STATISTICAL MODELLING OF CORROSION GROWTH IN MARINE ENVIRONMENT

(PEMODELAN SECARA STATISTIK PERTUMBUHAN PENGARATAN BAGI KAWASAN MARIN)

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ABSTRACT

Statistical and probabilistic methods are now recognized as a proper method to address the degree of randomness and complexity of the corrosion process. Nevertheless, the inclusion of this approach within corrosion model development is still rarely practiced in the structure assessment. This has led to the tendency by engineers and inspection personnel to use much simpler approaches in the assessment of corrosion progress. For example, the use of the linear model to predict the future growth of corrosion defects is widely practised despite its questionable accuracy. This work develops several corrosion-related models based on actual metal loss data with objectives to improve the data interpretation as well as prediction of future defect growth. Although this work deals specifically with data from oil pipelines and vessel's ballast tanks, the models has been designed to be generic, with no restriction on the types of structure or inspection tool. The procedure consists of three stages: data sampling, data analysis and probabilistic-based prediction. A statistical approach has been applied to model the corrosion parameters as a probability distribution. The issues raised by the presence of negative growth rate and unknown corrosion initiation time have been addressed by the development of new correction methods and a new data sampling technique. The research also demonstrates how the simple linear model can be modified to account for errors arising from the randomness of corrosion growth data and the variation in measured growth for severe defects. A proposed development of the linear-based model has been extensively used in the simulation programme. New data sampling techniques, data correction approaches, and alternative linear models have been developed to improve the assessment work on corrosion data. To conclude, this research was able to demonstrate how inspection data can be more fully utilised to optimise the application of information of corrosion progress to structural analysis.

ABSTRAK

Kaedah statistik dan kebarangkalian diakui sebagai kaedah yang sesuai bagi menangani tahap kerawakan dan bentuk kompleks proses pengaratan. Walau bagaimanapun, kaedah yang dinyatakan masih jarang digunakan dalam pembangunan model pengaratan bagi tujuan penilaian keadaan struktur. Ini menyebabkan jurutera dan pemeriksa terarah untuk menggunakan kaedah yang lebih mudah dalam menilai pertumbuhan pengaratan. Sebagai contoh, model linear sering digunakan dalam meramal kadar pertumbuhan pengaratan walaupun ketepatannya diragui. Kajian ini membangunkan beberapa siri model yang berkaitan dengan proses pengaratan berdasarkan data pengaratan sebenar dengan objektif untuk memperbaiki interpretasi data pengaratan dan juga unjuran kadar pengaratan. Walaupun kajian ini tertumpu kepada data pengaratan dari paip minyak dan tangki ballast kapal laut, model yang dibangunkan boleh juga digunakan ke atas sebarang jenis struktur mahupun jenis alat yang digunakan sewaktu pemeriksaan. Prosedur kajian terbahagi kepada tiga iaitu: pensampelan data, analisis data dan unjuran menggunakan kaedah kebarangkalian. Kaedah statistik digunakan bagi pemodelan pameter-parameter pengaratan dalam bentuk taburan kebarangkalian. Isu yang bekaitan dengan kadar pertumbuhan negatif dan masa permulaan pertumbuhan karat telah dikupas melalui pengenalan kepada kaedah pembetulan dan pensampelan yang baru. Kajian juga menunjukkan bagaimana model linear yang diubahsuai dapat menyelesaikan isu kerawakan dan serakan dimensi pengaratan. Model berasaskan pertumbuhan linear telah digunakan secara meluas di dalam program simulasi. Kaedah pensampelan data, pembetulan data dan model linear alternatif yang baru telah dibangunkan berasaskan data pengaratan yang sebenar bagi meningkatkan kualiti penilaian terhadap data pengaratan. Kesimpulannya, kajian ini telah berjaya menunjukkan bagaimana data pengaratan dapat ditingkatkan penggunaanya bagi mengoptimakan maklumat yang bakal diperolehi berkaitan dengan kadar pertumbuhan bagi tujuan analisis struktur.

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LIST OF SYMBOLS

$fn(t,E)$	=	mean valued function
$\in(t,E)$	=	zero mean error function
$c(t,E)$	=	the weight-loss of material
$\hat{x}$	=	independent variable.
λ	=	exponential parameter also known as failure rate.
δ	=	location parameter ($-\infty<\delta<\infty$).
θ	=	scale parameter ($0<\theta<\infty$).
β	=	shape parameter ($0<\beta<\infty$).
χ^2	=	chi-square value.
σ^2_{error}	=	variation of error
$\sigma^2_{measured}$	=	variation of measured defects
σ^2_{true}	=	variation of true defects
σ_{CR}	=	variation of corrosion growth rate
σ_t	=	variation of corrosion depth from the previous inspection
σ_{t+1}	=	variation of corrosion depth from the next inspection
σ_x	=	standard deviation.
λ_x	=	lognormal parameter.
ξ_x	=	lognormal parameter.
μ_x	=	mean value.
a	=	number of bin / class
a,c,m	=	non-negative integers.
c	=	y-axis intercept
c_x	=	concrete cover (cm)
C	=	confidence interval
C_1	=	annual corrosion rates
C_2	=	coefficient determines the trend of corrosion progress
C_b	=	a given bulk concentration
C_s	=	surface concentration
C_x	=	constant parameter.
COV	=	coefficient of variation.
CR	=	corrosion growth rate
CR_{cor}	=	corrected corrosion growth rate

CR_r	=	corrosion rate randomly selected from its corresponding distribution.
CR_{Ti}	=	corrosion rate in each single year
d	=	depth of corrosion defect
d_g	=	degree of freedom.
$d\%wt$	=	maximum depth of corrosion in terms of percentage
d_{ave}	=	fixed value of averaged defect depth.
d_{ave}	=	linear regression model of defect depth average
d_n	=	corrosion depth in year T_n
d_{n+1}	=	corrosion depth in year T_{n+1}
d_r	=	defect depth randomly selected from its corresponding distribution.
d_t	=	corrosion depth from the previous inspection
d_{t+1}	=	corrosion depthfrom the previous inspection
d_{T1}	=	corrosion loss volume in year 1
d_{T2}	=	corrosion loss volume in year 2
D	=	pipeline diameter (mm)
D_h	=	hydraulic diameter of the pipe. (D-2t) (mm)
E	=	expected value.
E_k	=	activation energy (31,580 cal/mol)
E_v	=	vector of environmental condition
$F(x_i)$	=	cumulative distribution function (CDF).
$f(x_i)$	=	probability density function (PDF).
$G(\,)$	=	limit state function.
i_{corr}	=	corrosion rate $\mu A/cm^2$
k	=	largest non-negative integer.
k_n	=	number of classes.
K	=	mass transfer coefficient
l	=	longitudinal extent of corrosion
L	=	measured length of corrosion defect
L_{T1}	=	corrosion length in year T1
L_{T2}	=	corrosion length in year T2
L_{max}	=	maximum allowable defect length
Loc	=	location of corrosion either internal or external.
L_x	=	likelihood function
m	=	slope.
n	=	number of observation (data)

N	=	number of trials
$n(G(x)\leq 0$	=	number of trials which violated limit state function.
nCO_2	=	fraction of CO_2 in the gas phase
O	=	observed value.
$O'Clock$	=	orientation of corrosion as a clock position of pipe wall thickness.
P_a	=	maximum fluid pressure
pCO_2	=	partial pressure of CO_2 (bar)
P_f	=	probability of failure.
p_{opr}	=	operating pressure (MPa)
P_p	=	maximum allowable operating pressure
Q	=	length correction factor
r	=	number of data (counted from 1 to the largest order).
R	=	resistance/demand.
R_o	=	9.55x1032 atoms/cm^2
R_u	=	universal gas constant (2 cal/mol/K)
s	=	random number.
S	=	load.
$SMTS$	=	specified minimum tensile strength
Std	=	standard deviation
$Std[cr]$	=	standard deviation of corrosion rate.
$Std[d/t]_o$	=	standard deviation of inspection tool in first year assessment.
$Std[d/t]_T$	=	standard deviation of inspection tool in the future.
std_d	=	linear regression model of defect depth standard deviation
t	=	pipeline radius (mm)
t_c	=	corrosion (mm/year)
t_m	=	time
t_p	=	time since corrosion initiation. (year)
t_t	=	nominal thickness of pipe in pipe spool
t_v	=	age of vessel (year)
T	=	prediction interval in year
T_0	=	year of installation
T_1	=	year of inspection T_1
T_2	=	year of inspection T_2
T_c	=	exposure time in year after breakdown of coating
T_k	=	temperature (K)
T_{mp}	=	temperature (^oC)

T_n	=	year of inspection T_n
T_{n+1}	=	year of inspection T_{n+1}
U	=	liquid flow velocity (m/s)
$Var(x)$	=	variance.
V_{cr}	=	corrosion rate (mm/year)
V_m	=	flow-dependent contribution to the mass transfer rate
V_r	=	flow-independent contribution to the reaction rate.
W	=	extent of corrosion around pipe circumference weld
w/c_e	=	water-cement ratio
x	=	random variable
x_d	=	corrosion depth
x_{norm}	=	normalised depth
x_j	=	observed data for observation order, j.
x_o	=	an offset, which is assumed to be known a priori (the smallest value).
y	=	dependent variable.
z	=	number of inspection

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18. S.H.M. Nor, N.M. Noor, N. Yahaya, S.R. Othman, 'A Probabilistic Modelling of Corrosion Growth In Marine Ballast Tank for Sustainable Maintenance Scheme', 8th UMT International Symposium on Sustainability Science and Management (UMTAS) 2009, Kuala Terengganu, 3rd-4th May. 39.

CHAPTER I - INTRODUCTION TO RESEARCH

1.0 Introduction

Corrosion has become a major cause of the loss of the strength in marine structures resulting in failures. Structural deterioration of liquid containment structures such as offshore pipelines and vessel's seawater ballast tanks due to corrosion attack is a common and serious problem, involving considerable cost and inconvenience to industry and to the public. Structural failures such as explosion and leakage may induce serious damages and cause environmental hazards. Heavy financial loss associated with production loss, repair or even the clean up of the polluted marine environment will be experienced by the company. Therefore, awareness among structure owners in maintaining high reliability of their structure system has risen dramatically. An accurate estimation of corrosion rates plays an important role in determining corrosion allowances for structural designs, planning for inspections, and scheduling for maintenance [Wang *et al.*, 2003]. Therefore, more inspections have been carried out so the corrosion progress can be monitored continuously. A robust and simple approach is required to optimize the information that can be acquired from the inspection data. Hence, the remaining life-time of structures and the probability of structure failure can be quantified and projected accurately into the future.

1.1 Background and Motivation

The use of inspection data in assessing and predicting the remaining lifetime of corroding structures has been widely applied by engineers. With proper empirical models, the extent of the corrosion could be monitored effectively to minimise the effects towards structure reliability. However, the complexity of corrosion empirical models owing to their dependency on so many variables such as temperature, chemical substances, penetration rate and partial pressure, which in certain circumstances are difficult to measure correctly, could affect the accuracy of the assessment results. In many cases, this information will not be recorded and may vary significantly over the period of service. On some occasions, the variables that have an effect on the corrosion theoretically have been proven less important for the actual field. Melchers [1999a] stated that the effect of water temperature on the corrosion of steel has long been recognised as a factor in laboratory testing but not in field observations.

Since these models are a function of many variables, which themselves can often be uncertain, a simpler model which is based solely on the corrosion wastage is appropriate as an alternative approach which would be complementary to the available empirical models [Melchers, 1999a]. The additional complexity introduced by more refined mathematical models has yet to prove the value of such an approach in improved corrosion prediction accuracy [Wang *et al*., 2003]. Based on the information provided by the inspections tools, repeated measurement of metal loss area could lead to developing a general and robust corrosion related model. Much of the previous work on corrosion assessment has been developed through extensive laboratory tests, in reality many issues regarding environmental uncertainties are not investigated accurately by such tests since the experiments have been run under a controlled 'pseudo' environment. Instead of relying on the data from laboratory work, a huge amount of commercial data from inspections on real structures might give better vision and information being at real scale and in more natural and uncontrolled environment. Inspection work on real structures could be perceived as a large scale example of experimental laboratory work. The collected data might be better compared to laboratory test data in terms of information on uncertainties, provided that the inspection is sufficiently accurate to produce high quality data.

Hypothetically, the study on the volume of corrosion wastage taken from real inspection data could eliminate the barrier posed by the diversity of the types of corrosions, corrosion mechanisms, structure designs, and inspection tools. Most of the inspection on corroding structures targets mapping and measuring the volume of metal loss by its depth, axial length, and circumferential length. If different data from different structures could be collected and studied together, generic corrosion-related models could be developed if common aspects can be identified. If this is achievable, a single assessment approach could be used on different types of structures with excellent flexibility, suiting the application of established empirical models or theoretical models or both.

1.2 Scope

A large part of the previous researches related to corrosion study involve extensive laboratory experimentation to examine the correlation between volume of metal loss and those parameters that are considered to influence metal loss such as pH, temperature, operational pressure and penetration rate of chemical substances. However this thesis concentrates on the analysis of corrosion data collected from inspection activities on site (secondary data). Two types of engineering structures/systems are considered (i) crude oil pipelines, and (ii) vessel's seawater ballast tanks. Other structures/systems are not included owing to limited amount of inspection data available. Repeated and random inspection data detailing the volume of metal loss is the key factor considered in this research. Corrosion potential readings, for example, which are available for reinforced concrete assessment is not considered in the study. The development of the corrosion-related models and the data correction approaches are totally based on the physical evidence from metal loss volume. The effects of material properties, operational condition, and environmental parameters upon corrosion growth are not considered in developing the generic assessment approach of corrosion data. Statistical analysis is used to analyse the variation of corrosion parameters. The analysis results are then used to assess the current and future remaining lifetime of corroding structures by using the Monte Carlo simulation.

1.3 Aims

The main goal of this thesis is to develop corrosion-related models including metal loss dynamic and error models for structures exposed to seawater environment. The proposed models will be wholly developed through large scale data collection from on-site inspection activities. The following aims were identified as steps towards achieving this goal:

1. Analyse real inspection data by using statistical and probabilistic approaches to extract important information regarding corrosion behaviour.
2. Develop simple corrosion-related model and data correction approaches based solely on metal loss evidence to eliminate the dependency of corrosion progress upon structure material and environmental properties.

1.4 Importance of Study

The study will provide much simpler models to analysing inspection data and evaluating the current and future condition of corroding structures. The corrosion-related models are fully developed from real inspection data to make it readily understood and practical during on site assessment owing to its independency on environmental parameters and structure material. This study will also provide correction methods to improve the interpretation of corrosion data. The whole package of the proposed model is designed to simplify the practical aspects of structural assessment and to identify inspection plans, both complying with specific requirements on the maximum acceptable annual probability of structural failure and at the same time minimising overall service life cost. Furthermore, this will encourage plant engineers and inspection personnel to make optimum use of the inspection data.

CHAPTER 2 - REVIEW ON CORROSION

2.0 Introduction

This chapter is intended to justify the purpose of this research by reviewing related corrosion issues. It begins with a general principle of corrosion including corrosion problems suffered by engineering structures or systems and corrosion behaviour including the corrosion electrochemistry, variation of corrosion forms and growth patterns. The discussion of corrosion forms is primarily in terms of pitting corrosion due to its severe destructive nature in perforating the wall thickness of liquid containment structures. A number of corrosion-related models have been discussed briefly with the intention of demonstrating the model complexity due to its dependency on environmental parameters and structural properties. Previous works on data analysis and structural assessment guidelines of pipelines and vessel tank structures has been covered to identify the potential future research on corrosion assessment guidelines. The last part of this chapter is the discussion on the major issues related to corrosion engineering and introduces the idea of a generic assessment approach of corrosion data and its application to structure reliability.

2.1 Corrosion in General

Corrosion encountered in engineering structures is an electrochemical process in nature with the presence of oxygen in some form [Peabody, 1967]. In general terms corrosion is defined as the destruction or deterioration of a material because of reaction with its environment [Fontana, 1986]. Although the term is usually applied to metals, all materials, including ceramics, plastics, rubbers, and wood, deteriorate at the surface to some extent when they are exposed to certain combinations of liquids and/or gases. Common examples of metal corrosion are the rusting of iron, the tarnishing of silver, the dissolution of metals in acid solutions, and the growth of patina on copper. In the structural engineering field, metal corrosion is considered as one of the most dominant failure mechanisms that significantly affects the reliability of structure. Corrosion rates may be reported as a weight loss per area divided by the time (uniform corrosion) or the depth of metal corroded, divided by the time (localised corrosion).

2.1.1 Corrosion in Engineering Structures

Reliability deterioration of engineering structures due to corrosion is a wide spread problem, inflicting huge financial loss and sometimes dreadful catastrophe. Corrosion is considered to be one of the most important factors affecting age related structural degradation of steel structures and therefore has attracted large scale research to explore and investigate the complexity of the corrosion process [Paik, 2004]. Corrosion decreases the ability of the structures to withstand loads and hence the level of safety of these structures diminishes with time due to accumulation of corrosion damage. Preserving structure lifetime when under corrosion attack is not a simple task. It requires deep knowledge of the corrosion process in order to predict the future growth of corrosion defects accurately.

In reinforced concrete structures, corrosion-initiated longitudinal cracking and associated spalling of the concrete cover are particularly common problems. Corrosion can cause a serious metal loss from the reinforcement bars causing the structure to lose its integrity. The corrosion product, rust accumulates causing tensile stresses inside the concrete which triggers internal microcracking, external longitudinal cracking and eventually spalling. These reduce the structural strength capacity due to reduction in the depth of concrete compression area [Thoft-Christensen, 2002]. Corrosion in steel beams can cause severe thickness loss from the web and flange areas. A corroding steel beam subjected to bending might fail in different ways, depending on its dimensions and the loading it undergoes, such as buckling of flanges, lateral-torsional buckling, and shear failure of the web and in bearing failure of the web. In a highly corrosive environment, initiation and subsequent propagation of pits can result in complete perforation of the structure wall of containment structure such as pipelines, water tanks, and ballast tanks. A fraction of the fluid that is carried or contained will be lost and might lead to contamination of the environment for example the contamination of seawater due to crude oil leaking from offshore pipelines.

2.1.2 Corrosion Electrochemistry

Corrosion is usually an electrochemical process in which the corroding metal behaves like a small electrochemical cell. The corrosion of iron by dissolved oxygen is taken as an example to illustrate the electrochemical nature of the process since it is the most common reaction occurring in the atmosphere. Figure 2.1 shows the illustration of the corrosion process represented by a sheet of iron divided into two different areas which are an anodic area and cathodic area.

When this sheet of iron is exposed to a water solution containing dissolved oxygen, iron is oxidized by reaction with dissolved oxygen to form ions and electrons. This first process is known as anodic or oxidation reaction. At the same time, the generated electrons are consumed by the second process and oxygen molecules in the solution are reduced at the cathodic areas. This is known as cathodic or reduction reaction. These two processes have to balance their charges. The sites hosting these two processes can be located close to each other on the metal's surface, or far apart depending on the circumstances. These two processes produce an insoluble iron hydroxide in the first step of the corrosion process. Generally, this iron hydroxide is further oxidized in a second step to produce $Fe(OH)_3$, the flaky, reddish-brown substance that is known as rust. Unfortunately, this new compound is permeable to oxygen and water, so it does not form a protective coating on the iron surface and the corrosion process continues. The whole reaction process can be represented by formulas as detailed in Table 2.1:

Table 2.1: The chemical reaction process of corrosion initiation

Reaction	**Formula**
Anodic reaction (oxidation) Cathodic reaction (reduction)	$2Fe^{2+} \rightarrow 2Fe^{3+} + 2e^-$ $\frac{1}{2}O_2 + H_2O + 2e^- \rightarrow 2OH^-$
Total reaction	$2Fe^{2+} + \frac{1}{2}O_2 + H_2O \rightarrow 2Fe^{3+} + 2OH^-$

2.1.3 Forms of Corrosion

There are eight common different forms of corrosion; uniform, galvanic, crevice, pitting, intergranular, leaching, erosion and stress corrosion. Normally, it is easy to classify corrosion into two different classes based on the metal loss area [Ahammed and Melchers, 1994]. For uniform loss of material thickness, it can be classified as general corrosion whereas non-uniform metal loss represents localised corrosion. General corrosion is a corrosion reaction that takes place uniformly over the surface of the material, thereby causing a general thinning of the component and eventually failure of the material. The geometry of a wide spread general corrosion is difficult to measure. In contrast localised corrosion comprises clearly defined, relatively isolated, regions of metal loss [O'Grady II, 1992a and 1992b]. Therefore, it is theoretically easy to measure the extents of axial and circumferential corrosion of a localised defect.

Pitting is categorised as a form of localised corrosion. A pit is a hole, for which the width is comparable with or less than its depth [West 1986]. Pitting is one of the most destructive forms of corrosion for many metallic structures and is well known as the predominant internal failure mechanism of steel offshore pipelines [Ahammed and Melchers, 1994; Fontana, 1986; Shi and Mahadevan, 2000]. Under aggressive circumstances due to the corrosive environment, propagation of pitting corrosion can result in perforation of the wall structure. A similar way to pitting corrosion, pinholes can occur which have a narrow depth, and also lead to a high-risk of leakage and spillage from a containment structure such as pipelines and water tank. Corrosion can also occur in other forms such as groove shape like a channel where its width is greater than its depth. The loss of metal section due to uniform corrosion is important for structural strength considerations while pitting is clearly of importance for containment.

2.1.4 Corrosion Growth

The assumption of linear growth is widely used by researchers in predicting the progress of corrosion due to its simplicity and lack of information to develop a proper growth model. Till now, there is no evidence that linear growth is the most accurate model for prediction purposes. It has been suggested that for long term prediction, the linear form is highly likely while less accurate for short term prediction [Caleyo, 2002].

