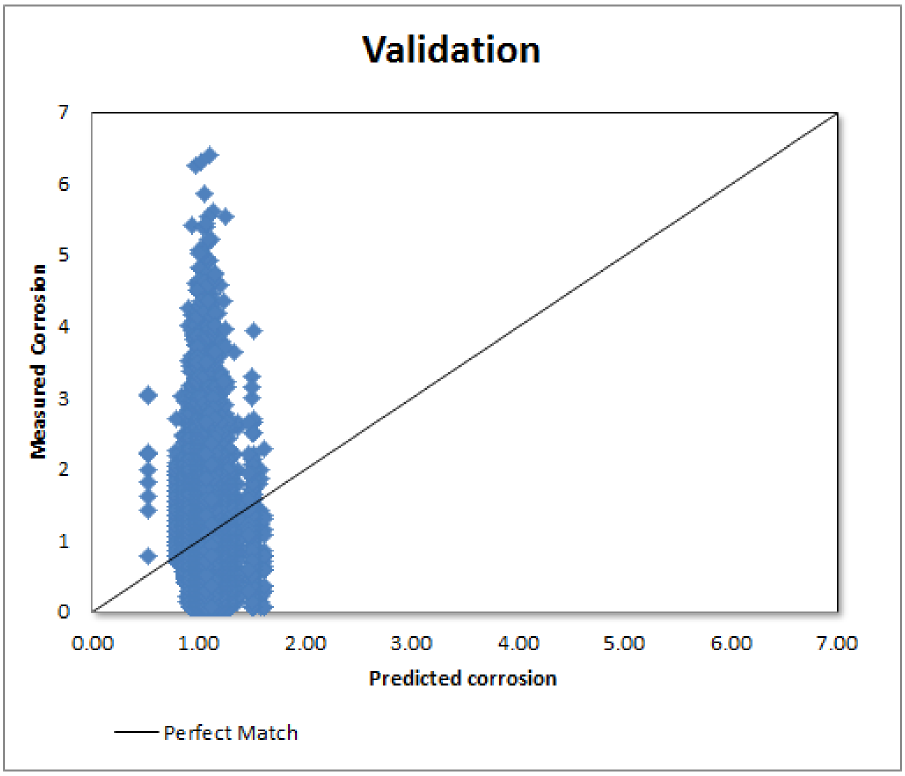

Figure 4-5. Predicted corrosion depth and measured corrosion depth.

The diagonal line represents the ideal case and it has a slope equal to 1. If a defect falls near this line, it means that the predicted corrosion is close to the measured corrosion. However, for this validation exercise, most of the defects do not fall consistently in regions close to this line, meaning that the prediction model is inaccurate and cannot be used as a baseline to predict corrosion in pipelines.

This is also confirmed by the statistical value of R^2=0.03 obtained from the regression model. Therefore, we can conclude that only 3% of the variation is explained by the regression and the rest is due to error.

4.8.3.2 Correlation between external corrosion and environmental factors: application of quantile regression

Quantile regression may be easily understood as an extension of the least square estimation of conditional mean models [89]. It estimates multiple rates of changes from the minimum to the maximum response [124]. Quantile regression provides a more thorough description of the relationships between variables, missed by multiple regression models.

Equations for some of the most relevant quantiles are represented in Equations 4.4 to 4.6.

The 0.5 quantile is important because it is the median of the distribution.

$$Corrosion\ depth\ (0.05\ quantile) = 1.35 \cdot 10^{0} + 7.80 \cdot 10^{-4}x_1 + 3.77 \cdot 10^{-2}x_2 - 1.95 \cdot 10^{-2}x_3 - 4.64 \cdot 10^{-1}x_4 - 1.70 \cdot 10^{-4}x_5 + 3.50 \cdot 10^{-4}x_6 \quad (4.4)$$

The 0.05 quantile (5th quantile) represents the corrosion depth for the 5% of the defects on the left of the probability density function (small corrosion depth).

$$Corrosion\ depth\ (0.5\ quantile) = -1.93 \cdot 10^{-1} - 1.00 \cdot 10^{-4}x_1 + 1.63 \cdot 10^{-2}x_2 + 1.59 \cdot 10^{-2}x_3 + 1.22 \cdot 10^{-1}x_4 + 4.40 \cdot 10^{-4}x_5 - 4.40 \cdot 10^{-4}x_6 \quad (4.5)$$

The 0.95 quantile (95th quantile) represents the corrosion depth for the 95% of the defects on the left of the probability density function (large corrosion depth).

$$Corrosion\ depth\ (0.95\ quantile) = 3.38 \cdot 10^{-1} + 7.55 \cdot 10^{-3}x_1 - 3.56 \cdot 10^{-1}x_2 + 4.18 \cdot 10^{-3}x_3 + 1.99 \cdot 10^{0}x_4 + 2.00 \cdot 10^{-3}x_5 - 1.20 \cdot 10^{-3}x_6 \quad (4.6)$$

Where x_1, x_2, x_3, x_4, x_5 and x_6 are defined in Section 4.8.3.1.

The 0.05 quantile shows how corrosion depth is being affected by environmental factors for small corrosion defects (left part of the probability distribution), whereas the 0.95 quantile shows how corrosion depth is being affected by environmental factors for deeper corrosion defects (right part of the probability distribution).

The 0.5 quantile is the median of the probability distribution and it shows how corrosion depth is being affected by environmental factors for medium corrosion defects (middle part of the probability distribution).

Figure 4-6 shows the graphical interpretation from equations 4.4 to 4.6. The quantiles of dependent variable are on the horizontal axis and the coefficient magnitudes on the vertical axis. The horizontal lines are the Multiple Regression coefficients and the horizontal doted lines above and below are the 95% confidence intervals. The Multiple Regression coefficients do not vary with quantiles because they calculate the average value for the dependent variable.

The quantile regression coefficients are plotted as points joined by straight lines varying across the quantiles. The 95% confidence intervals are plotted lines displayed above and below the quantile regression coefficients.

From a statistical point of view, if the quantile coefficients are outside the Multiple Regression confidence interval, then, there are significant differences between the quantile and Multiple Regression coefficients.

The quantile coefficients for the soil factors (independent variables) studied on corrosion depth (dependent variable) are significantly different from the Multiple Regression coefficients. The following main points can be concluded from Figure 4-6.

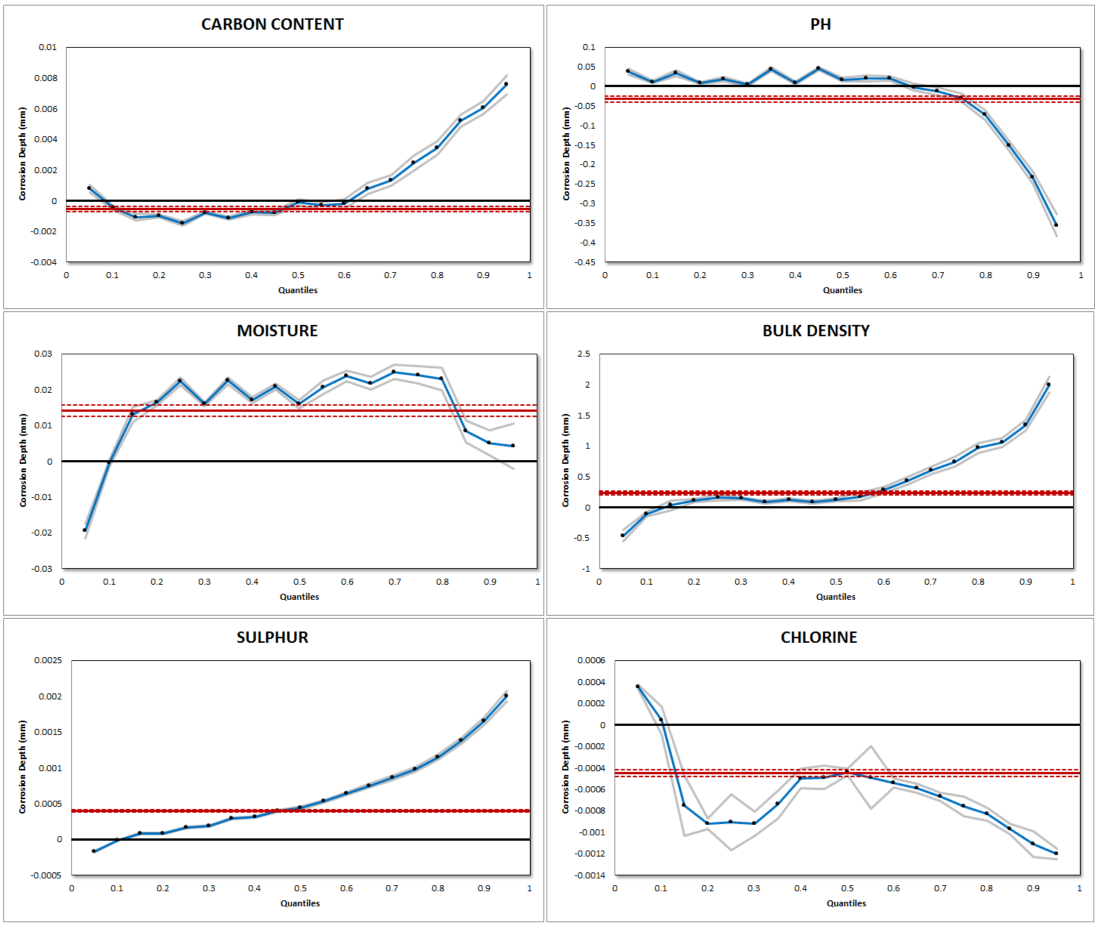

Figure 4-6. Quantile regression coefficients for different soil factors.