However, there are no specific guidelines on how to distinguish between long term and short term predictions. Yahaya [1999] described the linear model as robust and simple compared to other models, but noted it has some limitations. However in contrast, the author stated that the prediction of corrosion growth into the future should be done for short term only due to the unpredictable nature of corrosion rate. The variation of corrosion rate might be random due to unforeseen circumstances that can accelerate the corrosion rate such as accidental flow of corrosive product, structural degradation due to accident, unpredictable environmental conditions and changes in operating pressure. Therefore, continuous corrosion monitoring is essential in order to get a better insight and information.

Figure 2.2 illustrates alternative patterns of corrosion growth. The convex curve indicates that the corrosion rate is accelerating as the corrosion progress proceeds. This type of corrosion progression may be likely to happen in marine immersion conditions at sea, specifically in dynamically loaded structures where flexing continually exposes additional fresh surface to the corrosion effects [Paik and Thayambali, 2002]. The concave curve shows that the corrosion rate is increasing in the beginning but is decreasing as the corrosion progress proceeds. The formation of rust product on the steel surface will reduce the diffusion of the irons away from the steel surface. Also, the area ratio between the anode and the cathode is reduced. This suggests that the corrosion rate will reduce with time; namely, rapidly during the first few years after initiation but then more slowly as it approaches a nearly uniform level [Vu and Stewart, 2000]. This type of corrosion progression may be typical in a non-immersion environment of liquid (water or oil) since the corrosion lump at the steel surface can disturb the activation of corrosion progress [Paik and Thayambali, 2002].

2.1.5 Corrosion Rate Models

The corrosion process is time-variant and the amount of corrosion damage is normally defined by a corrosion rate with units of, say, mm/year, representing the depth of corrosion increase per year [Paik and Thayambali, 2002]. While the extent of corrosion presumably increases with time, it is not straightforward to predict the progress of corrosion. The only real alternative is then to pessimistically assume more corrosion extent than is likely [Paik and Thayambali, 2002]. There are theoretical and empirical models available to estimate the rate of corrosion growth. An empirical model such as deWaard and Milliams equation was developed through extensive lab tests on simulated corroding environment for offshore pipelines. Generally, empirical models are developed based on a defined relationship between material and environmental properties to estimate the corrosion rate. Unlike an empirical model, a theoretical model such as linear estimation can be simpler and practically available to estimate the average growth rate based on metal loss evidence regardless the effect of material and environment properties.

2.1.5.1 Linear Model

The corrosion growth rate can be calculated using a linear corrosion growth model. This theoretical model is normally used on metal volume loss data or corrosion depth by comparing two corresponding defect dimensions at different time. The linear equation is performed as below:

$$CR = \frac{d_{T2} - d_{T1}}{T_2 - T_1} \qquad \text{Equation 2.1}$$

where:

CR	=	corrosion growth rate
d_{T1}	=	corrosion loss volume in year T_1
d_{T2}	=	corrosion loss volume in year T_2
T_1	=	year of inspection T_1
T_2	=	year of inspection T_2

2.1.5.2 The deWaard & Milliams Model

The deWaard & Milliam empirical model has been widely used to estimate the averaged corrosion growth rate in an oil and gas pipeline subjected to CO_2-induced corrosion [DeWaard *et al*, 1991; Lotz *et al*, 1991]. In this model, the charge transfer controlled reaction of carbon dioxide and water with steel was represented algorithmically in terms of CO_2 partial pressure and an exponential temperature function. One of the main advantages of the deWaard-Milliams model is that it is capable of estimating corrosion rates without considering the actual corresponding dimension of corrosion defect in later inspection such as in the linear model procedure. The rates of corrosion are estimated by:

$$V_{CR} = \frac{1}{\frac{1}{V_r} + \frac{1}{V_m}}$$ Equation 2.2

where:

$$\log(V_r) = 4.93 - \frac{1119}{T_{mp} + 273} + 0.58\ \log(pCO_2)$$ Equation 2.3

and

$$pCO_2 = nCO_2\, p_{opr}$$ Equation 2.4

$$V_m = 2.45 \frac{U^{0.8}}{D_h^{0.8}} pCO_2$$ Equation 2.5

where:

D	=	pipeline diameter (mm)
D_h	=	hydraulic diameter of the pipe. (D-$2t$) (mm)
nCO_2	=	fraction of CO_2 in the gas phase
pCO_2	=	partial pressure of CO_2 (bar)
p_{opr}	=	operating pressure (MPa)
t	=	pipeline radius (mm)
T_{mp}	=	temperature (^{o}C)
U	=	liquid flow velocity (m/s)
V_{cr}	=	corrosion rate (mm/year)
V_m	=	flow-dependent contribution to the mass transfer rate
V_r	=	flow-independent contribution to the reaction rate.

2.1.5.3 Corrosion Model of Concrete Reinforcement Bar

This model was proposed by Vu and Stewart [2000] to predict the progress of corrosion of reinforcement bar in concrete structures. This model is applicable when the corrosion rate is governed by the availability of water and oxygen at the steel surface, and the concrete cover. This model indicates that corrosion rate will reduce rapidly with time during the first few years after initiation but then more slowly as it approach a nearly uniform level.

$$i_{corr} = \frac{37.8\left(1-\frac{w}{c_e}\right)^{-1.64}}{c_x}\left(\mu A/cm^2\right) \qquad \text{Equation 2.6}$$

where:

c_x = concrete cover (cm)

i_{corr} = corrosion rate ($\mu A/cm^2$)

w/c_e = water-cement ratio

By taking into consideration the effect of corrosion initiation time, the above equation can be written as:

$$i_{corr-t} = i_{corr}.0.85t_p^{-0.29}\left(\mu A/cm^2\right) \qquad \text{Equation 2.7}$$

where:

t_p = time since corrosion initiation. (year)

2.1.5.4 Erosion-Corrosion Model

Abdulsalem [1992] proposed a steady state model for erosion corrosion of feed water piping. The rate of erosion corrosion is dependent on two factors which are oxide dissolution and mass transfer based on the oxide dissolution. The kinetics of erosion corrosion is governed by two steps that operate in series. The first step is the kinetic rate of oxide dissolution, R_k expressed as:

$$R_k = R_o \exp\left(\frac{-E_k}{R_u T}\right)$$ Equation 2.8

where:

E_k = activation energy (31,580 cal/mol)

R_o = 9.55x1032 atoms/cm^2

R_u = universal gas constant (2 cal/mol/K)

T = temperature (^oK)

The second step involved is the estimation of mass transfer limit, R_{MT}:

$$R_{MT} = K(C_s - C_b)$$ Equation 2.9

where:

C_b = a given bulk concentration

C_s = surface concentration

K = mass transfer coefficient

Total erosion corrosion rate can be defined as:

$$Rate = \left(R_k^{-1} + R_{MT}^{-1}\right)$$ Equation 2.10

2.1.5.5 Probabilistic Model of Immersion Corrosion

Melchers [1999a] has proposed a probabilistic model for corrosion weight loss that is suitable for immersed structures. The proposed model was constructed from a mean value expression accounting for random and other uncertainties not modelled in the mean value expression, as follows:

$$c(t, E_v) = fn(t, E_v) + \in (t, E_v)$$ Equation 2.11

where:

$\in (t, E_v)$ = zero mean error function

$c(t, E_v)$ = the weight-loss of material

E_v = vector of environmental condition

$fn(t, E_v)$ = mean valued function

t = time

The proposed model accounts for the major processes involved in the corrosion process using *E* that involves initial corrosion, oxygen diffusion controlled by corrosion products and micro-organic growth, limitations on food supply for aerobic activity and anaerobic activity. The author suggests that to refine the model, further detailed field observations are necessary to gather more precise information on environmental conditions such as temperature, dissolved oxygen, pollutants, water velocity and factors that influence the microbiological growth.

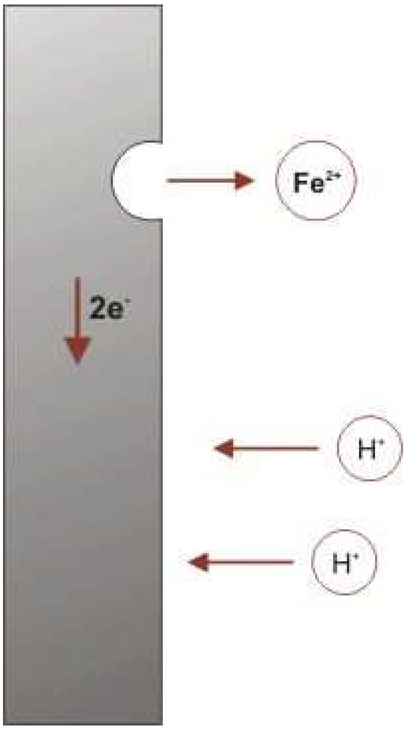

Figure 2.1: Corrosion Electrochemical Process

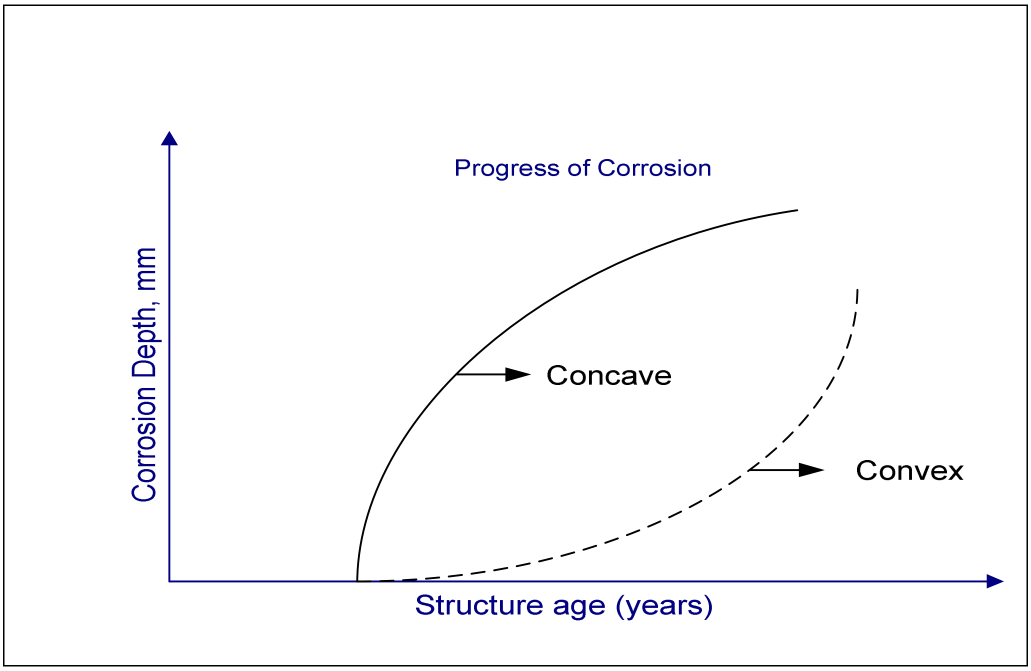

Figure 2.2: Corrosion progress model

2.2 Related Works

This section contains a literature review on corrosion data analysis for pipeline and liquid containment structures, and available assessment guidelines specifically developed on the statistical and probability basis. Due to limited sources of corrosion data from other types of structures, further analysis in this research is related solely to two general steel structures, namely oil and gas pipelines and vessel's seawater ballast tanks.

2.2.1 Corrosion of liquid containment structures

Paik and Thayambali [2002] present a methodology for modelling corrosion in a vessel's ballast tank based on corrosion depth measurement on outer bottom plating of a bulk ship. The reduction of plate thickness due to corrosion was expressed as a function of time (year) after the corrosion starts, namely

$$t = C_1 T^{C_2} \qquad \text{Equation 2.12}$$

where:

C_1 = annual corrosion rates

C_2 = coefficient determines the trend of corrosion progress

t = corrosion depth/loss (mm)

T = exposure time in year after breakdown of coating

The authors explain the coefficient of C_2 can be determined based on carefully collected corrosion data for existing ship structures. However, this approach is in most cases not straightforward to apply mainly because of the differences in data collection sites typically visited over the life of the vessel and also differing periods of time between visits [Paik and Thayambali, 2002]. This is part of the reason for the relatively large scatter of corrosion data in many studies by the authors. The simple alternative is to determine the value of corrosion rates, C_1 assuming a constant value of C_2 which measurements have suggested varied between 0.3-1.0. For practical design purposes, the authors assumed $C_2=1$ and was taken as the usual value.

Wang *et al*. [2003] presents an estimation of corrosion rates of structural members in oil tankers based on a corrosion wastage database of over 110,000 thickness measurements from 140 single hull oil tankers. The Weibull distribution was used to represent the distribution of corrosion rates. The mean, standard deviation and maximum values of corrosion rates for structural members were obtained based on the entire population of the database. They were then compared with the ranges of corrosion rate published by Tanker Structure Co-operative Forum (TSCF). A constant-rate corrosion progress model (linear model) was used to estimate the corrosion rates for each individual defect by assuming that there is no corrosion during the first five years of service for simplicity sake. The finding from this research shows that the average corrosion rates do not seem to depend on usage spaces (cargo or ballast tank) as shown in Table 2.2.

Paik [2004] focuses on the corrosion in seawater ballast tank structures of bulk carriers and oil tankers. Measured data for the corrosion of wastage of seawater ballast tanks of ocean-going oil tankers and bulk carriers have been collected using an ultrasonic measurement tool. Statistical analysis has been carried out to quantify the characteristic of corrosion data in terms of ship age and to develop time-dependent corrosion wastage model. Three assumptions were made for the analysis of corrosion in this study namely

1. The annualised corrosion rate is constant so that the relationship between the corrosion depth and the ship age is linear.
2. The life of coating applied on the structure wall is varied at 5, 7.5 and 10 years in the study, because no information about the breakdown of the coating is available.
3. Corrosion starts immediately after the coating breakdown takes places.

The loss of plate thickness due to corrosion is expressed linearly as a function of the time (year) after the corrosion starts. Corrosion rates were estimated individually by incorporating assumed values of coating life and found by best fit to the Weibull distribution function. The annualised corrosion rates were determined by including all of the data and the data only at the tail of 95% and above band (extreme model). Tables 2.3 and 2.4 summarise the computed results for the mean value and coefficient of variance of annualised corrosion rates. The main problem with the proposed assessment work by Paik and Thayambali [2002] and Paik [2004] is the assumed value of coating life. The author only made assumptions of the coating life to simplify the estimation of corrosion rate which might causes uncertainty in the prediction.

Structure	Tank	Mean	Deviation	Maximum	TSCF (1992)
Dk pl	Cargo	0.066	0.069	0.580	0.03 – 0.10
	Ballast	0.055	0.042	0.277	0.10 – 0.50
Dk long web	Cargo	0.055	0.055	0.807	0.03 – 0.10
	Ballast	0.047	0.051	0.444	0.25 – 1.00
Dk long fl	Cargo	0.037	0.030	0.243	-
	Ballast	0.044	0.041	0.175	-
Side shell	Cargo	0.044	0.046	0.547	0.03
	Ballast	0.043	0.038	0.573	0.06 – 0.10
Side long web	Cargo	0.040	0.034	0.567	0.03
	Ballast	0.042	0.042	0.800	0.10 – 0.25
Side long fl	Cargo	0.033	0.021	0.171	-
	Ballast	0.032	0.030	0.482	-
Btm shell	Cargo	0.085	0.076	0.690	0.04 – 0.30
	Ballast	0.049	0.051	0.320	0.04 – 0.10
Btm long web	Cargo	0.032	0.022	0.207	0.03
	Ballast	0.027	0.020	0.117	-
Btm long fl	Cargo	0.047	0.062	0.730	-
	Ballast	0.045	0.066	0.700	-
Long bhd pl	Btw cargo	0.049	0.059	0.654	0.03
	Others	0.051	0.046	0.470	0.10 – 0.30
Bhd long web	Cargo	0.038	0.031	0.411	0.03
	Ballast	-	-	-	0.20 – 1.20
Bhd long fl	Cargo	0.045	0.044	0.782	-
	Ballast	-	-	-	0.20 – 0.60

Abbreviations: btw – between, bhd – bulkhead, dk – deck, fl – flange, long – longitudinal, pl – plate

Table 2.2: Estimated mean, standard deviation and maximum values of corrosion rate for various structural members in oil tankers and comparison with the range of general corrosion by TSCF (1992) (unit: mm/year) [Wang *et al*., 203]

Table 2.3: Summary of the computed results for mean value and COV of annualised corrosion rate of bulk tanker's seawater ballast tank [Paik and Thayambali, 2002].

Corrosion data used		Coating life assumed	Mean of annualised corrosion rate (mm/year)	COV
Bulk Carrier	All corrosion data	5 years	0.0473	0.8388
		7.5 years	0.0621	0.9081
		10 years	0.0804	0.9031
	95% and above band	5 years	0.1678	0.1678
		7.5 years	0.2212	0.2212
		10 years	0.2997	0.2997

Table 2.4: Summary of the computed results for mean value and COV of annualised corrosion rate of oil tanker's seawater ballast tank [Paik and Thayambali, 2002].

Corrosion data used		Coating life assumed	Mean of annualised corrosion rate (mm/year)	COV
Bulk Carrier	All corrosion data	5 years	0.0463	0.7583
		7.5 years	0.0549	0.7596
		10 years	0.0684	0.7897
	95% and above band	5 years	0.1481	0.1428
		7.5 years	0.1777	0.1316
		10 years	0.1926	0.3630

2.2.2 Corrosion Analysis Guideline for Pipelines

Yahaya [1999] has used multiple sets of corrosion data from pipeline inspection of the same pipelines in three different years to examine the relationship between corrosion defect size and corrosion rate. Two different sampling methods were applied to match the data from one inspection with the corresponding data in the other inspections. The first approach is by sorting the depth of corrosion depth by its severity before locating the corresponding data while the second approach samples the data randomly. The description of the sampling approach is shown in Table 2.5. The author focuses on matching data with high depth severity in order to investigate the connection between rapid growth rate and severe corrosion pit. This connection is very important to establish the hypothesis that the deepest defects are most likely to grow at a faster rate and hence become the most likely site to fail [Yahaya, 1999]

The linear model was used to estimate the corrosion growth rate based on metal loss volume between the two matched data. An intensive statistical analysis was carried to study the correlation between corrosion depth, corrosion length and corrosion growth rate. The conclusions on data analysis are summarised as follows:

1. There is a weak relationship between corrosion peak depth and axial length, hence both parameters were considered independent.
2. Some of the sampling techniques resulted in negative average values of corrosion growth rate which is unrealistic and unacceptable for prediction purposes. The negative value is believed to be caused by certain factors such as random corrosion behaviour and measurement error due to improper tool calibration.
3. Based on a bivariate Normal distribution model, there was evidence of a very strong negative correlation trend between the measured depth and subsequent corrosion depth. This signified that on average, a substantial proportion of low-to-middle depth defects in the previous inspection grew more rapidly compared to some of the deeper features, contrary to the earlier hypothesis.

The author has introduced a correction method to reduce the deviation of corrosion distribution by eliminating the extreme negative and positive growth rate. A normal distribution of correction factor with zero mean value was introduced by assuming that there has been some level of error in the inspection measurement of defect dimensions. Yet, the proposed method is only applicable to Normal distribution of corrosion growth rate with positive mean value. With this limitation, better approaches are required to be developed to address different types of anomalies within corrosion data.

The problems of predicting the future size of corrosion defects from the inspection data and the effect of the uncertainty of such predictions upon the structural integrity assessment were highlighted. The large volume of detected data results in the involvement of several thousands of corrosion sites and so an extreme value statistic using peaks over threshold approach was adopted. The effect of the selection of threshold levels upon the structural reliability for the various limit states was also examined using Monte Carlo simulation and it was suggested that threshold levels over 30% for corrosion depth of pipeline wall thickness to be used as this retained a reasonable number of remaining data after the cut-off (25% at least from the amount of whole data) and the consistency of predicted failure probability. The proposed assessment procedure of pipeline corrosion data is shown in Figure 2.3.

Table 2.5: Examples of data sampling description [Yahaya, 1999]

Sampling method	Descriptions
Top 500 depth severity sorted in 1992	Data are sequenced based on depth severity in 1992, then the corresponding 500 matched features in 1990 and 1995 are located.
Top 500 depth severity sorted in 1992	Data are sequenced based on depth severity in 1995, then the corresponding 500 matched features in 1990 and 1992 are located.
Random sampling	Data are sampled randomly in 1995, and then the corresponding matched features are located in 1990 and 1992.

The Health & Safety Executive proposed guidelines for use of statistics for analysis of sample inspection of corrosion [HSE, 2002]. This guideline is intended to advise plant engineers and inspection personnel on methods for analysing and extrapolating inspections for large plant including vessels, pipeworks and pipelines, taking into account the statistical nature of corrosion. Moreover, it provides an introduction to the techniques and capabilities of the statistical methods with view to the wider application in industry. The widespread application of statistical analysis on corrosion data is not common, largely because the use of statistics requires specialist knowledge, and no reference standard exists. The statistical analysis comprising least square method and probability plot for determination of statistical distribution and the corresponding moment value, and extreme value theory to predict the likelihood of early wall perforation. The linear model was suggested for prediction of defect growth in the future due to its simplicity and non dependency upon operational condition, structure material, and environmental properties.