The effect of bulk density, pH, carbon and sulphur concentrations on corrosion depth is lower at lower levels of corrosion depth and higher as corrosion depth increases (starts near zero and increases along the quantiles). Lower quantiles (below 0.2) correspond to lower values in the y axis (values near the zero line), whereas higher quantiles (above 0.8) correspond with higher values in the y axis.

Corrosion depth increases with soil bulk density, carbon and sulphur concentration (values above zero, black horizontal line).

However, corrosion depth decreases with the pH (values below zero). Corrosion depth increases with acidity.

Moisture content has in general a positive influence in corrosion pitting (values more than zero). Once corrosion has initiated (after 10th quantile) and before the pipeline has been corroded to a larger extent (before 85th quantile), moisture is shown to cause corrosion

The results for chlorine seem to be very irregular, with no clear relationship between this parameter and corrosion depth was evident from the regression analysis.

Chapter 5

Practical implications and discussion

5.1 The use of DCVG data in ECDA to predict corrosion depth

DCVG data is used in ECDA to identify the pipeline locations to be excavated for direct examination; this is consistent with studies that have shown DCVG data to be reliable in knowing the location of coating breakdown. However, the correlation between %IR and corrosion depth is not strong and this case study confirms this aspect (Section 3.5). Corrosion depth is dependent on environmental factors and cathodic protection performance. This can be confirmed in further research in which a more comprehensive dataset that includes CP levels is analysed in multiple regression model, thus improving corrosion depth prediction.

5.2 The use of DCVG data in ECDA to predict coating defect area

A substantial improvement in the reliability of prediction can be made by considering not just DCVG data, but also other such as those relating to environment some of which are shown in Table 3-1. Factors such as prior corrosion and repair history that have been included in other studies may help make better predictions [126][127]. In the case study shown here multiple factors (to the extent possible, given the data available) have been taken into account in the regression analyses resulting in more reliable prediction (Section 3.6.3). This is supported by Masilela and Pereira [128] whose study states that DCVG enables comparison of located defects with other defects found in the same area. The %IR is used to reflect size/importance of a defect.

When ECDA is performed, at first instance, pipeline operators usually rely on DCVG values in order to provide an initial assessment of the line. This is a good practice to detect coating anomalies, typically used for new pipelines where the coatings are more likely to be damaged during pipe construction [128].

5.3 Correlation between coating defect area and corrosion depth

For corrosion to be present, two conditions must be active, a damaged coating and inadequate levels of cathodic protection [129]. However, pipeline corrosion depth cannot be predicted by the only use of coating defect area data.

Corrosion might appear in small coating areas (Figure 3-7). Deep pits materialise in small coating defect areas, meaning in locations that, following the severity classification given by NACE RP0502 [9], should be considered as minor severity. The relative size of the anode and cathode areas could be a critical factor in determining the amount of corrosion damage at these locations.

For a given potential difference, if the anode is large compared with the cathode area , the anode current density will be low and the corrosion is widely distributed, resulting in a more general corrosion loss in the absence of any interference effects. Whereas, if the anode area is small (high anode current density) with respect to the cathode area, the corrosive action is localised and severe local damage may result [32]. Anodic interference from stray currents such as grounded electric power sources, equipment or electric railways, causes corrosion. This type of corrosion is a combined effect of a relatively large potential difference or current plus the fact that the anode area, where the current leaves the pipe, is small.

AC corrosion, due to its own characteristics, usually happens at small/very small coating faults [130]. When a defect is small, the AC required to induce pitting corrosion is low. However, current density decreases because of the blocking effect of corrosion product which may accumulate at the defect [131].

5.4 Potential causes of anomalies in DCVG readings

DCVG is a good estimator for locating coating defect; however, DCVG readings are potentially affected by factors discussed in Section 3.8.

By analysing the outliers of the linear regression model and supported by literature review, it is likely that the presence of the following events will affect the performance of this technique:

- Surface scales.
- Presence of connetion to old sacrificial anode protection systems (cad welds).
- Presence of nearby underground pipelines.
- Presence of high voltage AC lines.
- Physical contact between pipeline and metallic support of an aboveground pipeline.

Corrosion activity is hard to model using indirect inspection techniques. It is subjected to uncertainty given the underlying factors which are especially difficult to model with the available data.

Some studies [94] assume homogeneous soil resistivity for the DCVG survey interpretation, nonetheless in this chapter it is used the on-site soil resistivity for each of the defect locations, resulting in better results as proposed by *McKinney* et al. [81] whose research dictates "soil resistivity plays a larger role in determining DCVG signals than coating flaw size."

5.5 Suggestions for improving the ECDA approach

In an ECDA assessment, the determination of the likelihood of corrosion occurring should place more emphasis on other factors such as the level of CP protection and environmental (soil) conditions rather than the estimated coating defect size.

It is suggested that Close Interval Potential Surveys (CIPS) should be carried out before DCVG in order to establish sections of the pipeline with poor protection. DCVG measurements should focus on these sections to ensure that all coating defects, whatever their size, are recorded for the assessment (Figure 5-1).

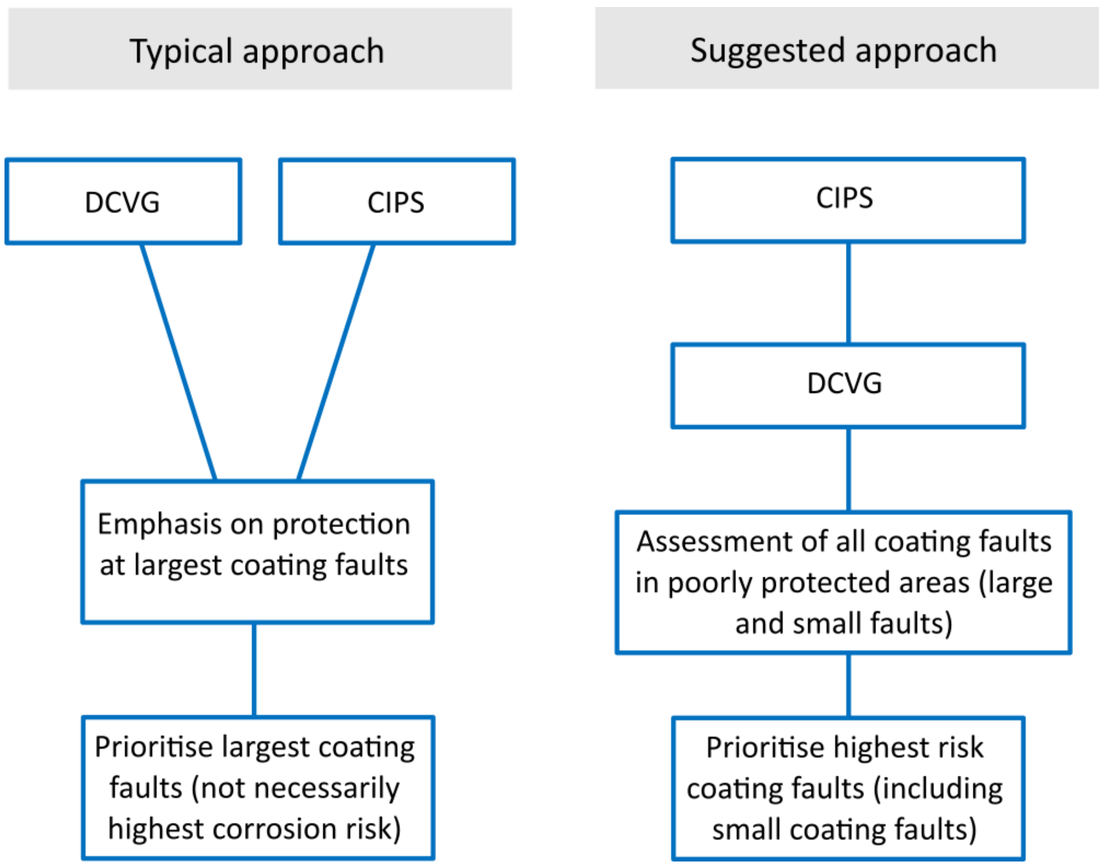

Figure 5-1. Suggested approach for carrying out ECDA indirect inspections.

The suggested approach is being discussed with stakeholders from industry and the initial response is positive. Further research is planned to compare the application of the two approaches and validate the level of improvement to be gained by the suggested change.

5.6 The orientation of defect

Corrosion defects tend to initiate in two main areas of the pipeline: the bottom and top of the pipeline. This is discussed in more detail in the following sections.

5.6.1 Corrosion defects at the bottom of the pipeline

The water level is the level below which the soil is completely saturated with water, also known as water table or phreatic surface (Figure 5-2). The water level is constantly changing and it is dependent on seasonal weather changes.