Desjardins [2002a and 2002b] presents a method for optimising the repair and inspection based on in-line inspection data corrosion growth modelling, and a probabilistic approach to defect severity predictions. The data matching procedure has been combined with risk assessment methodology to assessing future risk based on calculating the probability of failure due to corrosion at any point of time. By analysing the risk to a pipeline based on probable future corrosion severity and probability of failure, an optimised integrity strategy can be developed to either minimise the failure probability given a set integrity budget, or to minimise integrity costs while maintaining an acceptable level of risk. The proposed methodology is depicted in Figure 2.4

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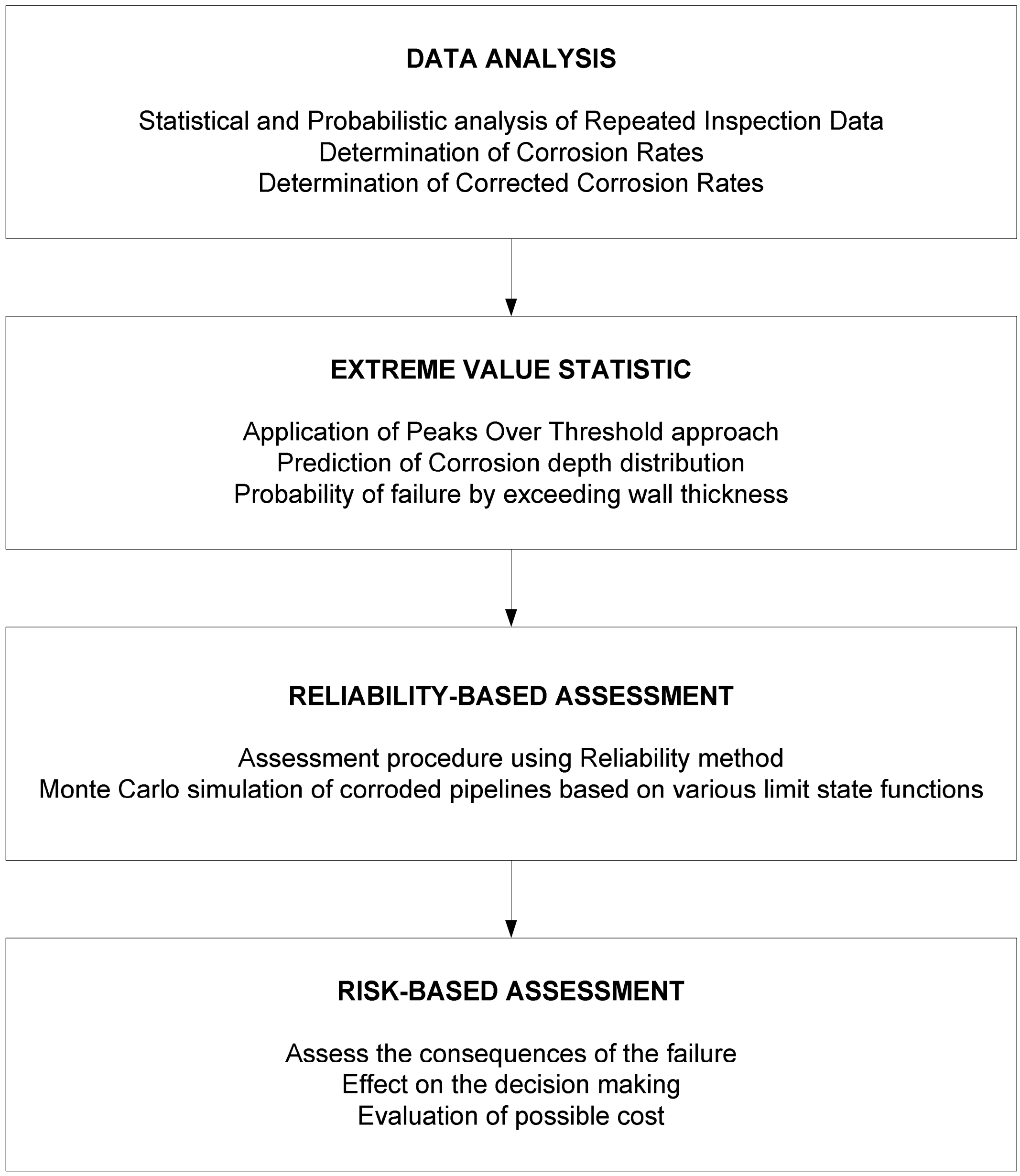

Figure 2.3: A general summary of overall procedure on the use of inspection data in the structural reliability assessment of corroding pipelines as proposed by Yahaya [1999].

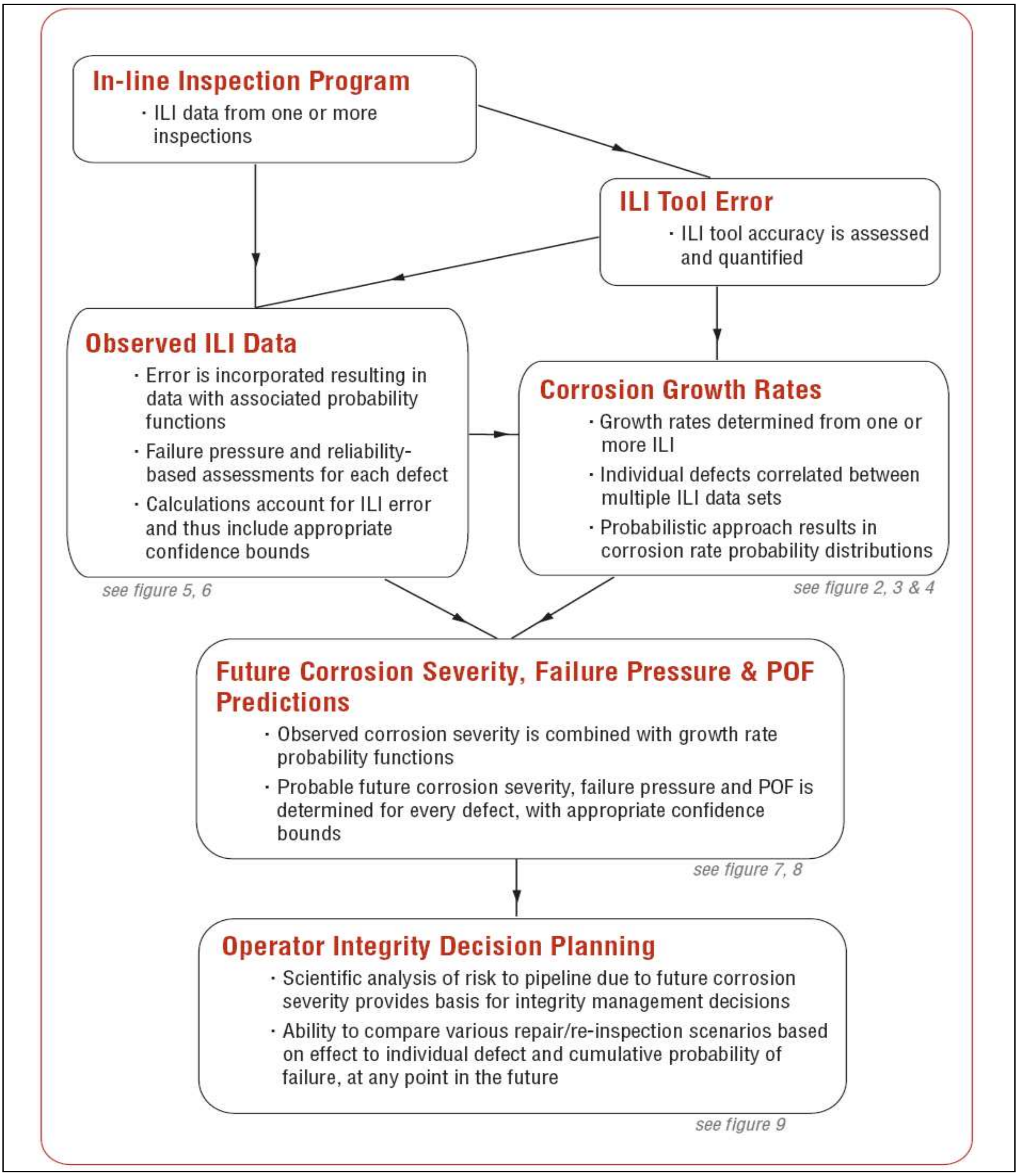

Figure 2.4: Corrosion growth analysis and probability of failure methodology by Desjardins [2002a and 2002b].

2.3 Corrosion Issues

The corrosion process in total is very complex and the modelling is often based on observations or speculations rather than a clear understanding of the physical and chemical processes [Thoft-Christensen, 2002]. For instance, the diffusion coefficient and surface chloride concentration in practice are assumed as independent derived variables [Vu and Stewart, 2000]. This is not so in reality. In nearly all reported data, diffusion coefficients and surface chloride concentrations that play major roles in governing corrosion growth rate in reinforced concrete are not obtained by physical measurements, but by 'best fits' to Fick's law [Vu and Stewart, 2000]. Simplicity in predicting corrosion progress such as the use of linear growth model based on assumption may be perceived as a conservative estimate of the corrosion rate. Consequently, it might be misleading in terms of residual safe life and hence might lead to premature condemnation of a structure. [Melchers, 1999a]

Despite some quite extensive, long term experimental test programs, the prediction of the likely corrosion loss of material is still rather simplistic and not well developed [Melchers, 1999a]. The complexity of corrosion nature is due to the unpredictable condition of the corrosion progress and the uncertainties related to material and environment properties. Corrosion empirical models have been extensively developed through proper laboratory testing. However, due to random nature and uncontrolled environment on the real sites, these tests sometime mislead the information on corrosion growth. Some parameters related to environmental properties such as temperature might have been shown to have a significant affect on corrosion growth based on laboratory testing. However, when further analysis was carried out on real field data, the relationship between these properties can hardly be identified [Melchers, 1999a].

The deWaard and Milliams model, for instance is able to estimate the average corrosion growth rate in oil and gas pipelines. Mostly, empirical corrosion models are presented as a function of many variables, which on some occasion the actual values are barely measurable. No matter how reliable the corrosion models are, if the required variables can't be measured accurately, it will affect the reliability of assessment results. The dependency of these models on so many variables would be perceived as impractical when precise information is not available.

The corrosion damage of steel structures is influenced by many factors, including the corrosion protection system and various operational parameters. This makes the corrosion an unpredictable process, complex, and randomly progress in time [Thoft-Christensen**,** 2002]. Even though the sources of corrosion can be identified and treated accordingly, the prediction of corrosion progress might still be inaccurate. This is because of other factors that can also trigger and accelerate the corrosion growth rate. Corrosion in concrete due to chloride penetration might be predicted by using chloride penetration model and corrosion initiation time model. However, the process is more complicated since chloride is not the only factor that governs the corrosion progress. Corrosion of reinforcement bar causes loss of area and the increased volume of rust causes concrete tensile stresses that may be sufficiently large to cause internal micro cracking. This internal cracking will create a very narrow opening on the outer surface which is large enough to allow other substances from outside, such as water and oxygen to reach the reinforcement bar surface. Hence, this may lead to acceleration in corrosion rate. This may explain why researchers believe that corrosion rate is not always constant with time, non-uniform and difficult to predict [Melchers, 1999a; Sarveswaran *et al*., 1998].

There is a dilemma in modelling corrosion growth. If the model contains too many variables, the inherent uncertainties associated with these variables might jeopardise the integrity of assessment results. Modelling corrosion growth based on metal loss volume may sound too simple and less technical. The assessment results might be too conservative. However, if proper research can fully utilise the information from field data, the inaccuracy of this simple model might be compensated by its great practicality. Morrison Inc. has been aggressively developing a practical yet simple approach in estimating the corrosion growth rate inside pipelines without relying on empirical models [Morrison *et al*, 2000b]. The corrosion assessment is based purely on the data matching procedure between multiple set of inspection data to obtain the actual growth rate. A better way in the handling of corrosion growth problem is by incorporating empirical model based on lab testing and statistical model based on field data study to achieve the best result of corrosion assessment. Both approaches can be seen as complementary to each other in order to minimise the inaccuracy of corrosion assessment due to unavoidable uncertainties.

2.4 Concluding Remarks

This chapter is intended to justify the proposed research by highlighting key points on corrosion issues. There is an ongoing interest in developing models for predicting corrosion wastage [Gardiner and Melchers, 2001]. There are several quotes which refer to corrosion as a complex and an unpredictable process. Moreover, the simplicity of the linear model cannot account for the random nature of corrosion. The available empirical models of corrosion are dependent upon operational conditions (such as working pressure), material properties, and environmental parameters, which can vary greatly in the real situation. Hence, an averaged value might miscalculate the possible corrosion growth rate. More effort is needed to improve the use of the linear model as an alternative to these empirical models.

The availability of real inspection data has greatly improved the understanding of the subject of corrosion. Nevertheless, corrosion assessment procedures, that are easily understood and conveniently applied by engineers and inspection personnel, are barely developed. It is important to compile systematically the assessment and analysis work on inspection data as a practical guideline. The application of the statistical and reliability approach on corrosion data and corroding structures is still not a widespread practice on sites. Moreover, there is a great lack of optimising the available inspection data to address any flawed information obtained, such as negative growth rate. More can be done to utilise fully the inspection data. Generalising assessment work on different types of corrosion data and structures is a large task, but if this can be done in a proper way it may simplify the assessment process and be of greater practicality.

Based on a review of previous research works and corrosion related subjects, this research is aimed towards developing a generic assessment approach of corrosion data and its application to structure reliability. The goal is to generalise the corrosion assessment work and to improve the understanding of the corrosion process by fully utilising the inspection data. The use of the statistical and reliability method is intended to address the random nature of corrosion which leads to uncertainties. Finally, the findings from this research may provide an alternative corrosion assessment procedure for application on site. The issues related to the complexity of the corrosion process and corrosion divergence will be addressed extensively, hence, providing a solution to encounter flawed information such as negative growth rate, and the lack of parameters such as corrosion initiation time.

CHAPTER 3 - STATISTICAL ANALYSIS OF PIGGING DATA

3.0 Overview

This chapter focuses on statistical analysis on multiple sets of real corrosion data collected through pigging inspection on three different offshore crude oil pipelines. The proposed analysis procedure consists of two parts, namely data observation and statistical analysis. Several corrosion-related models have been tested and developed based on the pigging data. Errors that are likely to be related to imperfect defects measurement by the pig tools have been encountered during the analysis process which leads to the introduction of correction methods to increase the reliability of the corrosion information. All of the corrosion-related models developed to date have been based solely on the measured metal loss volume with no attempt to include the specific effect of any environmental parameters or material properties. The aim is therefore to establish generic models for application to corrosion data from various types of inspection tools and structures. The methodology described here has been developed particularly for use on multiple sets of data from the same structures, since the information between two inspections at different times enables engineers to monitor the corrosion progress efficiently.

3.1 Data Analysis

In this study, an extensive amount of pigging data was gathered through in-line inspection activities on the same pipelines at different times. These databases of pigging data were collected from three different pipelines, named *Pipelines A, B and C*. *Pipelines A* and *B* consist of three sets of data, recorded in years 1990, 1992 and 1995. *Pipeline C,* however, includes only two sets of data collected from inspections done twice in year 1998 and 2000. Normally, pigging data provides valuable information on the internal and external corrosion defect geometry, such as depth and length, orientation, defect location and types of corrosion regions. The physical dimensions and other related information of these three pipelines are presented in Tables 3.1 and 3.2.

All data represent internal defects in the form of corrosion pits. Therefore, other types of corrosion defects such as groove were not considered in the sampling procedure. The types of pig tools used in the inspection for *Pipelines A, B and C* were magnetic flux leakage devices. The crude data obtained from pig devices were in the form of electric signals. The measurement system converts the leakage field into an electrical signal that can be stored and analysed [Nestleroth and Batelle, 1999]. This electric signal was then converted by the inspection contractors to actual dimensions, measured in distance units or expressed as a ratio. Table 3.3 presents a typical form of a listing of converted corrosion data recorded by the pig device over a certain distance. The data were collected in accordance to the direction of flow, i.e. from the launching point to receiving point.

Table 3.1: Summary of recorded pigging data

INFORMATION	PIPELINE A	PIPELINE B	PIPELINE C
Diameter (mm)	1066.8	914.4	242.1
Inspected distance (km)	2	150	22
Wall thickness (mm)	14	22.2	9.53
Year of inspection	1990,1992,1995	1990,1992,1995	1998,2000
Year of installation	1977	1977	1967
No. of data (all sets)	7734	7009	6639

Table 3.2: Number of recorded defects for each set

Set of data	PIPELINE A			PIPELINE B			PIPELINE C	
	1990	1992	1995	1990	1992	1995	1998	2000
Number of data	1425	2995	3314	1397	1528	4084	2581	4058

Table 3.3: A typical presentation of pigging data

Spool Length (m)	Relative distance (m)	Absolute distance (m)	*d% wt*	*l* (mm)	*W* (mm)	O'clock	*t* (mm)	Loc.
11.6	6.6	1016.5	18	32	42	6.00	14.2	Internal
11.5	11.5	1033.0	19	46	64	5.30	14.2	Internal
11.8	10.6	1043.6	12	18	55	5.30	14.2	Internal
11.7	1	1045.8	13	28	83	5.30	14.2	Internal

where:

Absolute distance	:	Distance of corrosion from start of pipeline
d%wt	:	Maximum depth of corrosion in terms of percentage
l	:	Longitudinal extent of corrosion
Loc	:	Location of corrosion either internal or external.
O'Clock	:	Orientation of corrosion as a clock position.
		of pipe wall thickness.
Relative distance	:	Relative distance of corrosion from upstream girth
Spool length	:	Length of pipe between weld (10m to 12m approximately)
t_t	:	Nominal thickness of pipe in pipe spool
W	:	Extent of corrosion around pipe circumference weld

3.1.1 Data Sampling

Because of the very large number of defects, a sampling process was used to match corresponding inspection results from different years in order to estimate the exact growth of metal loss caused by the corrosion process which reflects the corrosion growth rate value. The use of repeated inspection data for corrosion growth modelling has been practised in the past by Yahaya and Wolfram [1999] and Worthingham [2000]. Feature-to-feature data matching is carried out by locating the corresponding matched feature on every set of pigging data. One of the advantages of this method is that the growth is estimated using the actual dimension of the defects in each inspection. This approach should encourage pipeline operators to utilise the inspection data fully to make it worthwhile spending a substantial amount of money on in-line inspections. The data will possibly give a better indication of what has happened and what might happen in the future. Before the data matching procedure can take place, it is necessary to review the data to pinpoint any potential errors and determine the quality of the data.

3.1.1.1 Observation Stage

The main reason for observing the data prior to sampling is to determine the early sign of errors. A principal source of error can be generated owing to the limited resolution of the pig devices [Bhatia *et al*, 1998]. Also, if the operator has used a dissimilar type and setting of inspection tool with perhaps a different manufacturer or resolution of magnetic flux, the data may be difficult to match. Thorough observation was carried out successfully on the all sets of pigging data used in this study. The presence of variation in the spatial position of the defects is most easily detected by observing the total length of inspected pipelines. If the readings of the total inspected length from previous inspection do not match the new reading from the current inspection, this indicates the possibility of errors related to defect distance.

The total inspected length of *Pipelines A* and *C,* as recorded by the pig tools on each occasion are equal (see Table 3.4). On the other hand, the overall inspected pipeline distance of the first inspection of *Pipeline B* in year 1990 was 142.996 km, approximately six km short of the recorded distance of 149.853 km and 149.237 km in years 1992 and 1995 respectively (see Table 3.4). It is very obvious that each spool of *Pipeline B* was recorded shorter than the spool distance recorded in the next two inspections. The difference of inspected distance in year 1990 from that in years 1992 and 1995 might increase the difficulty in tracing the corresponding data on each inspection of *Pipeline B*.

Table 3.4: Comparison of absolute distance

Set of data	PIPELINE A			PIPELINE B			PIPELINE C	
	1990	1992	1995	1990	1992	1995	1998	2000
spool no. (pig retrieving point)	1850	1850	1850	122510	122510	122510	19360	19360
Overall distance (km)	2.017	2.017	2.017	142.966	149.853	149.273	22.333	22.333

3.1.1.2 Feature-to-Feature Data Matching

The data sampling procedure has been conducted to match corresponding inspection results from different years manually. To find the corresponding defects, information of spool number, relative distance and defect orientation are referred to. The existence of distance error may cause difficulties in locating the corresponding corrosion defect with the closest relative distance in the next inspection. Therefore, a reasonable error margin on the relative distance was allowed until the numbers of matched data were believed to be sufficient to produce a proper distribution.

The negative growth of defects is possible as a result of inherent uncertainties which cause variation in measurement. Some of the matched corrosion defects might not show any increment in the depth and length, indicating no growth [Dawson and Clyne, 1997]. The possibility to find a matched data that produced negative corrosion rate is quite likely [Yahaya and Wolfram, 1999]. This might be triggered by the error of the inspection tools or human error during data matching. To minimise human error, data matching has been done and checked repeatedly.

In this study, the matching process has matched 418 data from *Pipeline A*, 627 data from *Pipeline B* and the highest number of 1074 data from *Pipeline C*. The matching process was applied to every pair of data points. Yahaya [1999] demonstrated a data matching process by sequencing the data on depth severity (descending); then the corresponding matched features on other inspections are then located. This method was used to establish a relationship between the rapid growth rate of corrosion and severe corrosion features. The present research work, however, places more emphasis on finding all possible matched corrosion features regardless of severity in order to establish the variation of corrosion growth rates.

Localized forms of corrosion, such as pitting and crevice corrosion, are difficult to quantify and model because the corrosion rate at a particular location on a sample depends sensitively on the many local microscopic material and environmental conditions. As a result, at a macroscopic level, pitting and crevice corrosion often appears to occur in a random, probabilistic manner [Vajo *et al.,* 2003]. Therefore, it is important not to exclude the non severe pairs of data since the growth rate is of great concern than the depth severity. Estimating the exact value of corrosion growth is the main objective of this section. A simple extreme model is proposed in a later section to tackle this matter. Table 3.5 shows an example of the results of the matched data for *Pipeline C*. The matching procedure is summarised and presented by a flow chart in Figure 3.2.