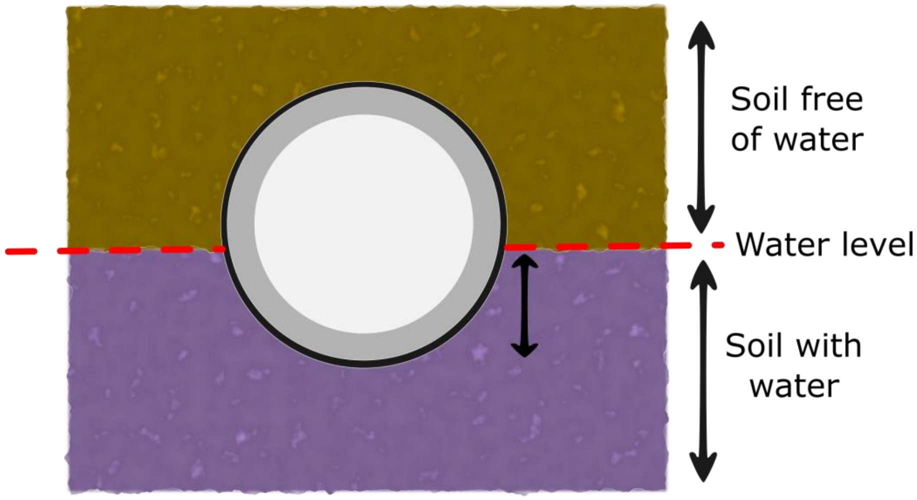

Figure 5-2. Soil water level in underground pipelines.

Three different scenarios might occur when this interacts with a buried pipeline:

1. The water level is above the top of the pipeline and the whole surface is surrounded by water.
2. The water level is below the bottom of the pipeline and the whole surface is free of water.
3. The water level is at some point between the top and bottom of the pipeline and the pipeline is only partially exposed to water.

The bottom of the pipeline will be exposed to water for the cases 1 and 3, whereas the top of the pipeline will be exposed to water for the case 1. Therefore, the presence of water is more likely to appear at the bottom of pipelines, and hence, corrosion is also more likely to occur near the 6 o'clock position.

Furthermore, not taking account of the concentration of defect at the very top of the pipe, which are generally considered to be caused by other reasons (see next section), the likelihood of finding water near a corrosion defect decreases when we are moving from the bottom to the top of the pipeline, and consequently, the likelihood of finding a corrosion defect. This has been supported by results from Section 4.8.1.

5.6.2 Corrosion defects near the 12 o'clock position

Figure 5-3 illustrates a simplified model of soil stress acting on pipelines. During the first few months of a coating life, when the pipeline is either commissioned or recoated, the soil around the pipe settles, as it expands and contracts, and that is the period when it will experience the most severe soil stress.

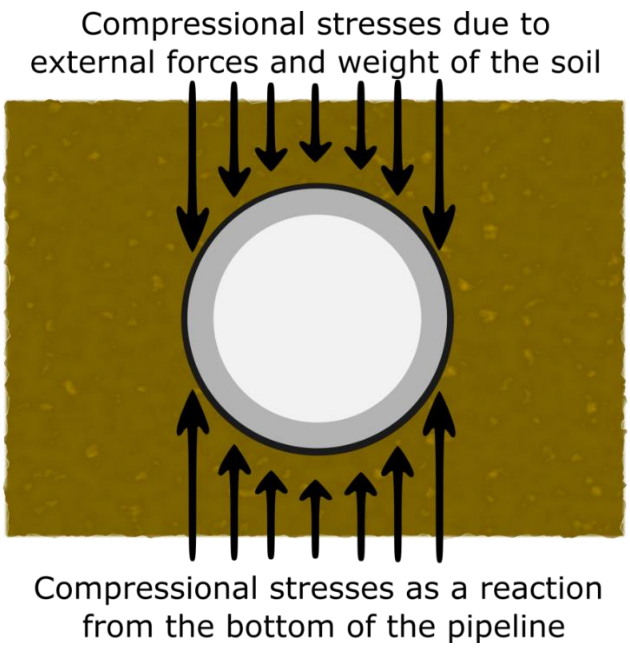

Figure 5-3. Compressional stresses due to external forces and weight of the soil.

Compressional stresses resulting from external forces applied to the soil, and the weight of the soil itself will act on the pipeline coating perpendicular to the soil surface. These forces, applied mainly at the top of the pipeline, are translated into a reaction from the bottom of the pipeline, also resulting in compressional stresses from the soil acting on the coating in this location (Figure 5-3).

It is common to find coating breakdown (metal exposed) at the 12 o'clock position. As a consequence of soil stresses, the coating at the 12 o'clock position is subjected to tensile stresses, thus, accelerating its breakdown (Figure 5-4).