Table 3.5: Example of matched data from *Pipeline C*

Spool Number	Year 1				Year 3			
	Absolute Distance	Orientation	Depth	Length	Absolute Distance	Orientation	Depth	Length
10	10.307	03:20	10	19	10.109	03:20	14	18
20	2.481	01:30	14	52	2.440	00:30	14	17
30	11.636	03:50	12	6	11.589	04:00	13	11
30	11.721	03:50	12	6	11.692	04:10	16	9
30	11.885	05:10	14	58	11.824	04:50	14	8
40	2.859	02:20	14	8	2.857	01:00	10	13
40	3.369	01:40	10	8	3.389	02:40	11	12

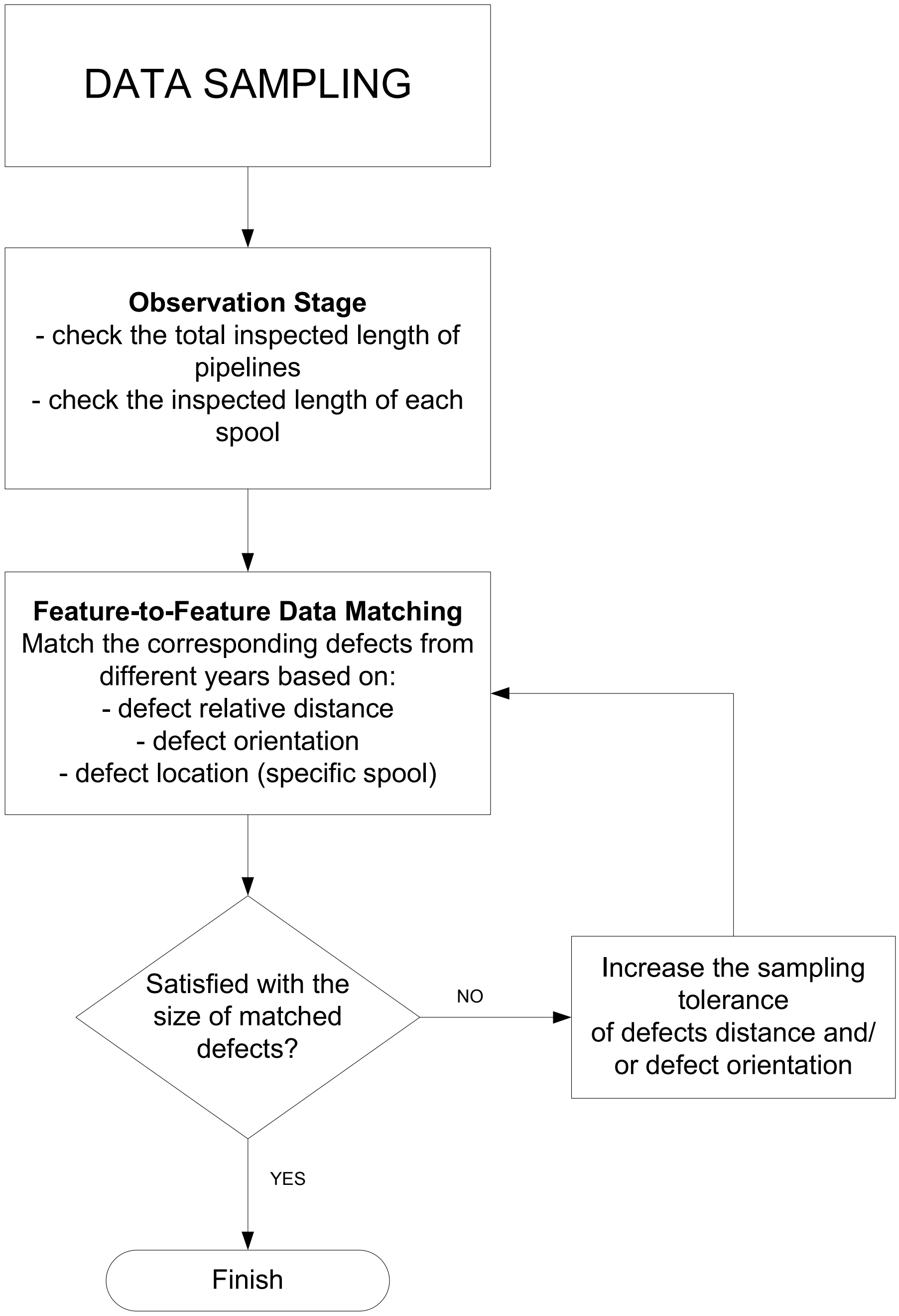

Figure 3.2: The flow chart of data sampling process

3.2 Statistical Analysis

This section describes the statistical analysis of the matched data with the main objective to determine the corrosion growth rate value for each corrosion pit (see Figure 3.3). The main concern is the depth growth caused by the risk of perforation through pipeline wall thickness causing leakage and bursting. This analysis is vital in identifying the characteristic of the corrosion dimension and establishing the relationship with the extreme growth rate.

3.2.1 Sampling tolerance

It is important to examine the quality of the information acquired from the matching procedure by estimating the averaged tolerance between recorded distances and orientations. Two main criteria are applied to locate corresponding defect features from different years of inspection. The relative distance and orientation of each matched defect are compared to estimate the averaged tolerance. The average is the sum of the differences of relative distance and orientation (between two inspection sets) divided by the total number of defects.

Table 3.6: Difference in the relative distance for matched data

Pipeline	PIPELINE A			PIPELINE B			PIPELINE C
Matched set	**90-92**	**92-95**	**90-95**	**90-92**	**92-95**	**90-95**	**1998-2000**
Average (mm)	29	21	27	219	53	211	61
Average (o'clock)	0:25	0:30	0:12	0:18	0:20	0:18	0:23

As shown in Table 3.6, the averaged tolerance of relative distance used to find corresponding features in *Pipeline A* shows a great consistency on all sets with values ranging from 21mm to 29mm. However, the averaged tolerance of *Pipeline B* is too large to consider the set to be matched based on data in year 1990. This is in agreement with the earlier statement regarding the absence of inspected length in year 1990 (see Section 3.2.1). The averaged tolerance of relative distance of matched data from year 1990 to year 1992 and year 1990 to year 1995 is found to be greater than 200 mm while matched data from year 1990 to year 1995 yield only averaged tolerance of 53mm. This is most likely the consequence of the imperfect measurement of corrosion location and inaccurate record of inspected length by the inspection tools during the first inspection in year 1990. Based on this observation, it is believed that the *Pipeline B* data collected in year 1990 is somewhat uncertain owing to the missing inspected length and has a high tolerance of relative distance. For *Pipeline C*, only one set of matched data can be produced with approximately 60 mm of averaged tolerance of relative distance.

Only a few features matched with a tolerance of relative distance more than one metre. Some of these defects are located solely in one single spool. Even though the tolerance of relative distance was more than one metre, strong indication given by other criteria such as defect orientation and the same number of defects in a specific spool influenced the decision making. For instance, in spool *52490* of *Pipeline B*, two defects in year 1990 were located in the same spool section in year 1992 with tolerance of relative distance more than one metre as shown in Table 3.7. Most of the spool lengths of *Pipeline B* recorded in year 1990 were between 0.2 metre and one metre, which is less than the recorded distance in years 1992 and 1995. This clearly explains the matching difficulty and high tolerance limit applied on matched sets based on data set in year 1990. However, in contradiction to the mixed results of measured tolerance of relative distance, the averaged features orientation does not show any distinct anomaly on all pipelines. This indicates that it was much easier to locate the corresponding features by referring to the circumferential orientation rather than relative distance.

Table 3.7: Example of matched data with difference of relative distance more than 1 metre (*Pipeline B*)

Year 1990				Year 1992			
Spool No.	Spool Length	Relative Distance	Orientation	Spool No.	Spool Length	Relative Distance	Orientation
112130	11.5	10.969	07:00	112130	12.8	12.188	07:00
57260	11.6	7.180	06:00	57260	12.3	6.000	06:00
52490	11.2	11.098	06:00	52490	12.2	12.102	06:00
52490	11.2	11.098	05:30	52490	12.2	12.102	06:00
36000	12.1	10.883	05:00	36000	12.3	9.402	05:00
11310	11.1	6.062	05:30	11310	11.9	5.000	06:00

3.2.2 *Corrosion Dimension Analysis*

Theoretically, the average of defect depth in the later inspection is expected to be higher than the previous one as a result of corrosion growth. Negative growth is illogical and there is no reasonable explanation of how certain defects can recuperate the volume of metal loss. The apparent appearance of negative growth calculated from the matched data can arise from several causes, the most likely of which are imperfect measurement by the inspection tools and/ or incorrect data conversion or human error during the matching process. An indication of this negative rate phenomenon was found from the matched data sets of *Pipeline B and C* when lower average depths were measured on the later inspection compared with the previous one. Table 3.8 summarised the average and standard deviation value of corrosion depth for each pipeline based on all of the matched data.

Table 3.8: Average and standard deviation of corrosion depth sample

Parameter (mm)	**PIPELINE A**			**PIPELINE B**			**PIPELINE C**	
	1990 $\mathbf{d_{A90}}$	**1992** $\mathbf{d_{A92}}$	**1995** $\mathbf{d_{A95}}$	**1990** $\mathbf{d_{B90}}$	**1992** $\mathbf{d_{B92}}$	**1995** $\mathbf{d_{B95}}$	**1998** $\mathbf{d_{C98}}$	**2000** $\mathbf{d_{C00}}$
Average	2.706	2.776	2.915	4.045	3.929	4.518	1.317	1.160
Std	0.865	0.718	0.546	2.084	2.137	2.003	0.442	0.320

3.2.3 *Corrosion Growth Analysis*

The availability of two and three sets of pigging data from the same pipeline segment enables the pattern of corrosion growth to be examined in detail for each single defect. This is due to the fact that inspection data, although near to each other, seemed to be growing at different rates [Jones, 1997]. The corrosion growth rate can be calculated using a simple linear equation. The linear equation is as follows:

$$CR = \frac{d_{T2} - d_{T1}}{T_2 - T_1} \qquad \text{Equation 3.1}$$

where:

CR = corrosion growth rate

d_{T1} = corrosion depth in year T_1

d_{T2} = corrosion depth in year T_2

T_1 = year of inspection T_1

T_2 = year of inspection T_2

The depth of a located defect can then be predicted using Equation 3.2

$$d_{T2} = d_{T1} + CR \times (T_2 - T_1) \qquad \text{Equation 3.2}$$

Table 3.9 shows the results of corrosion growth rate analysis for the three pipelines. It can be seen that the corrosion rates for *Pipeline B* ($CR_{B90\text{-}92}$) and *Pipeline C* ($CR_{C98\text{-}00}$) are negative, as expected (see section 3.2.2.2). Data set in year 1990 of *Pipeline B* have shown early sign of error owing to the absence of six km of inspected length. Moreover, the averaged depth of defects in year 1990 is higher than the average in year 1992, resulting in negative growth. *Pipeline A* is the only data set that produces a sensible average of corrosion growth rate for all matched sets.

With the limited set of data in *Pipeline C*, the negative growth rate problems may be difficult to resolve. In the case considered here, most defects have a smaller measured depth in the 2000 inspection than in the 1998 inspection. These matched pairs of inspection results therefore imply a negative average corrosion rate, which is of course impossible, so there is not just uncertainty in the data, but also some bias that must be addressed. Furthermore, it is not clear if the 1998 inspection measurements are, on average, overestimates of defect size, or whether the results in year 2000 are underestimates. That is to say, it is not clear which set of measurements is biased, indeed, it is possible that there is some bias in both sets. Neglecting all matched features which yield negative rates is not recommended as this leaves only a small sample of positive values.

Some methods to overcome this problem are proposed in the next section. Wolfram and Yahaya [1999] suggested that the negative corrosion rates may be caused by the presence of corrosion scale deposits or alien products (wax for example) within the pipeline. The wax may fills local corrosion pits, hence prevent the pits being detected and measured accurately during inspection [Tiratsoo, 1992].

Table 3.9: Corrosion growth rate for defect depth

Parameter (mm/year)	PIPELINE A			PIPELINE B			PIPELINE C
	90-92 CR_{A90-92}	**90-95 CR_{A90-95}**	**92-95 CR_{A92-95}**	**90-92 CR_{B90-92}**	**90-95 CR_{B90-95}**	**92-95 CR_{B92-95}**	**98-2000 CR_{C98-00}**
Average	0.035	0.040	0.044	-0.087	0.073	0.179	-0.081
Std	0.420	0.179	0.241	0.810	0.314	0.484	0.157

3.2.4 Extreme growth rate

Since pig tool resolution has advanced to the point where it will often identify thousands of corrosion defects on a pipeline, including very shallow defects (less than 5%wt), the number of recorded data is not the main indication of the current state of the pipeline. Instead, the peak depth of corrosion defects is the best indication to predict the time to failure of the pipeline. However, there is a question concerning whether deeper defects corrode faster than shallow defects. There is a possibility that when the defects start to grow at a certain rate, once they reach a certain level the defects might grow faster. This is possibly owing to the downgrading of structural integrity by persistent corrosion attack. When a corroded area is severely weakened by the loss of metal, even though the factor that contributes to the corrosion growth is no longer significant (temperature, pH), the defects could still growing faster in theory.

Worthingham *et al*. [2002] in their research work on pigging data have proposed this relationship between severe defects and extreme growth rate. Based on matched data results, they found that the corrosion rate tends to be higher for deeper corrosion defects than for shallower defects. Figure 3.4 shows and compares the distribution of corrosion rates for various depths. The slowest corrosion rates are for defects with depth between 0 and 0.5mm while corrosion defects deeper than 1.0mm have the highest corrosion rate. It is obvious that corrosion defects which are larger must have grown more rapidly in the past. The question arises will that rapid growth rate continue? On the other hand, Yahaya [1999] found that a substantial proportion of low-to-middle depth defects grew more rapidly compared with some of the deeper features. The rapid growth of severe defects is still unproven and not certain as stated in previous publications [Ishikawa *et al*., 1981; Scarft and Laycock, 1994].

Corrosion data from matched sets have been plotted against their corresponding corrosion growth rate to establish the relationship between severe defect depth and extreme growth for all pipelines. Figures 3.5 and 3.6 indicate no strong correlation of rapid growth with large defects except for Pipeline *B* (see Figure 3.7). The scattered pattern indicates that some of the large defects grow at a slow rate and some even grow at apparent negative rates. The relationship is hard to identify owing to the nature of the data. Unless the uncertainties and errors can be eliminated, it is impossible to tell if the large defects continue to have a particularly fast growth rate. Since the evidence for a strong correlation between growth rate and depth is somewhat contradictory and prone to error the analysis in the present work assumes that the corrosion growth rate is statistically independent of the variation of defect depth.

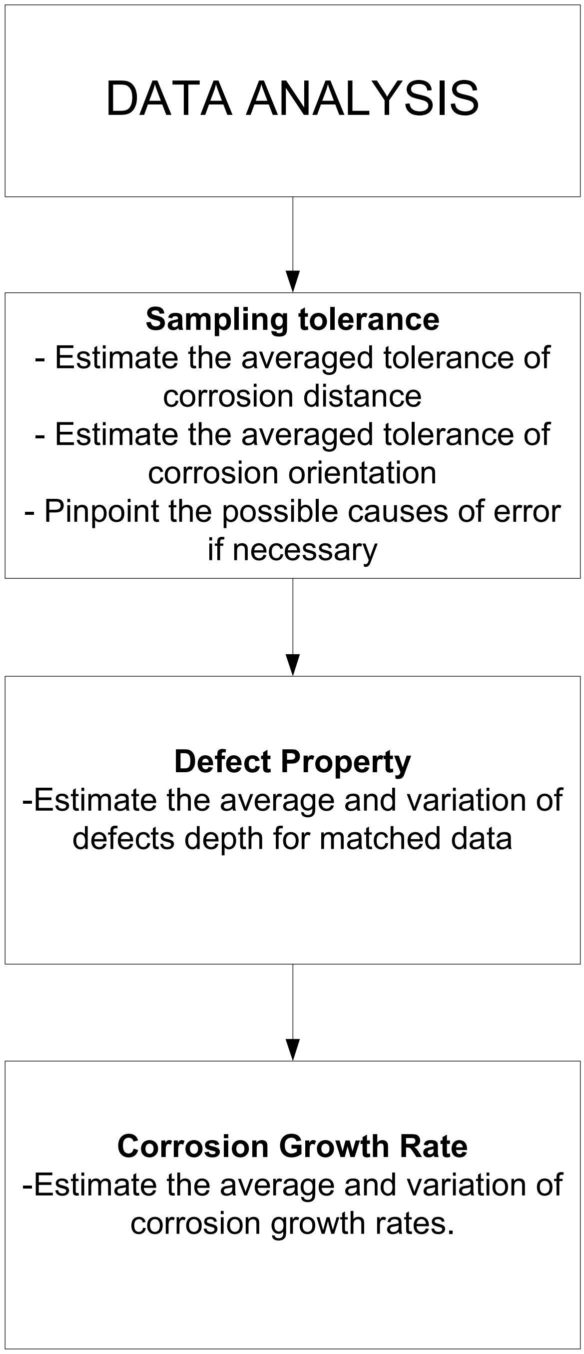

Figure 3.3: The flow chart of statistical analysis on matched defects

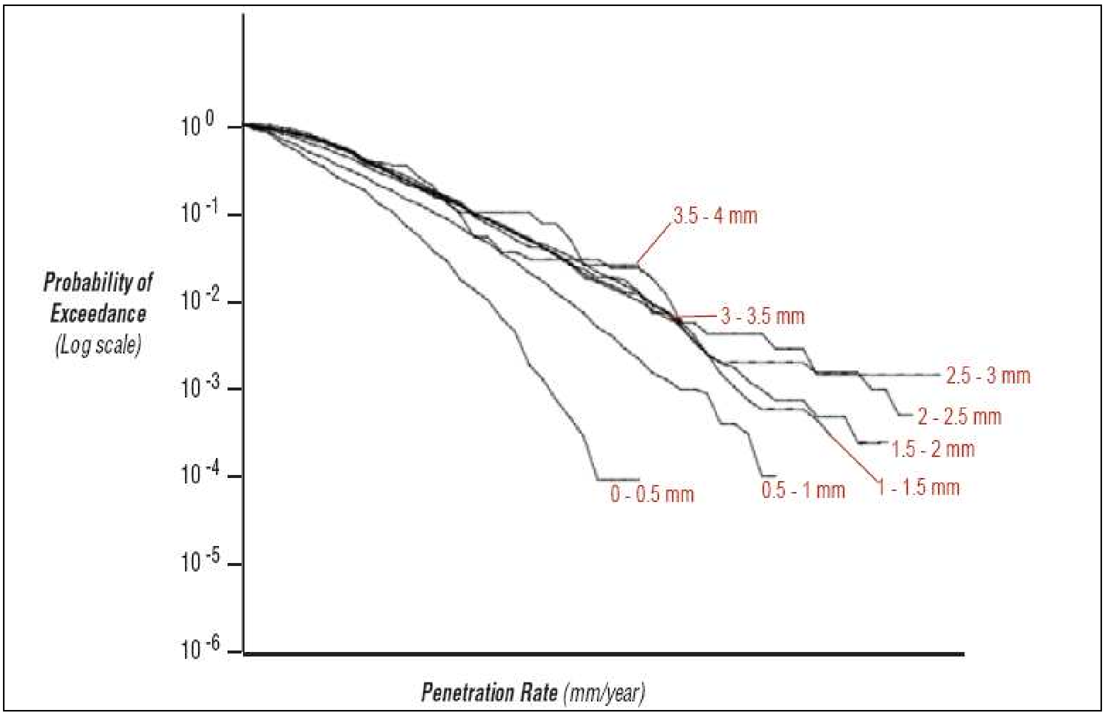

Figure 3.4: Corrosion rate exceedance distribution. [Worthingham *et al.*, 2002]

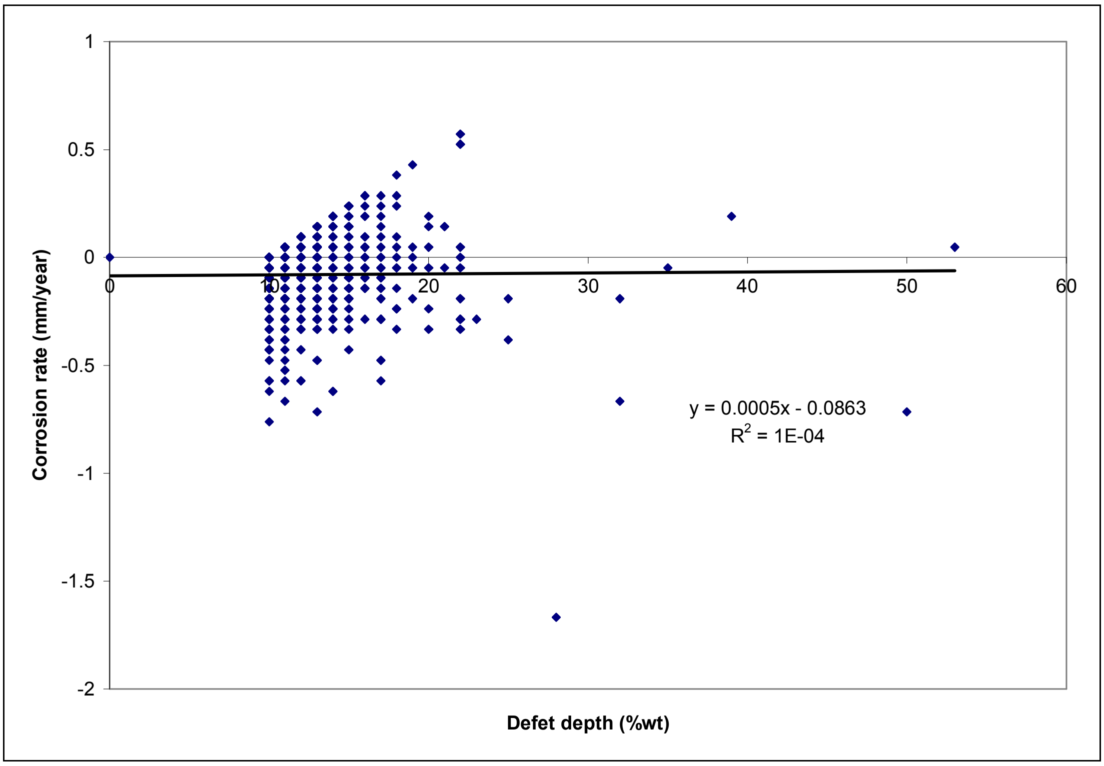

Figure 3.5: Corrosion rate, $CR_{C98\text{-}2000}$ plotted against defect depth, $d_{C\text{-}2000}$ with linear regression line.

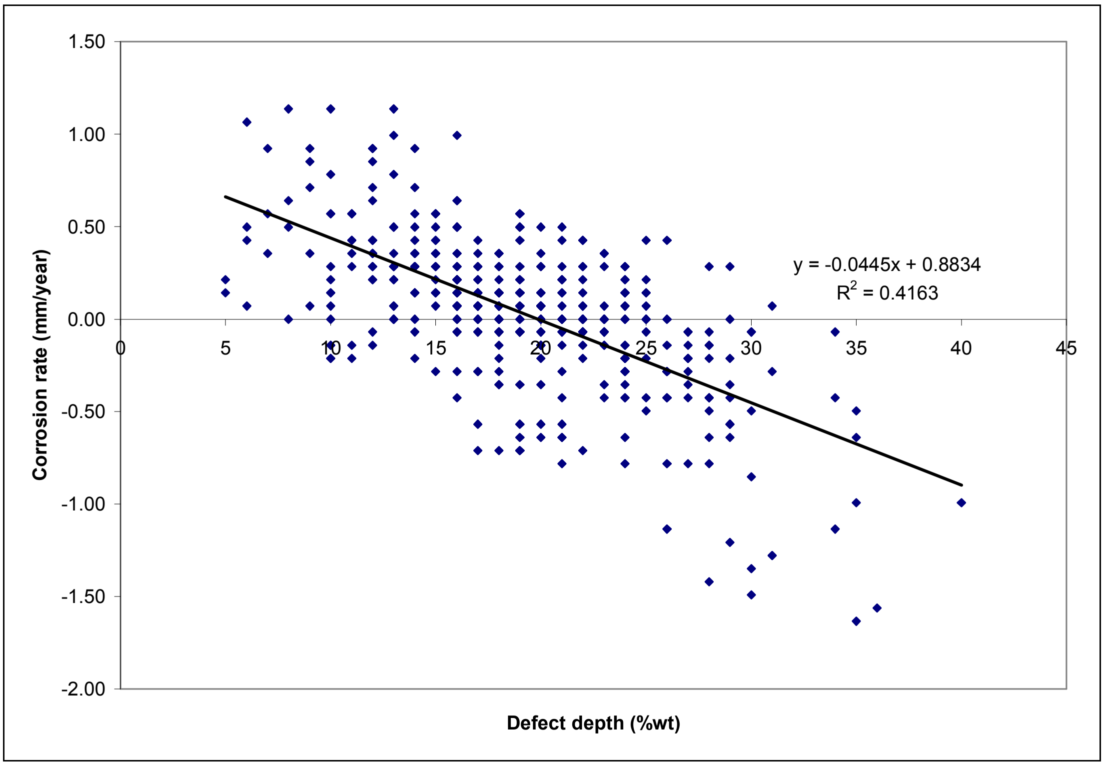

Figure 3.6: Corrosion rate, CR_{A90-92} plotted against defect depth d_{A92} with linear regression line.

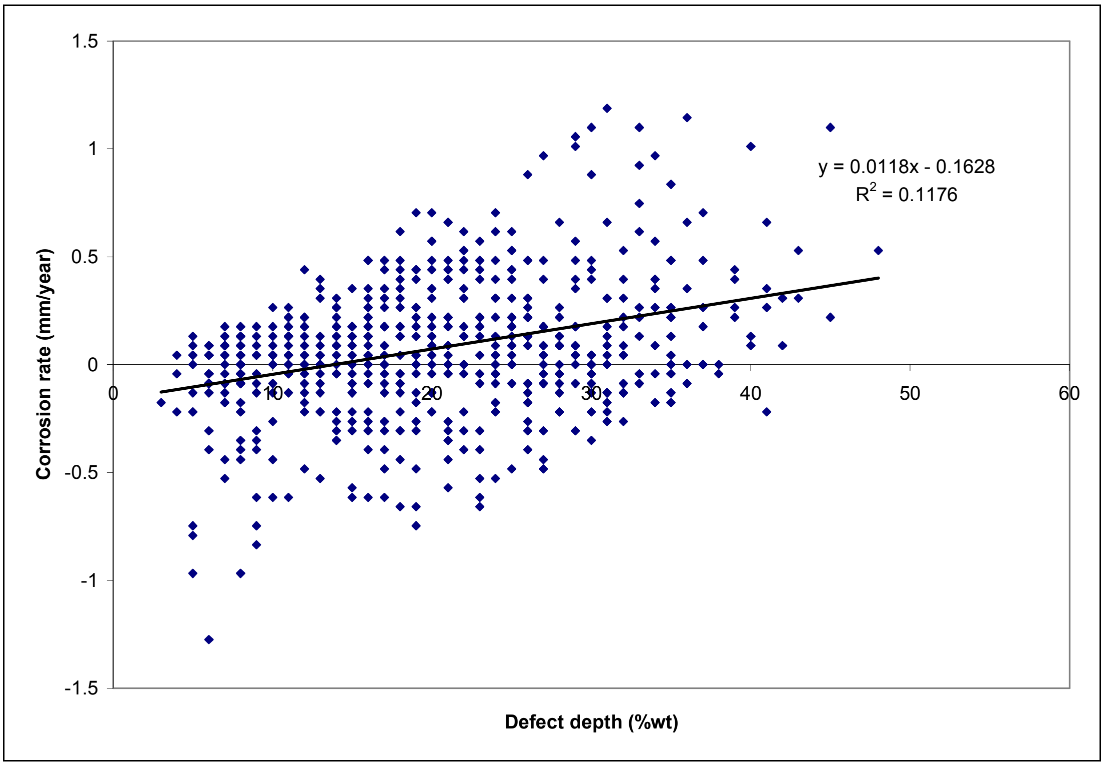

Figure 3.7: Corrosion rate, CR_{B90-95} plotted against defect depth d_{B95} with linear regression line.

3.2.5 *Theory of Time Interval-based Error*

It can be seen that the standard deviation (*Std)* of corrosion growth rate estimated between two inspections with shorter time interval is smaller for some sets of matched data (see Table 3.9). The decreasing of the *Std* value is theoretically associated with the time interval between the two inspections. The longer the time interval between two inspections, the smaller variation of corrosion growth rate. This theory is satisfied by some of the *Std* values taken from Tables 3.9. For instance, the *Std* value of corrosion growth rates obtained from the matching procedure between years 1990 and 1992 (2 years' time interval) is expected to produce the highest *Std* value while the smallest *std* of corrosion rates will be produced by a set of matched data between inspections in year 1990 to year 1995 (5 years' time interval). The best results that comply with this theory are from three sets of matched data from *Pipelines A and B*.

Figure 3.8 presents the illustration of time interval-based error. The actual defects in T_1 might appear to grow in a wide range of rates owing to uncertainties within the data. The variation of predicted defect sizes in T_2 and T_6 are the likely dimensions in the future based on random corrosion growth rate. It may be presumed that if the variation of predicted dimension is similar, the higher variation angle of corrosion growth rate would be the prediction with a shorter time interval from T_1 to T_2. This variation angle represents the quality of knowledge gained from the two sets of inspection data. Given that the corrosion progress is a slow process, information from two repeated inspections within a short period of time, for example two years, is unlikely to reveal definite information on the progress of corrosion. The growth pattern could be more obvious if the defects are given more time to grow. Therefore, an inspection undertaken five years after the first inspection is expected to reveal more knowledge of corrosion behaviour as well as minimising the uncertainties, compared with an inspection carried out only two years after the first inspection. This argument can be explained mathematically. The corrosion rate equation can be written as:

$$CR = \frac{d_{t_{1+1}} - d_{t_i}}{T} \qquad \text{Equation 3.3}$$

where $T = t_{i+1} - t_i$ and is a constant value.

If corrosion depth d is assumed statistically to be varied, the variation of corrosion rate can be expressed as:

$$\text{variance}(CR) = \text{variance}\left(\frac{d_{t_{1+1}} - d_{t_i}}{T}\right) \qquad \text{Equation 3.4}$$

Since the time interval, T is a single value with no variation, Equation 3.4 can be rewritten as:

$$\sigma_{CR}^2 = \frac{1}{T^2}.\text{variance}\left(d_{t_{1+1}} - d_{t_i}\right) \qquad \text{Equation 3.5}$$

and simplified into:

$$\sigma_{CR}^2 = \frac{1}{T^2}\left(\sigma_{t_{i+1}}^2 - \sigma_{t_i}^2\right) \qquad \text{Equation 3.6}$$

Therefore, the relationship between inspection time interval and the variation in corrosion growth rate can be presented as:

$$\sigma_{CR} = \frac{1}{T}\sqrt{\left(\sigma_{t_{i+1}}^2 - \sigma_{t_i}^2\right)} \qquad \text{Equation 3.7}$$

where:

σ_{CR}	=	variation of corrosion growth rate
σ_{ti}	=	variation of corrosion depth from the previous inspection
σ_{ti+1}	=	variation of corrosion depth from the next inspection
d_{ti}	=	corrosion depth from the previous inspection
d_{ti+1}	=	corrosion depth from the previous inspection
T	=	time interval between two inspections

From this expression, the smaller the time interval, T, the higher the variation of corrosion rate value, CR, and vice versa. Therefore, it is important to keep a reasonable time interval between the two inspections so that the information gained from two inspection data will reflect as closely as possible the actual inner condition of the pipeline. Even though a longer time interval would theoretically give much better information of about the progress of the corrosion, if the time interval between inspections is too long, the structure might experience an extreme condition which may increases the maintenance and failure cost. Hence, the reduction of inspection cost might not compensate the huge loss incurred by expensive maintenance work.

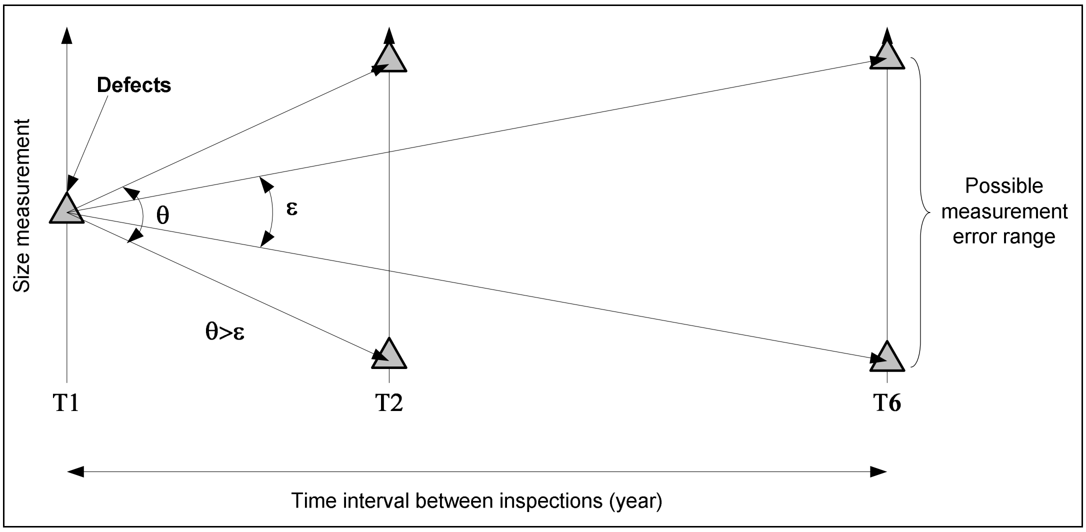

Figure 3.8: Illustration of the Time interval-based error theory. The uncertainty produced by measurement error upon growth rate reduces as the interval increases.

3.3 Probability Distribution of Corrosion Parameters

To take into account the various uncertainties associated with corrosion, a probabilistic treatment is essential [Paik and Thayambali, 2002]. Statistical distributions are required to represent each parameter obtained from the data analysis rather than averaged values. The variation in corrosion parameters needs to be considered in order to minimise the effect of uncertainties upon corrosion growth prediction. The following steps were implemented in order to define the corresponding distribution and its parameters for corrosion size dimensions and corrosion growth rates as depicted in Figure 3.9:

i. Construction of the frequency histogram.
ii. Estimation of the parameter distribution.
iii. Verification of the proposed distribution.

4.3.1 Construction of histogram

The histogram is the most important graphical tool for exploring the shape of data distributions [Scott, 1992]. The shape examined from the histogram puts the type of distribution into view. A histogram was constructed by plotting the frequency of observation against the midpoint class of the data. Figures 3.10-3.11 illustrate the constructed histogram of corrosion depth and corrosion growth rate. It would appear from the histograms that the corrosion depth could be represented by the Weibull distribution. Normally, the adequate numbers of bin can be computed using Equation 3.8:

$$a = 1 + 3.3\log_{10} n \qquad \text{Equation 3.8}$$

where:

a : number of bin / class

n : number of observation (data)

3.3.2 Estimation of Distribution Parameter.

From the hypothesis made on the type of distribution based on the shape of histogram, the distribution parameters must then be estimated. For the Weibull distribution, three parameters are required, these are β, θ and δ. A probability plot was used to determine the possible distribution parameters (see Figure 3.12). This graphical method is less accurate but much simpler than other established method such as Maximum Likelihood Estimator (MLE).

3.3.3 Verification of Distribution

The probability plot and Chi-square goodness-of-fit test were used for the verification of the proposed distributions. The Probability plotting is used not just to estimate the distribution parameters such in section 3.3.2 but it can also be used to determine the best distribution by linear fitting. The correlation coefficient, *R,* is used to verify the proposed distribution. The *R* value that approaches one indicates that there is a high possibility that the data can be represented by the proposed distribution. Most of the corrosion data was well represented by the Weibull distribution, with the majority of probability plots having *R* values close to one (see Figure 3.9 as an example). Table 3.10 shows the estimated Weibull parameters for all pipelines.

The second goodness of fit test used was the Chi-square test. An attractive feature of the Chi-square goodness of fit test is that it can be applied to any types of distributions for which the CDF can be calculated [Snedecor and Cochran, 1989]. The chi-square goodness of fit test has been applied to binned data as shown in Table 3.19. Therefore, histogram or frequency table should be constructed first before generating the chi-square test. However, the value of the chi-square test statistic is dependent on how the data is binned. As mentioned in section 3.4, Chapter 3, the disadvantage of the chi-square test is that it requires sufficient sample size in order for the chi-square approximations to be valid. In this case, the corrosion data is more than enough to produce a good result.

Table 3.11 demonstrates the calculation of chi-square value, χ^2 for each bin based on Equation 3.37. The test statistic follows, approximately a chi-square distribution with degrees of freedom, $d = 4$ ($d=k-1$) where k is the number of non-empty cells. Expected frequency, E was estimated by multiplying the probability from CDF with observed frequency, O. The hypothesis of an underlying Weibull distribution for corrosion depth, d_{C98} was accepted at significance levels of 0.05 or 5% where the total χ^2 value of 6.963 was less then $\lambda^2_{(0.05,4)}$ value of 9.488, taken form chi-square standard table (see Appendix C).

Table 3.10: Estimated Weibull parameters of corrosion depth

Pipelines	Depth	Probability Plot		
		β	θ	δ
Pipeline A	d_{A90}	2.2881	2.3419	0.700
	d_{A92}	2.0483	2.1717	0.980
	d_{A95}	2.9689	1.7558	1.400
Pipeline B	d_{B90}	1.9037	4.3521	0.666
	d_{B92}	1.6601	3.9083	0.666
	d_{B95}	1.9312	4.4028	0.666
Pipeline C	d_{c98}	1.0925	0.4183	0.953
	d_{c00}	0.9001	0.2315	0.953

Table 3.11: Estimation of chi-square value for corrosion depth, d_{C98}

Lower Class (%wt)	**Upper Class (%wt)**	**Probability**	**Observed Frequency, O**	**Expected Frequency, E**	**χ^2=(O-E)^2/E**
10	15	0.7416	815	795	0.503
15	20	0.1826	198	196	0.020
20	25	0.0525	38	56	5.786
25	30	0.0159	14	17	0.529
30	35	0.0050	2	5	0.125
35	40	0.0016	2	2	
40	45	0.0005	0	1	
45	50	0.0002	1 $\}$ 7	0 $\}$ 8	
50	55	0.0001	1	0	
55	60	0	0	0	
60	65	0	1	0	
				$\Sigma\chi^2$	**6.963**

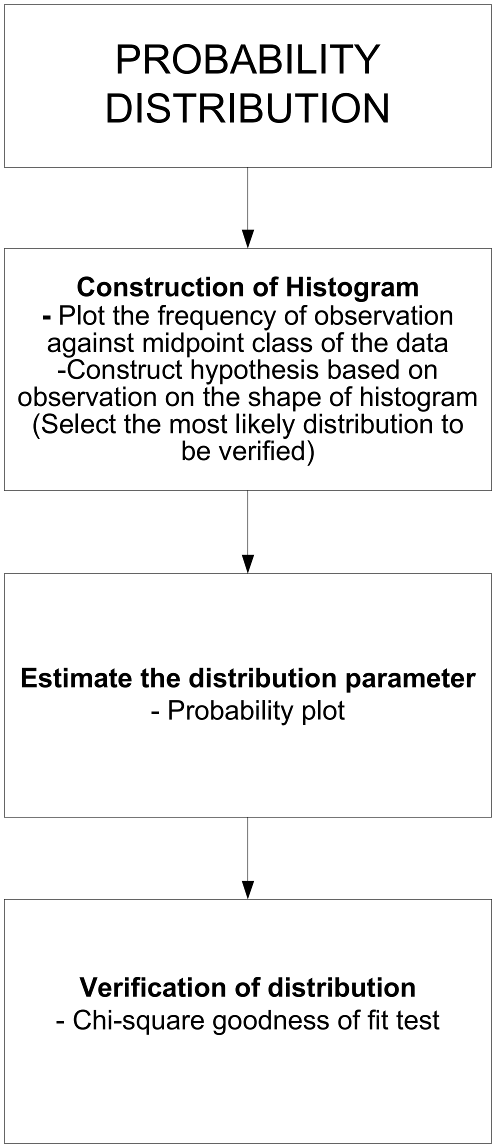

Figure 3.9: The flow chart of construction of probability distribution

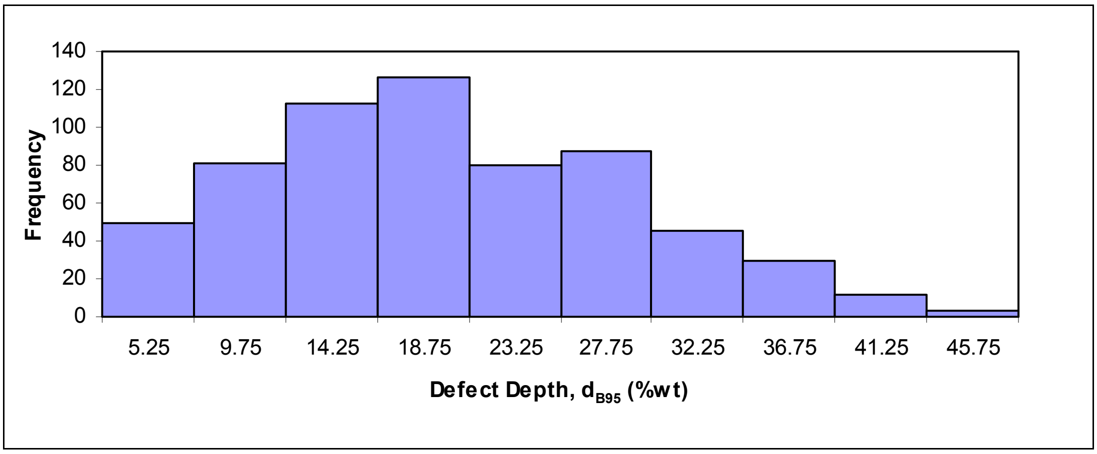

Figure 3.10: The histogram of corrosion depth, d_{B95} (*Pipeline B*)

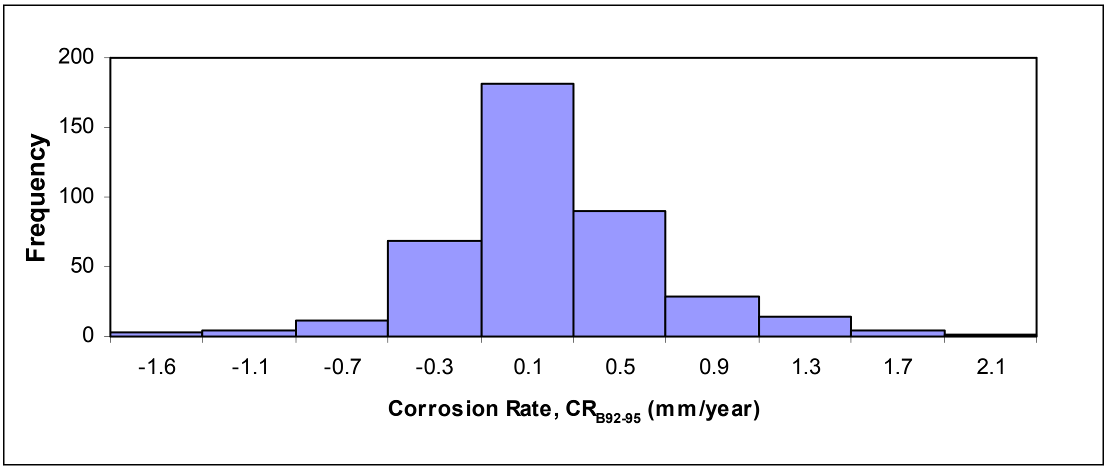

Figure 3.11: The histogram of corrosion rate, $CR_{B92\text{-}95}$ (*Pipeline B*)

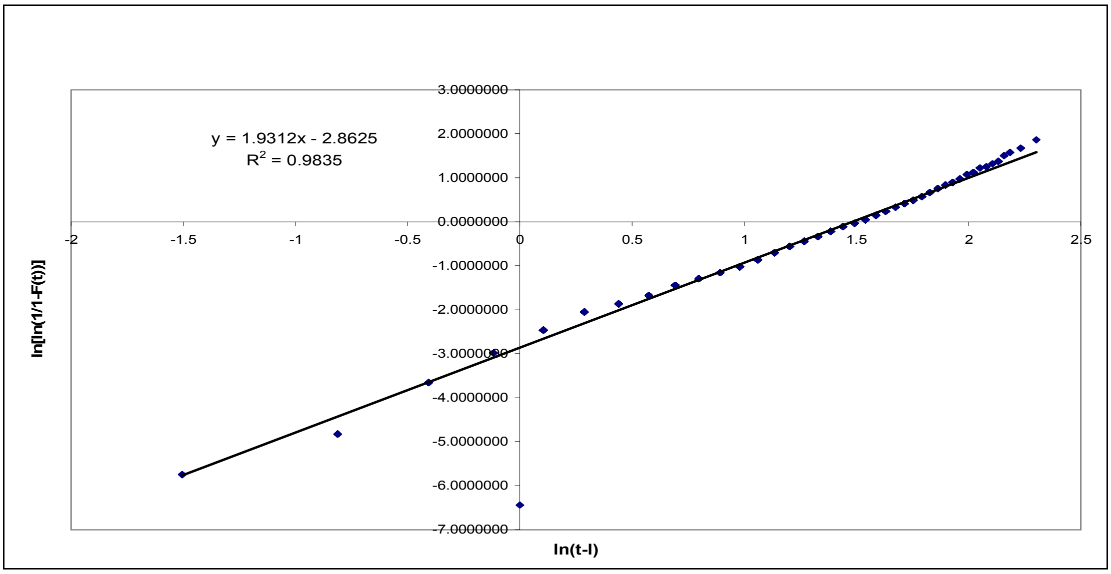

Figure 3.12: The Weibull Probability plot for corrosion depth, d_{B95} (*Pipeline B*)

3.4 Correction for Erroneous Corrosion Rate

Apparent negative rates of corrosion growth are useless for prediction of corrosion progress in time. However, it is impossible to eliminate uncertainties within the inspection data. What the engineer can do is to minimise the effect of uncertainties on the reliability of the inspection data. This section focuses on developing correction methods to reduce the effects of negative growth rates on the prediction of corrosion progress.