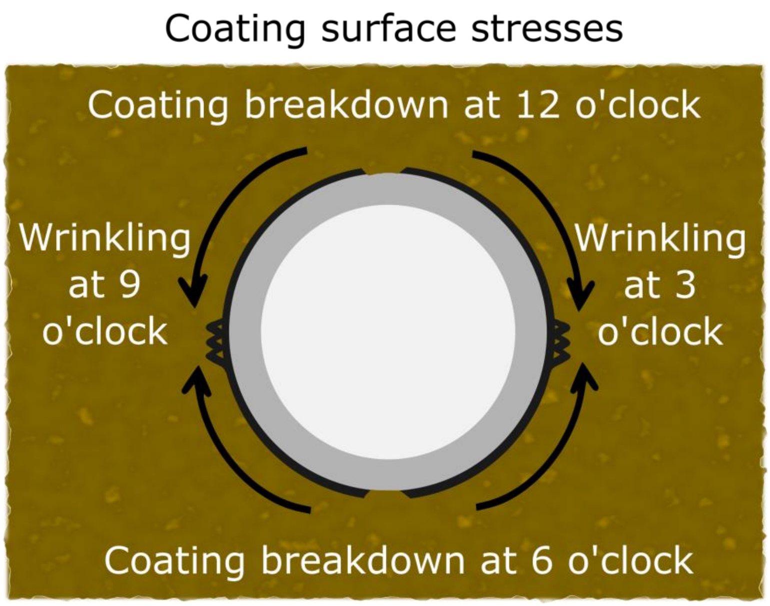

Figure 5-4. Coating surface stresses.

Results reported in Section 4.8.1 indicate a high density of corrosion defects at the top of the pipelines. A total of 7,843 corrosion defects were located at the 12 o'clock position. The two adjacent areas (1 and 11 o'clock) reported much less number of defects. A possible reason to explain this anomaly is the effect of soil stresses, enhancing coating breakdown at the 12 o'clock position, thus exposing the metal to the soil environment.

Furthermore, during seasonal changes and in particular in the presence of rain, when the water filtrates through the soil, small drops of water might stay on the top of the pipeline where the metal is exposed. This, of course, will increase the likelihood of corrosion to take place.

The coating will also transmit the compressional soil stresses along itself from the 12 and 6 o'clock positions to the 3 and 9 o'clock positions. Finally, compressive stresses will appear at the 3 and 9 o'clock positions. Therefore, it is common to find wrinkling and coating disbondment at the 3 and 9 o'clock positions.

5.7 Corrosion at weld joints

Weld joints are well known to be areas of high risk of corrosion. Corrosion failures of welds might occur due to a diversity of factors such as weldment design, oxide films and scales, moisture contamination and presence of high residual stresses, documented in [132].

Since the density of defects and corrosion depth is nearly the same along the pipeline (Figure 4-4), it was confirmed that weld regions, for this case study, does not have an increased risk of corrosion as compared to the rest of the pipeline.

Installation of field joint coatings at weld joints is a difficult task. If this is not carried out correctly, it is common to find coating failures at weld joints which may lead to corrosion. However, in the pipelines studied, the results indicate that the weld regions and the rest of the pipe are both equally well coated.

This case study shows that the likelihood of finding external corrosion is totally independent of the proximity to welded joints. The inference that can be drawn from this result is that in this case study, there are no systematic factors causing additional susceptibility to corrosion in areas close to welds.

5.8 Influence of soil properties in external corrosion

The analysis carried out showed that the soil factors have a varying influence at different degrees of corrosion depth. It also showed that multiple linear regression models do not fit well in predicting the behaviour of corrosion using the soil factors. This is either due to the nature of the kinetics of corrosion or because of the lack of other environmental parameters. More intelligence on soil factors influencing external corrosion was gained from the quantile regression results.

5.8.1 Bulk density, carbon and sulphur concentration

The effect of bulk density, carbon and sulphur concentrations on corrosion depth was lower at low levels of corrosion depth and higher as corrosion depth increases. Once corrosion has initiated and evolved into a severe defect (after the 60th quantile) bulk density and carbon concentration were shown to enhance corrosion. One possible reason for this could be due to direct and indirect factors related to soil volume changes.

Most soils decrease in volume when they dry out and increase in volume when they are wet again; this is known as volume shrinkage [32]. In soils rich in organic matter (high in carbon concentration), shrinkage caused by drying produces cracks could provide a path for oxygen in the atmosphere to reach the exposed metal. Oxygen stimulates corrosion by combining with metal ions to form oxides, hydroxides, or salts of metals [32].

The effect of sulphur concentration on corrosion increases along the spectrum of the quantiles is almost linear. After the 10th quantile (corrosion defect is initiated), it was found that the deeper is the defect, the stronger the effect of sulphur on corrosion. It has been discussed in previous studies the effect of sulphate concentration in underground corrosion. It has been found that for concentrations below 200 ppm, the soil corrosivity is considered to be mildly corrosive [133]. However, the quantile regression model gives a more comprehensive understanding of the corrosion process for different levels of corrosion.

These 3 factors have little or no effect on corrosion of pipelines at low levels of corrosion damage; this means that they may not have a large influence in the initiation of corrosion. However, once corrosion is initiated and began to progress, they will have a catalytic effect on corrosion and they will accelerate the corrosion mechanism.