3.4.1 Reduction of corrosion rate variation.

This correction method is based on the assumption that the corrosion rate for a set of matched defects is normally distributed. The main aim of this method is to reduce the standard deviation of the corrosion rate estimates, while maintaining the mean value to remove, as far as possible, the effects of measurement error. By reducing the standard deviation, the effect of negative rates upon corrosion growth can be avoided. This type of correction method was introduced earlier by Yahaya [1999].

3.4.1.1 Modified Variance (Z-score method)

Yahaya [1999] assumes there has been some level of error in the inspection measurement of the defect dimension, resulting in errors in the calculated corrosion rates. The original corrosion rate distribution was corrected using this expression:

$$\sigma^2{}_{measured} = \sigma^2_{true} + \sigma^2_{error} \qquad \text{Equation 3.9}$$

where:

$\sigma^2{}_{error}$	=	variation of error
$\sigma^2{}_{measured}$	=	variation of measured defects
$\sigma^2{}_{true}$	=	variation of true defects

The true value can then be calculated by eliminating the error since the measured value has been affected with a certain level of uncertainty, which increases the spread of the data from its mean value as illustrated in Figure 3.13.

$$\sigma^2_{true} = \sigma^2_{measured} - \sigma^2_{error}$$ Equation 3.10

The variance of measured corrosion rate distribution is reduced to eliminate negative values by using the Normal distribution representing an error with zero mean value, $N(0, \sigma^2_{error})$. The drawback of this method is the need to estimate the value of variance of error. With limited information, it is difficult to estimate an actual value. Yahaya [1999] solved this problem by fixing the variance based on the percentage of allowance of negative corrosion rate. He allowed 1% of negative value which is somewhat arbitrary.

The same principle can be applied much more easily by fixing the coefficient of variation of corrected corrosion rate distribution according to the *Z-value* of the standard normal distribution, $N(0,1)$. The corrosion rate of *Pipeline B* is taken as an example. The normal distribution of this corrosion rate has a mean value of 0.179 mm/year and standard deviation of 0.484 mm/year. The problem can be addressed by transforming the original random corrosion rate denoted as X, into a standard normal variable with zero mean and unit standard deviation as follows (see Figure 3.14):

$$Z = \frac{X - \mu_x}{\sigma_x}$$ Equation 3.11

where:

σ_x	=	standard deviation of corrosion rate.
μ_x	=	mean of corrosion rate.
Z	=	Z-score value for standard normal distribution.

In the actual normal corrosion rate distribution, the X value that is equal to three units of standard deviation, Z=-3 is in the left side area of the mean value and can be calculated as follows:

$$-3 = \frac{X - 0.179}{0.484}$$

X = -1.273 mm/year

Since the standard deviation of the original corrosion rate is so high, it produces a large fraction of outcomes with a negative rate. To eliminate the negative value, X is fixed at the origin axis of zero with Z-score value of –3. With mean value still remaining constant, the new value of the standard deviation can be calculated as follows:

$$-3 = \frac{0 - 0.179}{\sigma_x},$$

and hence:

$$\sigma_x = \frac{0.179}{3} = 0.058 mm / year$$

With this new standard deviation, omitting the left and right tail of the Normal distribution diminished the uncertainties in the corrosion rate variable. The area under the distribution from Z=-3 (left tail) to Z=3 (right tail) was covered by 99.7% of the variable (see Figure 3.14). Therefore, 99.7% of the corrosion rate underlying this corrected distribution has a positive value. The coefficient of variance of this new distribution was approximately 33% and just slightly exhibits the suggested limit of coefficient of variance of statistical parameters of 30% [Melchers, 2000]. From the derived equation, this correction method can be rewritten in a simple form:

$$\sigma_{corrected} = \frac{\mu_x}{3} \qquad \text{Equation 3.12}$$

3.4.1.2 Modified Corrosion Rate

Unlike the first method, this second reduction method is used to modify one of the matched set of data, which is assumed to be erroneous, so that the modified set can be applied with its corresponding set to recalculate the corrosion rate. The modification of corrosion depth value is intended to minimise the error hence reducing the variance of the corrosion rate distribution. To demonstrate the correction procedure, the matched set of *Pipeline A* is taken as an example.

Theoretically, if a prediction is made from year 1992 to year 1995, the amount of uncertainty in the measured defect sizes will grow larger given there is no improvement in the inspection tools and procedure, hence resulting in higher variation and mean value of corrosion depth. The expression can be written as:

$$\sigma^2_{95-measured} \geq \sigma^2_{92-measured} \qquad \text{Equation 3.13}$$

Nevertheless, the variation of d_{B92} is found higher than d_{B95}, reflecting the severity of errors and uncertainties in the 1992 set (see Table 3.9). There is a significant improvement of the quality of data collected from inspection in year 1995 judging by the smaller variation of corrosion depth. This is possibly owing to the improvement of the inspection tools. The measured data on both occasions are assumed to be the real or the true value of corrosion depth with a certain level of error which is unknown mathematically in this case and can be expressed as follows:

$$\sigma^2_{95-measured} \leq \sigma^2_{92-measured} \qquad \text{Equation 3.14}$$

where

$$\sigma_{measured} = \sigma_{real} + \sigma_{error} \qquad \text{Equation 3.15}$$

where:

σ_{real} = variation of real data with no error

therefore:

$$\sigma^2_{95-real} + \sigma^2_{95-error} \leq \sigma^2_{92-real} + \sigma^2_{92-error} \qquad \text{Equation 3.16}$$

By assuming that the variance of real depth should be no greater in year 1992 than in year 1995, the measured variance in years 1992 and 1995 is assumed equivalent. Hence, the variance of error from the inspection in year 1992 becomes larger than the 1995 variance as shown by following equations.

$$\sigma^2_{95-real} = \sigma^2_{92-real} \qquad \text{Equation 3.17}$$

therefore:

$$\sigma^2_{95-error} < \sigma^2_{92-error} \qquad \text{Equation 3.18}$$

The principle of this correction method is to use information from set 1995 (which is assumed to be more accurate) to reduce the corrosion depth variance of set 1992, in accordance with the relation expressed in Equation 3.12. In other words, an inspection in year 1995 is assumed to be more accurate; therefore if the same accuracy is applied to the prior inspection carried out in year 1992, the real variation of set in year 1992 will be the same or smaller than the measured variance in year 1995. With reference to Equation 3.19, the real (modified) variance of d_{B92} as it should be in theory can be represented by:

$$\sigma^2_{92-modified} = \sigma^2_{92-measured} - \sigma^2_{correction} \qquad \text{Equation 3.19}$$

and it is assumed:

$$\sigma^2_{92-modified} = \sigma^2_{95-measured} \qquad \text{Equation 3.20}$$

When the variance of modified depth in year 1992 is assumed equal to the variance of measured depth in year 1995, the end result will warrant a smaller variation of set in year 1992 compared with that of year 1995. The variance of the correction factor is assumed to be dependent upon the variance of depth of both sets in years 1992 and 1995. To reduce measurement error in year 1992 so that it matches with the error severity in year 1995, measured data in year 1992 have to be resampled by using a simulation procedure. The modification of depth data in year 1992 can be written as follows:

$$d_{92-modified} = d_{92-measured} - c \qquad \text{Equation 3.21}$$

where

$$c = \left(d_{92-measured} - \mu_{92-measured}\right).\sqrt{k^2} \qquad \text{Equation 3.22}$$

The correction factor, *c,* will randomly shift the measured depths towards the mean value of the corrosion depth hence reducing the spread of the data. The correction factor, *c,* is assumed to be dependent upon *k*, which is a variation factor assumed to be normally distributed. In deterministic form, *k* is expressed as:

$$k^2 = \frac{\sigma^2_{92-measured} - \sigma^2_{95-measured}}{\sigma^2_{92-measured}} \qquad \text{Equation 3.23}$$

therefore, statistically the mean value of *k* is equal to:

$$\mu_k = \sqrt{\frac{\sigma^2_{92-measured} - \sigma^2_{95-measured}}{\sigma^2_{92-measured}}} \qquad \text{Equation 3.24}$$

the variance of *k* can be written as (see Equations 3.19 and 3.20):

$$\sigma^2_k = \sigma^2_{92-measured} - \sigma^2_{95-measured} \qquad \text{Equation 3.25}$$

If the variance of corrosion depths in years 1992 and 1995 is equal, the *k* value will be zero as will be the *c* value, indicating no changing in the variation of corrosion depth. The bigger the difference between variance values of both corrosion depths, in years 1992 and 1995 in this case, the larger the *k* value resulting in a large reduction of variance of corrosion depth for the earlier inspection. Figure 3.15a depicts the idea of this correction method.

The proposed correction approach was applied to reduce the variance of corrosion data of *Pipeline B* in year 1992 using the data in year 1995. The corresponding parameters and the results are shown in Tables 3.12 to 3.14. The variance of the corrosion distribution in year 1992 (see Table 3.9) was successfully reduced by approximately 53% from the measured variance. Nevertheless, the modified data still produced negative corrosion rate despite the 34.5% of variance reduction compared with uncorrected variance of corrosion rate distribution. The possible explanation of the appearance of negative rates despite the modification of the measured data is a result of the true quality of the data in year 1995. It was assumed that the data of 1995 is the real data with no uncertainties so the corresponding information can be used to correct the erroneous data of 1992 . In fact, the error could still be large in the 1995 data. The variance of corrosion depth in year 1995 could still be associated with a certain degree of error (see Figure 3.15b). The proposed procedure has then removed only a small amount of the errors in the 1992 data. Therefore, the proposed variance reduction method could be more effective if the last inspection data contains a small amount of errors regardless of the severity of error of data from the earlier inspection.

Table 3.12: Parameters used to reduce the variation of corrosion depth taken from verified distribution.

Parameter	Value
$\sigma^2_{92-measured}$	0.967
$\sigma^2_{95-measured}$	0.328
k^2	0.661
μ_k	0.813
σ_k	0.800

Table 3.13: Comparison between measured and modified data (raw data)

	Measured data, d92	Modified data, dm92	%Δ
Average	2.776	2.773	0.1
Variance	0.516	0.241	53.3
Std	0.718	0.491	31.6
COV (Std/Average)x100%	25.9%	17.7%	-

Table 3.14: Comparison between uncorrected and corrected corrosion growth rate distribution parameters (*CR_{A92-95}*)

	Uncorrected CR	Corrected CR	%Δ
Average	0.044	0.045	2.27
Variance	0.058	0.038	34.5
Std	0.241	0.195	19.1
COV	547%	433%	-

3.4.2 Exponential Correction Distribution

In spite of the capability of variance reduction techniques to reduce the numbers of negative growth values from the corrosion rate distributions, there are some drawbacks. The corrected Normal distribution still predicts a significant number of negative values which should be avoided during the structural assessment stage. In fact, the Normal distribution is a poor choice as there is always a negative tail. The other drawback of this approach is the limitation whereby it is only suitable for a Normal distribution with a mean value greater than zero. If the mean value of corrosion growth rate is zero or approaching zero presumably less than 0.03 mm/year; the shape of the corrected distribution will become extremely slender with very low dispersion, as shown by Figure 3.16 This will reduce the number of values at the upper extreme, hence producing less variation in corrosion rate values which is vital in reliability analysis.

A different approach could be taken to avoid the abovementioned drawback. Instead of assuming that the erroneous data came from the left side and the right side of the distribution tail area, it is possible to adjust for all of the negative growth values, leaving the positive values to be considered as the likely value of corrosion rates. If the actual Normal distribution of corrosion growth rate has a mean value equal to zero or approaching zero, the positive side of the distribution is seen to be close in shape to the Exponential distribution. Therefore it is proposed that an Exponential distribution could be used to represent the distribution of the corrosion rate values. The principle of the corrected Exponential distribution approach is totally different from the Z-score approach (see Section 3.4.1.1) based on the assumption of the erroneous data in the tail area. For instance, by taking corrosion rates estimated from year 1990 to year 1992 for *Pipeline B* ($CR_{A90\text{-}92}$) with a mean value of 0.033 mm/year and *Std* of 0.420 mm/year, the Normal distribution has been transformed into a new Exponential distribution. The inverted mean value of uncorrected corrosion growth rate was calculated as 3.731. The probability density function of this Exponential distribution can be written as:

$$f(x) = 3.731.\exp^{-3.731x} \qquad \text{Equation 3.26}$$

The drawbacks arising from the Z-score correction method were overcome by using the Exponential correction distribution approach. All corrosion data under the Exponential distribution are positive forming values. It is suggested that to apply the mean value of corrosion rate from its initial Normal distribution as shown in Table 3.9 (see Section 3.2.2.3). Therefore, only the distribution shape is changed from Normal to Exponential while the averaged corrosion growth rates underneath the positive area are not required for recalculation. The basic principle of this simplified distribution is based on the assumption that the avoidance of all negative values will not change the total average of corrosion growth rate prior to the actual Normal distribution. If only the positive corrosion growth rate is considered to form an Exponential distribution, the higher mean value might over-predict the corrosion growth considering that the values at the upper extreme are flawed as negative values.

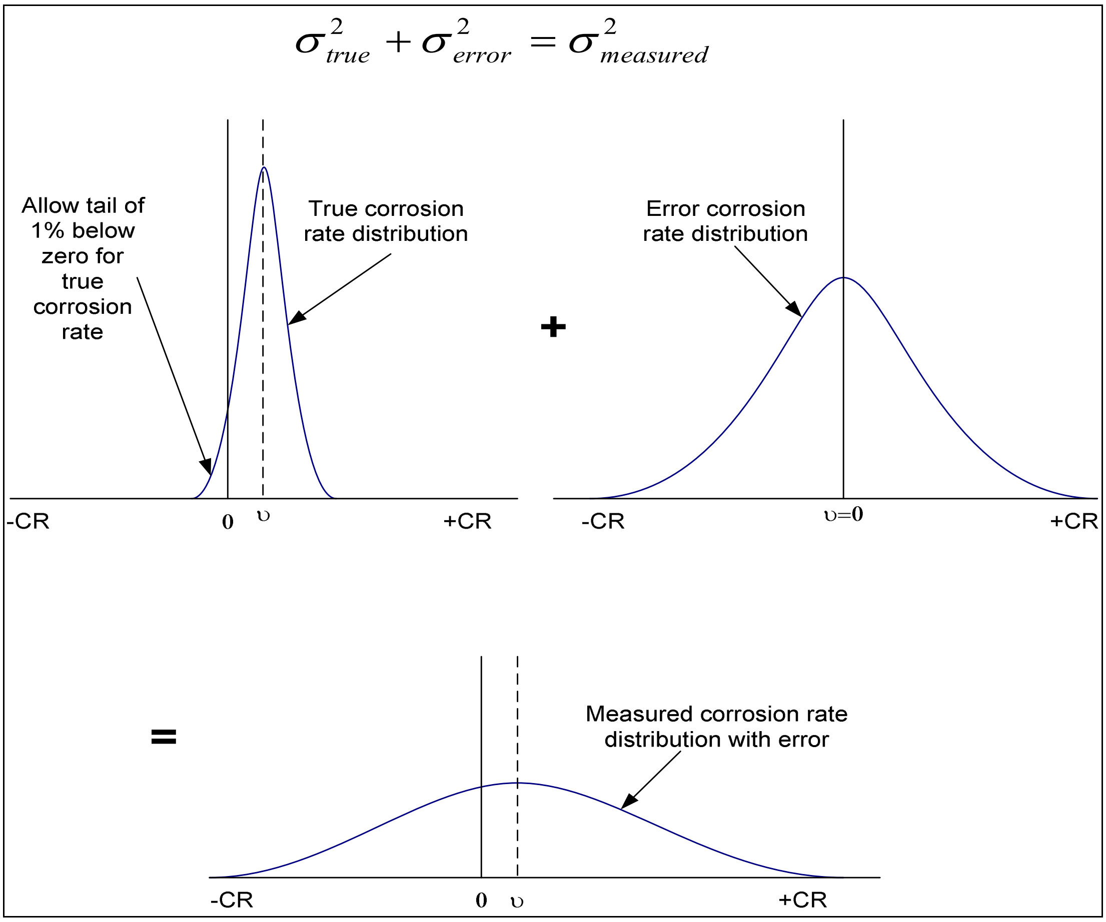

Figure 3.13: The relationships between measured, 'true' and error corrosion rates distribution according to Yahaya [1999].

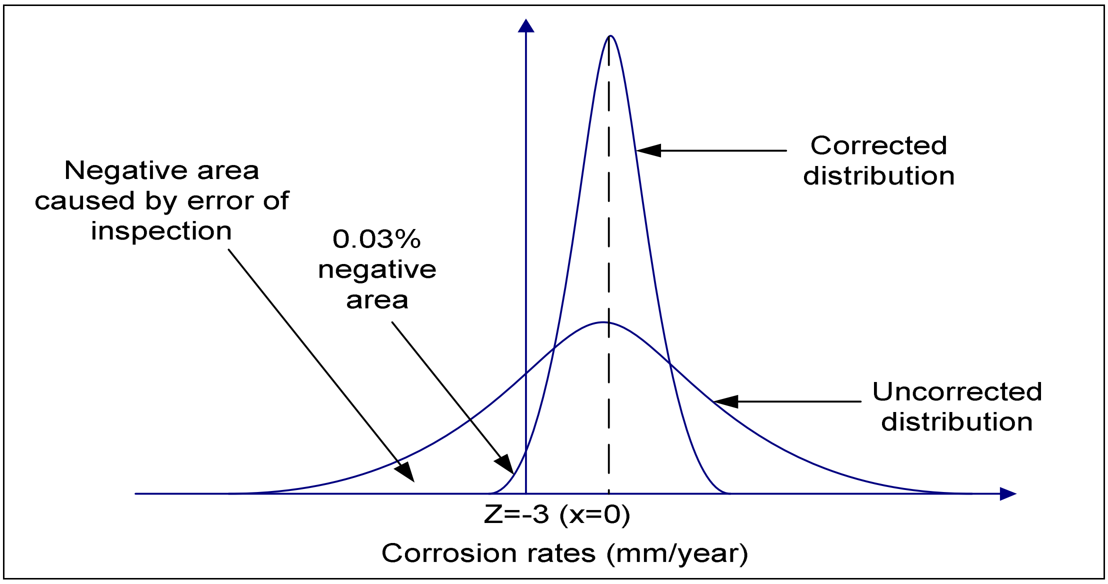

Figure 3.14: Corrected corrosion rates distribution ($CR_{B92\text{-}95}$) using Z-score correction method.

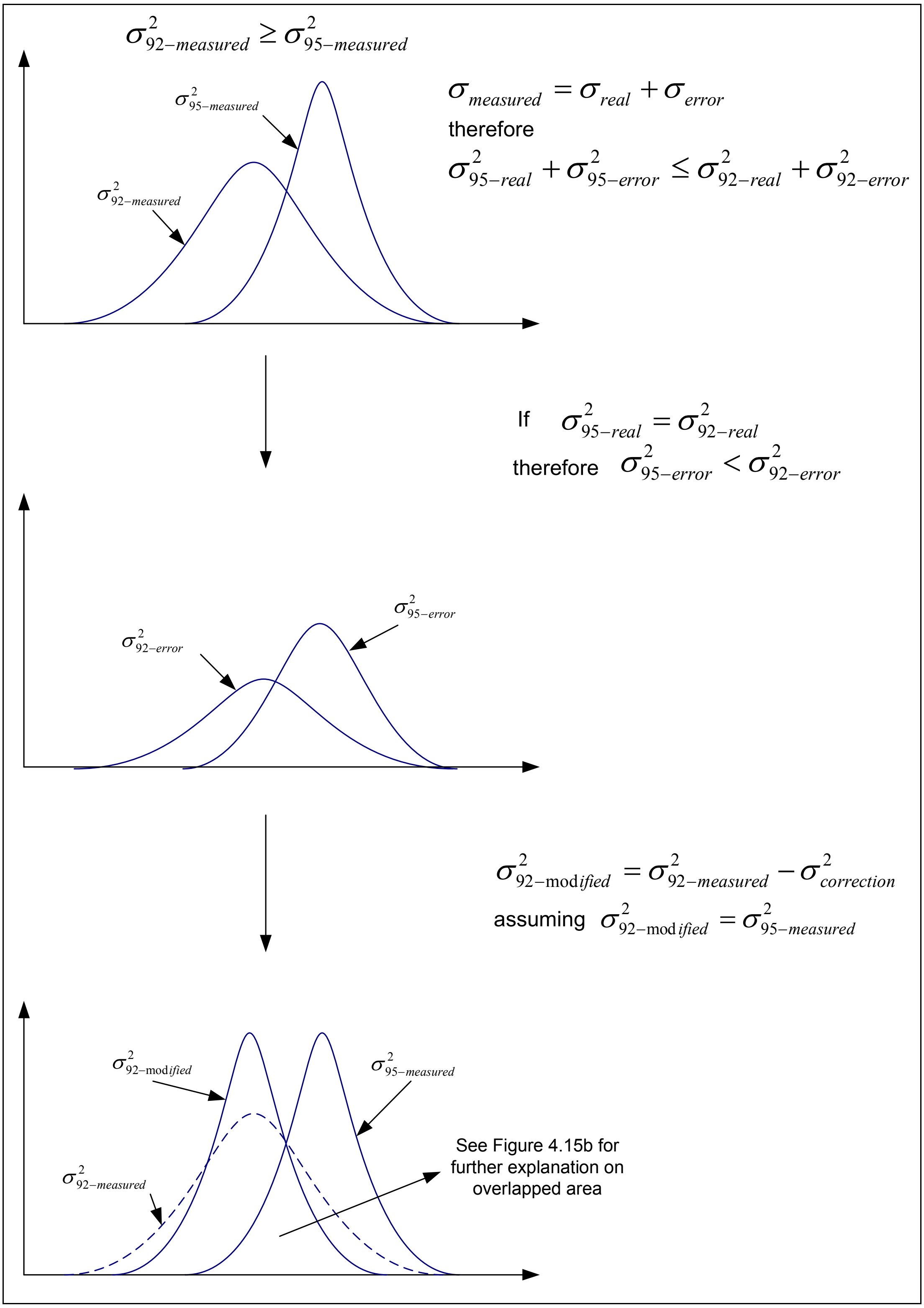

Figure 3.15a: Illustration of modified corrosion rate.

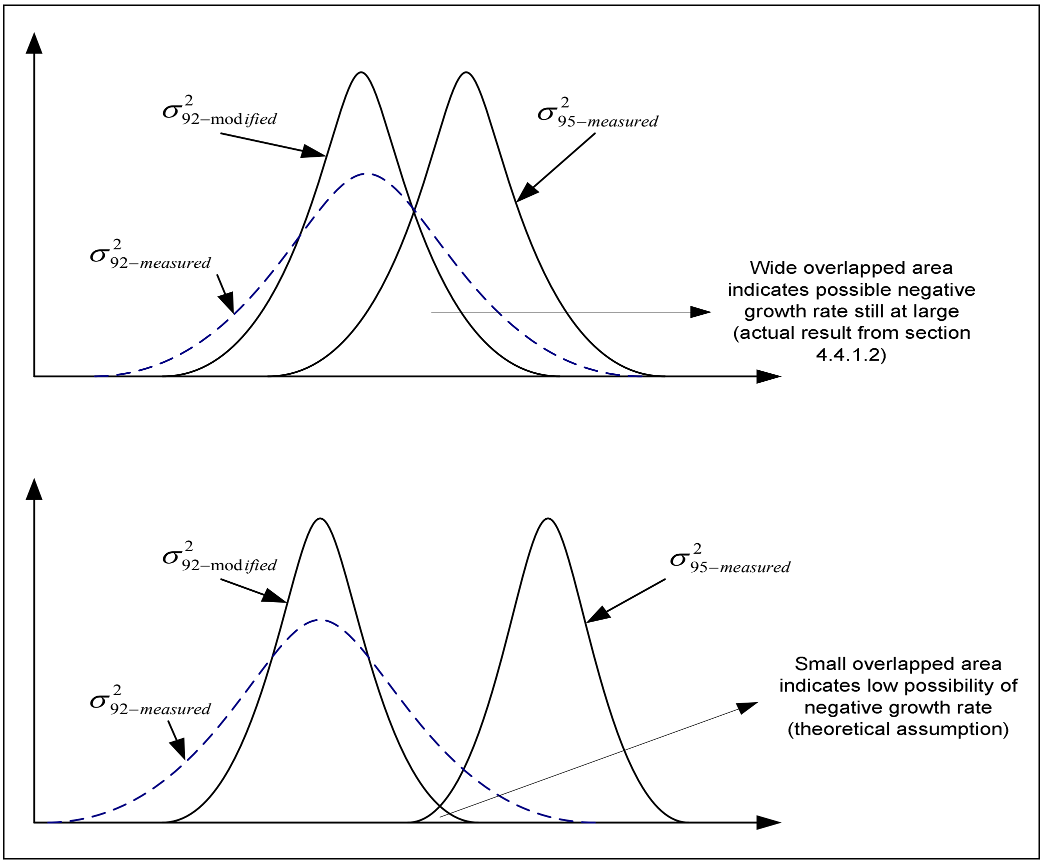

Figure 3.15b: Illustration of modified corrosion rate.

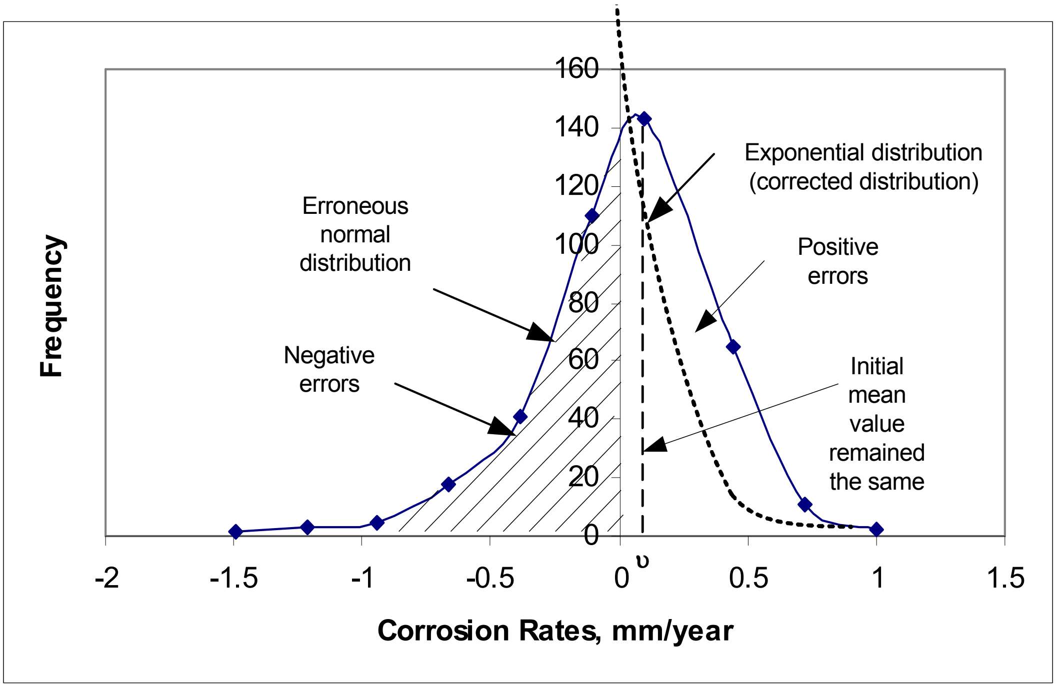

Figure 3.16: Exponential distribution extracted from Normal distribution of actual corrosion rate, CR_{A90-92}.with mean value given by sample mean from normally distributed raw data.

3.4.3 Defect-free method

The implementation of the aforementioned correction techniques is valid only for the corrosion rate distribution with a positive mean value. For the corrosion rate distribution with a negative mean value, another method has to be used to correct the error. One possibility is that the corrosion rate can be recalculated based on the assumption that the pipeline is free from defects at the time of installation. The corrosion rate therefore can be estimated from the day the pipeline had been installed for service to the time of inspection. This method can be performed as follows:

$$CR_{cor} = \frac{d_{T1}}{T_1 - T_0} \qquad \text{Equation 3.27}$$

where:

CR_{cor} = corrected corrosion rate

d_{T1} = corrosion depth in year T_1

T_0 = year of installation

T_1 = year of inspection in year T_1

Hence, for this approach accurate information on the year of construction and installation of the pipeline is imperative. This straightforward approach has been applied previously by other researchers. Previous work however ignored the possibility of delay in the onset of corrosion due to the resistance given by the internal coating system [Desjardins, 2002a].

For pigging data of *Pipeline B* and *C*, the corrosion rates have been recalculated using this method. The mean value for the corrected corrosion rate distribution from all pipelines was found higher compared with the actual corrosion rate distribution. Without information on the coating resistance, the estimated growth rate might over-predict the growth of the defect depth. Table 3.15 shows the estimated corrected corrosion rate for defect depth of *Pipelines B* and *C*.

Table 3.15: Corrected corrosion growth rate for defect depth using Zero-defect correction method

Set of data	PIPELINE B			PIPELINE C	
	1977 to 1990 $CCR_{B77\text{-}90}$	1977 to 1992 $CCR_{B77\text{-}92}$	1977 to 1995 $CCR_{B77\text{-}95}$	1967 to 1998 $\mathrm{CCR}_{C67\text{-}98}$	1967 to 2000 $\mathrm{CCR}_{C67\text{-}00}$
Average (mm/year)	0.311	0.258	0.245	*0.042*	*0.035*
Standard deviation (mm/year)	0.852	0.929	0.899	0.013	0.010

3.4.3.1 Delay of the Corrosion Onset

The protection of the internal surface of a pipeline from corrosion attack relies wholly on the applied coating systems which can effectively delay the onset of corrosion. According to Paik and Thayambali [2000], the time interval, which is assumed to be lognormally distributed, is greatly dependent upon the resistance lifetime of the coating system applied and the transition time once the coating system completely loses its durability completely. The transition time is that time between the loss of coating effectiveness and the time of corrosion initiation, as illustrated in Figure 3.17. Paik and Thayambali [2000] also state that the transition time can often be considered an exponentially distributed random variable. In the particular case considered here, the time for the coating to fail and the transition time are not considered separately. It is just assumed that the corrosion will start at some time after installation of the pipeline. Therefore, if repeated inspection data fail to deliver a reasonable corrosion growth rate (positive rate), information on corrosion initiation time due to resistance by the coating system is required. A new approach of projecting the future growth of corrosion depth without relying on corrosion initiation time has been applied on the corrosion data of vessel's seawater ballast tank, this is described in Chapter 5.

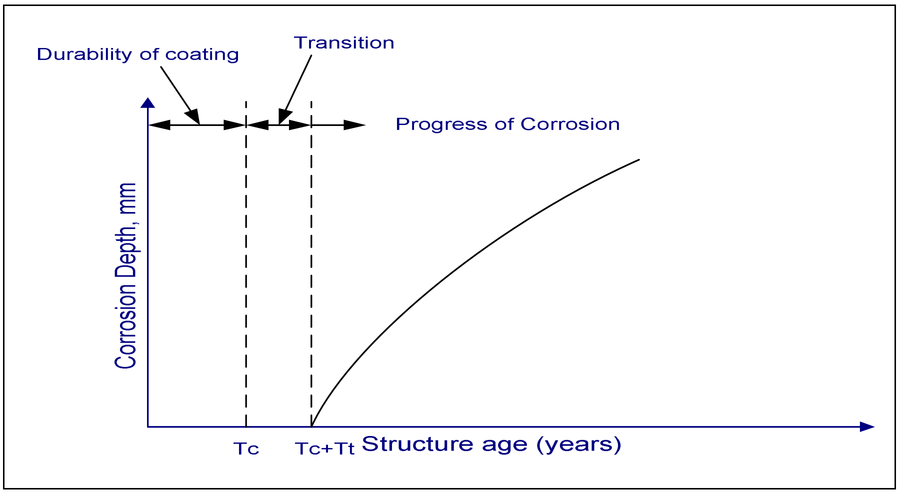

Figure 3.17: The corrosion initiation time of coated structures [Paik and Thayambali, 2002]

3.4.4 Linear Prediction of Future Corrosion Defect Sizes

Prediction of future defect size can be used to examine the accuracy of the proposed data sampling and correction approaches. This can be done by predicting forward from earlier inspection results to the year of a more recent inspection. By comparing the predicted defect depth distribution with the real field data, the differences which can give an indication of the quality of the inspection data and the validity of the analysis process can be calculated. In this regard, a prediction of corrosion data from year 1992 to year 1995 has been made by using different corrected corrosion growth rates for *Pipelines A and B*. *Pipeline C* was excluded owing to the negative value of the corrosion growth rate.

Figures 3.18 to 3.21 present the prediction results for *Pipelines A* and *B* by using the Z-score method and Exponential correction distribution. The proposed variance reduction method (modified corrosion rate) is not used in the comparison since the early results still indicate the existence of a substantial amount of negative growth rate. Based on a comparison of the results predicted by the Z-score method and Exponential method, with the actual data, the corrected distributions have produced much better predictions compared with those using the uncorrected corrosion growth rate. The best prediction results were obtained from *Pipeline B*. The prediction of data distribution from year 1992 to 1995 is almost similar in shape to the actual distribution of corrosion data in year 1995.

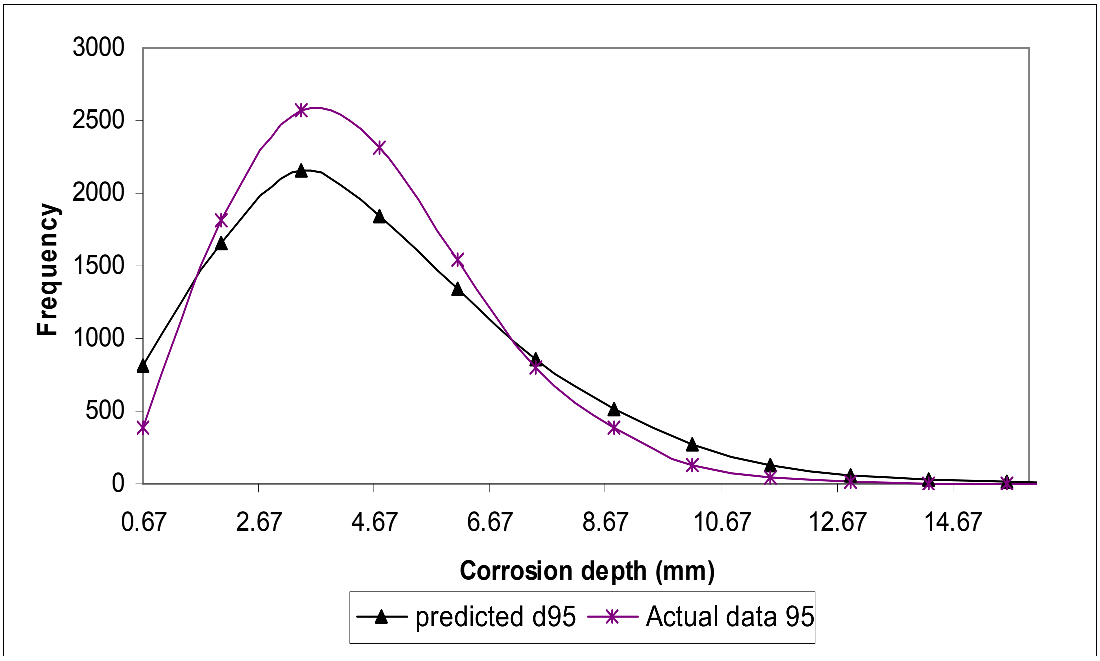

Figure 3.18: Comparison result: Prediction of data from 1990 to 1995 using uncorrected corrosion growth rate (*Pipeline A*).

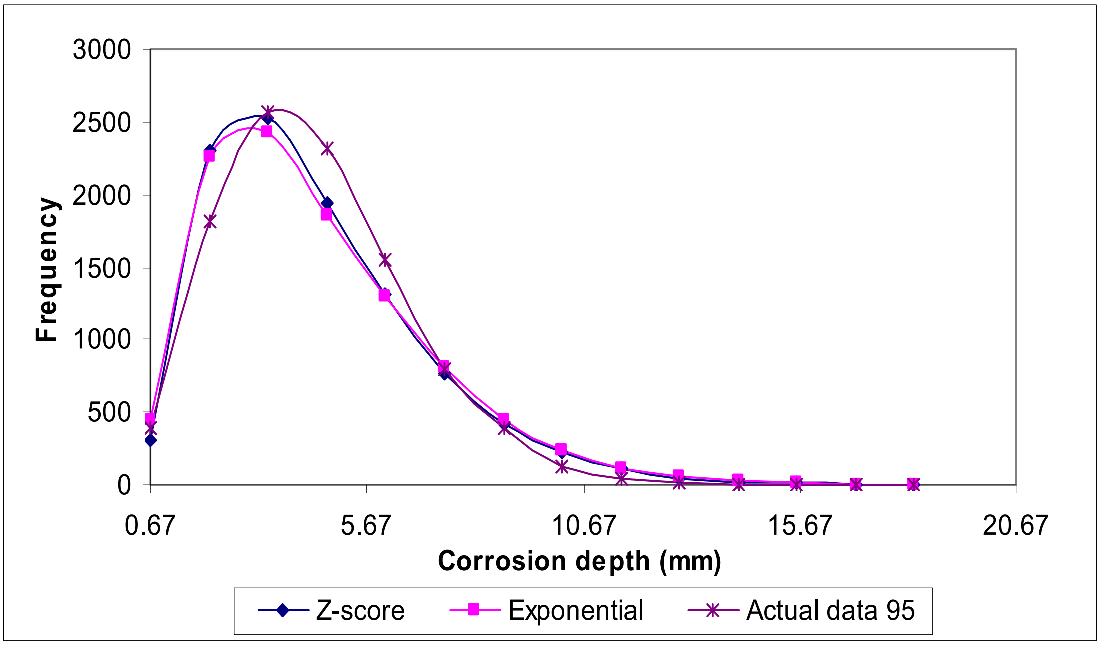

Figure 3.19: Comparison result: Prediction of data from 1992 to 1995 using corrected corrosion growth rate (*Pipeline B*).

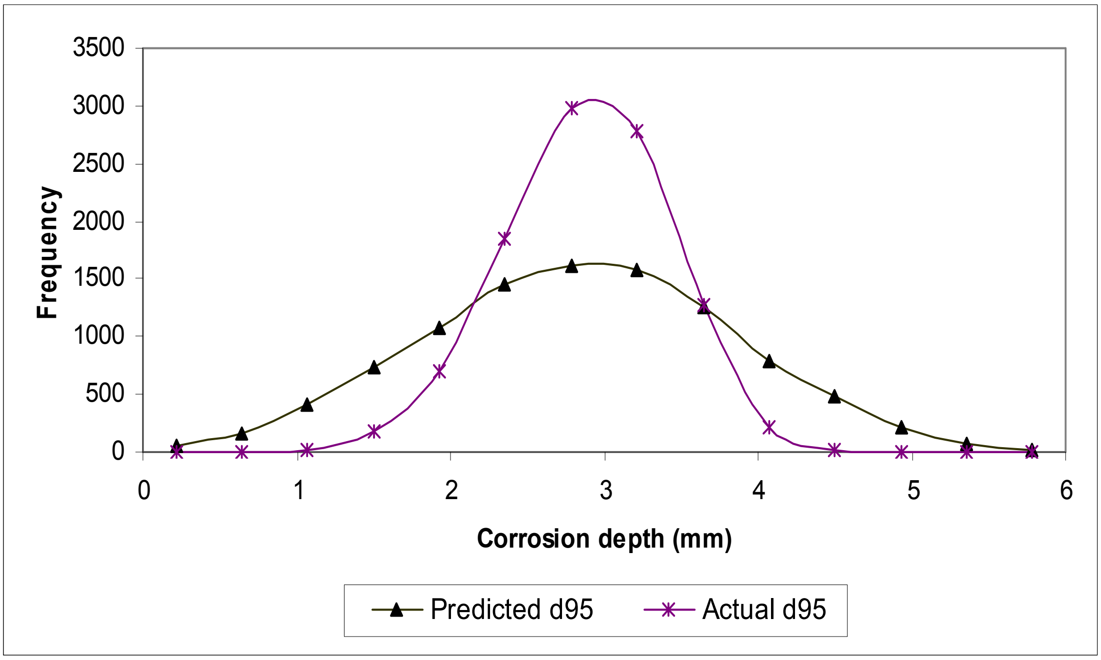

Figure 3.20: Comparison result: Prediction of data from 1992 to 1995 using uncorrected corrosion growth rate (*Pipeline B*).