5.8.2 Soil pH

It has been found that corrosion depth is inversely proportional to the value of soil pH, represented by values below zero in Figure 4-9. Therefore, corrosion depth decreases with alkalinity (higher values of pH). When the pH increases (OH ions concentration increase), passivation occurs on the pipeline surface [134], which will protect the pipeline from further corrosion. Once corrosion has initiated and evolved into larger defects (after 70th quantile), soil pH is shown to decrease corrosion. The effect of soil pH on corrosion depth is lower at low levels of corrosion and higher as corrosion depth increases.

Previous studies have determined that the corrosion rate decreases with increasing pH, being highest at pH 4 and lowest at pH 9 [135]. The study carried out in this paper proves that the pH is inversely proportional to corrosion, however, a better understanding of the effect of soil pH on underground corrosion has been obtained from results of the quantile regression.

5.8.3 Moisture and chlorine concentration

From the results it is found that moisture content, in general, has a positive influence on corrosion depth (values more than zero along the quantile spectrum in Figure 4-10), as also demonstrated in [136]. Once corrosion has initiated (after the 10th quantile) and before the pipeline has been corroded to a larger extent (before the 85th quantile), moisture is shown to cause an increase in corrosion. It is plausible that, once the defects reach a certain size the effect diminished because other factors become more important and have a more dominate effect.

There was little or no correlation between chlorine concentration and corrosion depth. One reason for this could to due to the fact that it has been assumed in this study that chlorine concentration is proportional to chloride ion concentration. This relationship may not be straightforward or there may not be any correlation between the two parameters in the form the data was extracted from the soil databases.

Chlorine by itself does not have a negative effect on pipeline corrosion; it is only when chloride ions are present that the pipeline corrode is accelerated [137]. Therefore, a more complete soil database, which includes chloride concentration, is required in order to evaluate pipeline corrosion on a more accurate manner.

Chapter 6

Concluding remarks and future research

6.1 Concluding remarks

Underground pipelines are extensively used in transportation of liquids and gases around the world and its reliability is key aspect of many industrial applications. One of the most common damage mechanisms associated with underground pipelines is external corrosion.

The topic of this research and the background related to this thesis is described in Chapter 1. This chapter also describes the aim of this research as well as the main contributions to the knowledge.

Chapter 2 presents a literature review of external corrosion in underground pipelines, its control and mitigation, Pipeline Integrity Management programs. This chapter also describes the statistical tools previously applied to Pipeline Integrity Management programs.

Chapter 3 describes a novel regression model (quantile regression) applied for first time to data from an External Corrosion Direct Assessment. A mathematical formulation describing the regression model is presented in this chapter. Research presented in Chapter 3 is related to non-piggable pipelines and concludes that:

1. The DCVG %IR value from the indirect inspection step correlates well with the measured coating defect size when soil properties and pipeline design parameters are introduced in the regression model.
2. It has been found that quantile regression is a useful tool in order to understand the effect of %IR for small and large coating defects in comparison with the simplicity of multiple regression models.
3. The correlation between the %IR value and the measured coating defect size is non-linear with sensitivity as the %IR increases. Larger %IR values are linked, proportionally, to larger coating defect areas.
4. Measured corrosion depth does not correlate with the DCVG %IR value from the indirect inspection step.

5. The measured coating defect size does not correlate with the measured corrosion depth. The likelihood of corrosion taking place at small defects and also at large defects are similar.

Therefore, small indications detected during pipeline survey need to be treated with caution. It is required to consider both small and large coating anomalies for cathodically unprotected pipelines, otherwise high corrosion rated might occur in small defects in the presence of adverse environmental conditions. On the other hand, large coating defects are easy to detect as demonstrated with the application of the quantile regression model. High values of %IR will be generally linked to large coating defect.

Chapter 4 presents the application of quantile regression to data from In-Line Inspection and environmental (soil) factors. Research presented in Chapter 4 is related to piggable pipelines and concludes that:

1. Corrosion defects are more likely to appear at the top and bottom of the pipeline and near the 12 and 6 o'clock positions.
2. Corrosion at the bottom of the pipelines is likely to be dependent on the water level which is constantly changing and in itself dependent to seasonal weather changes.
3. Soil stresses contribute to the coating breakdown at the top of the pipeline, thus, exposing the pipeline to the soil environment.
4. For pipelines equally well coated throughout at coating field joints, the likelihood of finding external corrosion is independent to the proximity to weld joints.
5. Bulk density carbon and sulphur concentration have little effect on corrosion for pipelines in early stages of corrosion damage; they are unlikely to be major contributing factors in the initiation of corrosion. However, once corrosion is initiated and the corrosion of the pipelines progresses, they will have a catalytic effect and will accelerate the corrosion mechanism.
6. Corrosion depth is directly proportional to the alkalinity of the soil.

7. Moisture content is directly proportional to the corrosion depth. Moisture causes an increase in corrosion once corrosion has initiated and before the pipeline defect reaches larger sizes.

6.2 Future work and ongoing research

As discussed in Chapter 5, to rely only on DCVG data to assess damage (from both, coating breakdown and reduction in the thickness of the pipeline as measured in depth of corrosion) is potentially misleading. A multiple regression such as shown in section 3.6.2 that takes account of environmental and other factors is more accurate in predicting coating defect area. However, it requires specific data to be available. To be able to make more accurate predictions, updating techniques are being used so that new information can be used in the analyses as and when it is available. Also, there are techniques that enable the combination of data from difference sources using Bayesian methods [138].

The regression techniques for prediction of corrosion damage must be viewed as complementary to other techniques such as Bayesian Belief Networks [139][104][107]. A pipeline integrity management approach may have inputs from elements of an ECDA approach, physics based corrosion models, structural reliability models such as in [140], and risk based decision support models that include the impact of consequential failure such as shown in [141].

The choice of approach and the techniques used often depends on the sort of data that is available. There is a strong case for sharing corrosion data among stakeholders and the use of data mining techniques to analyse such data for common benefit [142]. Getting data from a wider sample may be particularly useful when situation/location specific data is not easily available; such data could then be calibrated with specific inspection data when it becomes available.

The following research issues are proposed to follow this PhD thesis:

- Application of the developed regression models to different pipeline datasets in different environment. This will help to improve the accuracy of the models.

- Develop a software tool by implementing a corrosivity risk ranking map considering soil properties.
- Analysis of Close Interval Potential Survey inspection by introducing it into the correlation model developed in Chapter 3. This will increase the accuracy of the external corrosion regression model.

Quantile regression has been shown to perform effectively when applied to data from underground pipeline inspection. However, the effectiveness of the proposed method has not been validated in other types of pipeline or pipelines under different environmental (soil) conditions. In addition, quantile regression has been validated for non-piggable pipelines in desert conditions and for piggable pipelines for soils in the UK. Thus, the application of this novel method in other types of soil should be further investigated.

Appendix A. Quantile Regression

Quantile regression is a type of regression analysis used in statistics and econometrics. It estimates either the conditional median or other quantiles of the response variable. It is a statistical technique used to estimate and draw inference on conditional quantile functions [88][89]. It can provide a complete statistical analysis of the stochastic relationships among random variables.

Quantile regression is desired if conditional quantile functions are of interest. One advantage of quantile regression, relative to the ordinary least squares regression, is that the quantile regression estimates are more robust against outliers in the response measurements.

To understand quantile regression, first it's required to explain what quantiles are.

Let Y be a real valued random variable with cumulative distribution function $F_Y(y) = P(Y \leq y)$. The τth quantile of Y is given by:

$$Q_Y(\tau) = F_Y^{-1}(\tau) = \inf\{y: F_Y(y) \geq \tau\}$$

Where $\tau \in [0,1]$

Define the loss function as $\rho_\tau = y(\tau - I_{(y<0)})$, where I is an indicator function. A specific quantile can be found by minimizing the expected loss of $Y - u$ with respect to u. This can be shown by setting the derivative of the expected loss function to 0 and letting q_τ be the solution of:

$$0 = (1 - \tau) \int_{-\infty}^{q_\tau} dF_Y(y) - \tau \int_{q_\tau}^{\infty} dF_Y(y)$$

This equation reduces to:

$$F_Y(q_\tau) = \tau$$

Therefore, q_τ is τth quantile of the random variable Y.

For the calculation of the conditional quantile and quantile regression, suppose the τth conditional quantile function $Q_{Y|X}(\tau) = \mathrm{X}\beta_{\tau}$. Given the distribution of Y, β_{τ} can be obtained by solving:

$$\beta_{\tau} = \mathrm{argmin} E(\rho_{\tau}(Y - X\beta))$$

Solving the sample analog gives the estimator of β.

List of Publications

- Francisco Anes-Arteche, Keming Yu, Ujjwal Bharadwaj, Chi Lee, and Bin Wang, "Challenges in the application of DCVG-survey to predict coating defect size on pipelines.", Materials and Corrosion, November 2016.
- Francisco Anes-Arteche, Keming Yu, Ujjwal Bharadwaj and Chi Lee, "An analysis of factors influencing external corrosion based of soil, weld location and defect orientation data.", Materials and Corrosion, submitted.
- Francisco Anes-Arteche, Ujjwal Bharadwaj, Keming Yu and Chi Lee, "Correlation of pipeline corrosion and coating condition with ECDA survey results.", EUROCORR16 Conference, September 2016, Montpellier (France)
- Francisco Anes-Arteche, Ujjwal Bharadwaj, Keming Yu and Chi Lee, "Influence of soil properties on corrosion pitting in underground pipelines.", NSIRC Conference, June 2015, Cambridge (UK).
- Francisco Anes-Arteche, Ujjwal Bharadwaj, Keming Yu and Chi Lee, "Correlation of pipeline corrosion and coating condition with ECDA survey results.", NSIRC Conference, June 2016, Cambridge (UK).

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