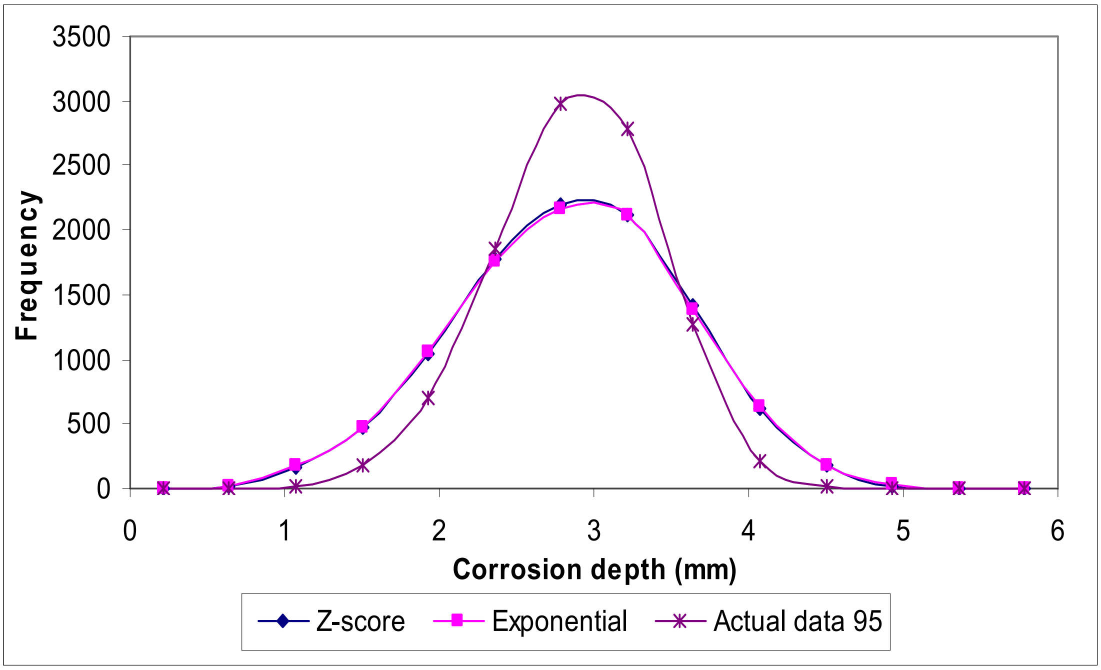

Figure 3.21: Comparison result: Prediction of data from 1992 to 1995 using corrected corrosion growth rate (*Pipeline B*).

3.5 Corrosion Linear Model for Severe Defects.

Pipeline failure caused by serious leakage is not totally dependent on the number of defects that occur inside or outside of the pipeline. The most important factor is the number of defects with severe depth. Pipeline as a series system, leaking in a certain section, will cause failure to the whole pipeline system. If the pipeline operator is more concerned with the effect of extreme data upon structure reliability, it is suggested that the extreme growth of corrosion defects to be considered. The proposed model is developed specifically for predicting the future growth by using numerical simulation procedures.

3.5.1 Extreme growth model

Theoretically, the corrosion defects inside the pipeline grow randomly, subject to variation of the corrosion rate value for each single defect [Thoft-Christensen, 2002]. If an extreme characteristic is considered by assuming that the severe corrosion defects will keep growing faster than the non severe defects, the corrosion rate model can be written as:

$$CR_{extreme} = CR_r \times \frac{d_r}{d_{ave}} \qquad \text{Equation 3.28}$$

where:

CR_r = corrosion rate randomly selected from its corresponding distribution.

d_{ave} = fixed value of averaged defect depth.

d_r = defect depth randomly selected from its corresponding distribution.

Then, the linear model with extreme corrosion rate can be rewritten as:

$$d_{n+1} = d_n + \left(CR \times \frac{d_r}{d_{ave}} \times T \right) \qquad \text{Equation 3.29}$$

This model continues into the future with the rapid growth of existing severe defects. In the simulation, each randomly selected corrosion rate will be multiplied by the ratio between the (random) corrosion depth and averaged corrosion depth. If the selected corrosion depth is higher than its depth average, the new corrosion rate will be higher than the initial selected corrosion rate and vice versa. By using this model, the possibility that the existing severe corrosion defects will perforate through the thickness of pipeline wall can be determined to be high or low. This model is expected to give a more conservative result for structural assessment compared to the use of the actual random corrosion growth rate values.

3.5.2 Extreme growth model with partial factor

A partial factor is added so the extreme model can represent both non-extreme and extreme growth conditions, as shown by Equation 3.37.

$$CR_{extreme} = (CR \times w) + \left((1 - w) \times CR \times \frac{d}{d_{ave}} \right) \qquad \text{Equation 3.30}$$

The partial factor can takes a range of values from 0 to 1. If w is equal to zero, the extreme corrosion rate is fully dependent upon the ratio between the random corrosion depth and its average. Otherwise, if w is equal to 1, there will be no indication of rapid growth for the larger defects. To determine the effect of this partial factor to the prediction results, two simulations have been conducted to predict future data in year 1995 from year 1992 for *Pipelines A* and *B*. The partial factor is chosen to be 0 and 1, representing the extreme and non-extreme model respectively. The predicted data in year 1995 shows no significant difference between the prediction based on w=0 and that based on w=1. The partial factor seems not to give any significant contribution within its range from 0 to 1 (see Figures 3.22 and 3.23). The random selection of large defects is balanced by the random selection of small values of corrosion rate since both parameters are treated independently, which minimises the effect of the extreme growth of larger defects.

To minimise the effect of the selection of a random sample of smaller defects, the large defects derived from the tail area of the distribution were extracted using the extreme value theory. The extraction of the large defects can be represented by an extreme distribution produced from its parent/actual distribution. A prediction is carried out similar to the earlier prediction using the whole data from the Weibull distribution. By using the extreme Weibull distribution, as expected, the predicted distribution when w=0 is more extreme, compared with w=1, as shown in Figures 3.24 and 3.25. Thus, it can be concluded that the proposed extreme growth model has more significant effects on larger defects. This is different from the prediction of future growth based on the whole data including the fact that non severe defects will not be significantly affected by different values of the partial factor.

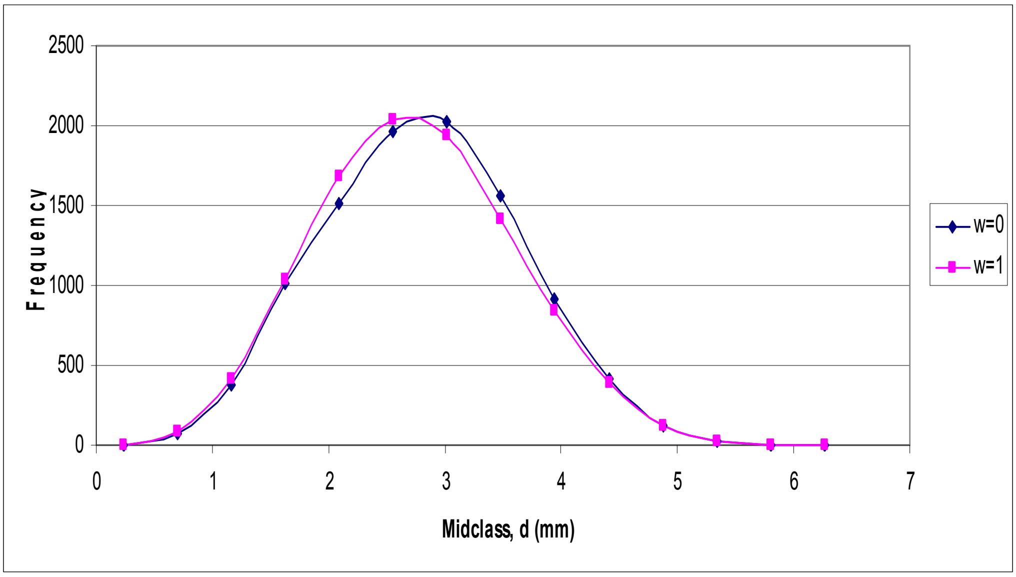

Figure 3.22: Comparison of predicted defect depth to actual depth based on extreme growth model and partial factor of 0 and 1 (*Pipeline A*)

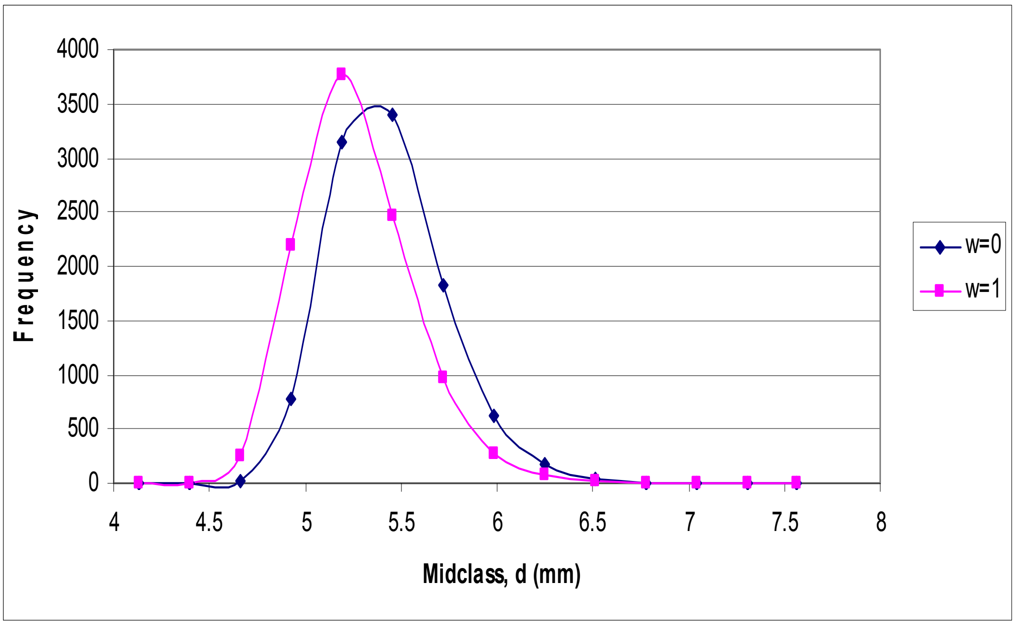

Figure 3.23: Comparison of predicted extreme defect depth to actual depth based on extreme growth model and partial factor of 0 and 1 (*Pipeline A*)

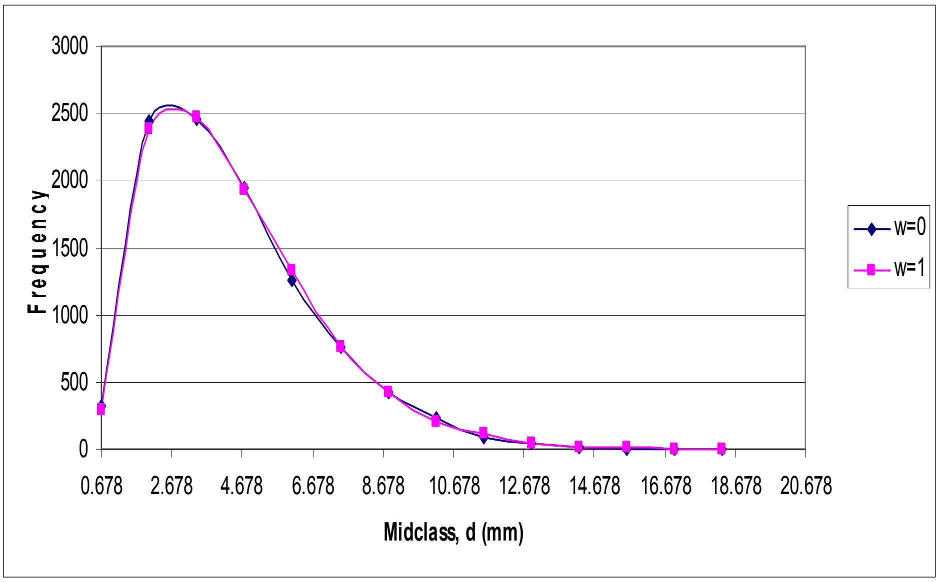

Figure 3.24: Comparison of predicted defect depth to actual depth based on extreme growth model and partial factor of 0 and 1 (*Pipeline B*)

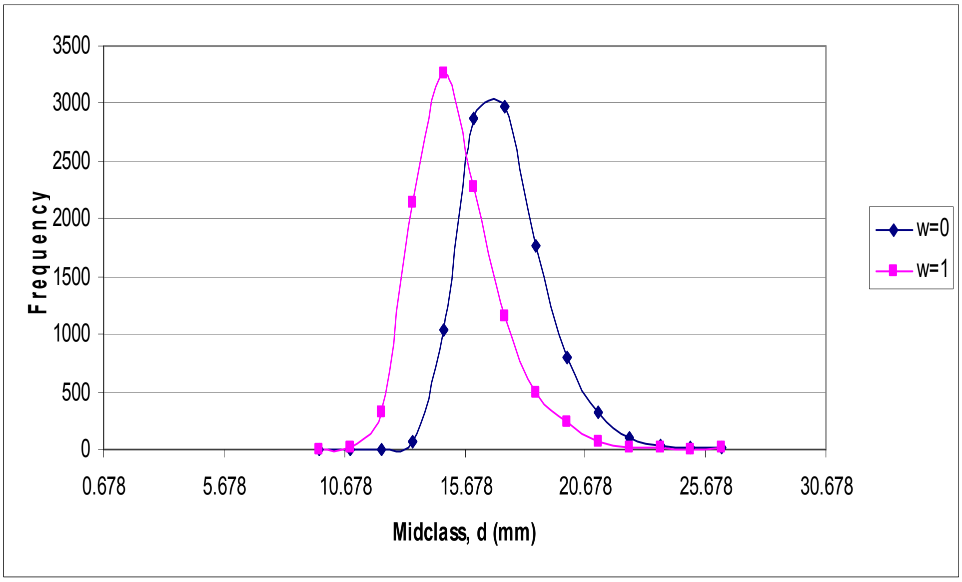

Figure 3.25: Comparison of predicted extreme defect depth to actual depth based on extreme growth model and partial factor of 0 and 1 (*Pipeline B*)

3.6 Random Linear Model

For structural prediction purposes, the growth pattern of corrosion defects is usually assumed to be linear [Caleyo *et al.*, 2002]. However, some modification on this general theoretical model can be introduced by inserting random elements. The basic linear model assumes that the corrosion rate for each defect is the same for all future years but a so-called random linear model implies that the future corrosion growth rate will vary from one year to the next in a random manner. Equations 3.38 and 3.39 represent the basic linear and random linear model for corrosion growth respectively. These models are depicted in Figure 3.26.

$$d_{n+1} = d_n + CR(T_{n+1} - T_n) \qquad \text{Equation 3.31}$$

$$d_{n+1} = d_1 + \sum_{i=1}^{n_a} CR_{Ti} \qquad \text{Equation 3.32}$$

where:

CR_{Ti}	=	corrosion rate in each single year
d_n	=	corrosion depth in year T_n
d_{n+1}	=	corrosion depth in year T_{n+1}
n_a	=	number of inspection
T_n	=	year of inspection T_n
T_{n+1}	=	year of inspection T_{n+1}

A sensitivity analysis was conducted to ascertain the effects of this new model on the prediction results. Three different dimensions of corrosion rates were chosen arbitrarily and fixed as 5 mm, 10 mm and 15 mm for the purpose of illustration. Each defect is linearly predicted for a time interval of twenty years from year T_0 to year T_{20}. Two models are used; the basic linear model (deterministic model) and the random linear model. A simulation procedure was utilised to select three different values of the corrosion growth rate for each defects based on the basic linear model. For predictions using the random linear model, each defect was provided with twenty random values of corrosion growth rate. Each corrosion rate represents the growth value for a time interval of one year. The arbitrary selection of the corrosion rate value is based on the Exponential distribution of the corrected corrosion growth rate (see Equation 3.26 in Section 3.4.2).

The prediction result can be seen in Figures 3.27 to 3.29. For a long term prediction, the differences predicted by these models are significant.

Hence, another comparison has been carried out by predicting the future depth of defects in year 1992 to year 1995 (short-term projection), and year 2010 (long-term projection). One thousand data were generated randomly from extreme defect depth distribution in year 1992 and projected to years 1995 and 2010. Similar to the deterministic comparison, the short-term prediction from year 1992 to year 1995 for *Pipelines A* and *B* shows no significant difference between prediction results as opposed to long-term prediction where the random linear model yields higher averaged value of defect depth (see Figures 3.30 to 3.33). The basic linear model is being used widely to predict the future growth of corrosion defects due to its simplicity and lack of data from on site observation. No robust proof is available to relate the linear model with the corrosion growth process. Therefore, a random linear model can be a solution to incorporate the uncertainties associated with the growth pattern.

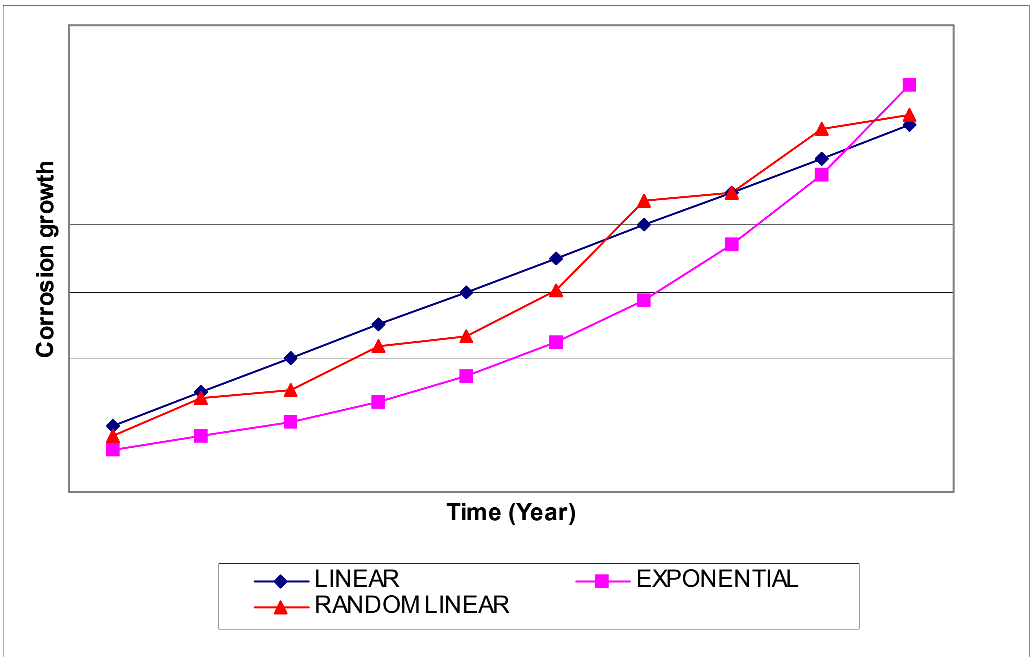

Figure 3.26: An illustration of three different patterns of corrosion growth

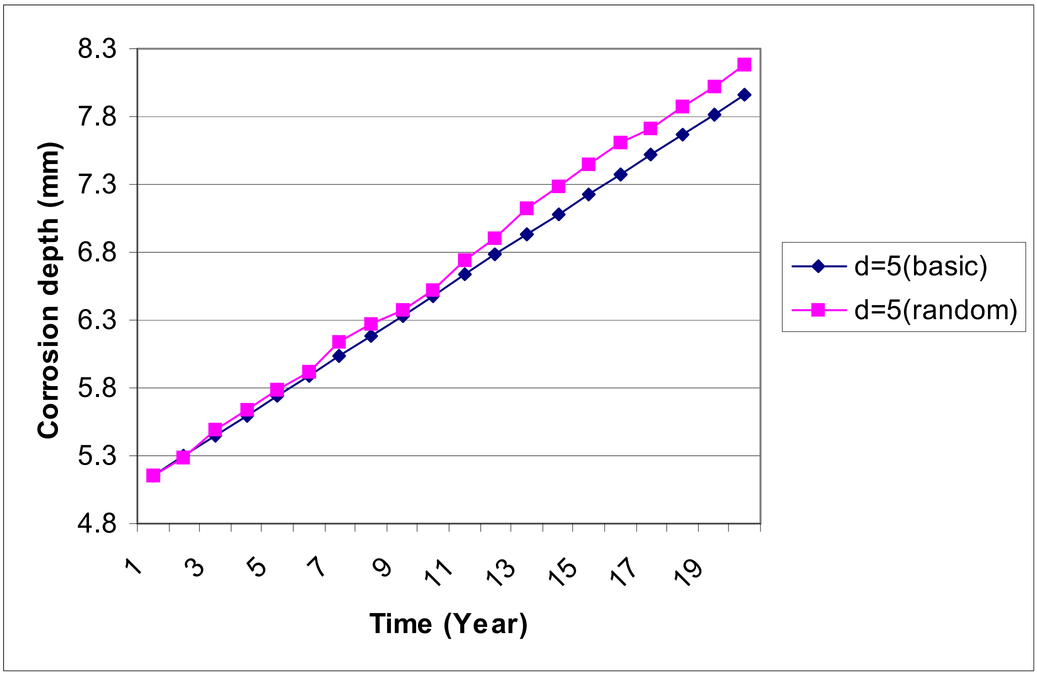

Figure 3.27: Linear prediction of corrosion defects by using basic and random linear models (d=5mm)

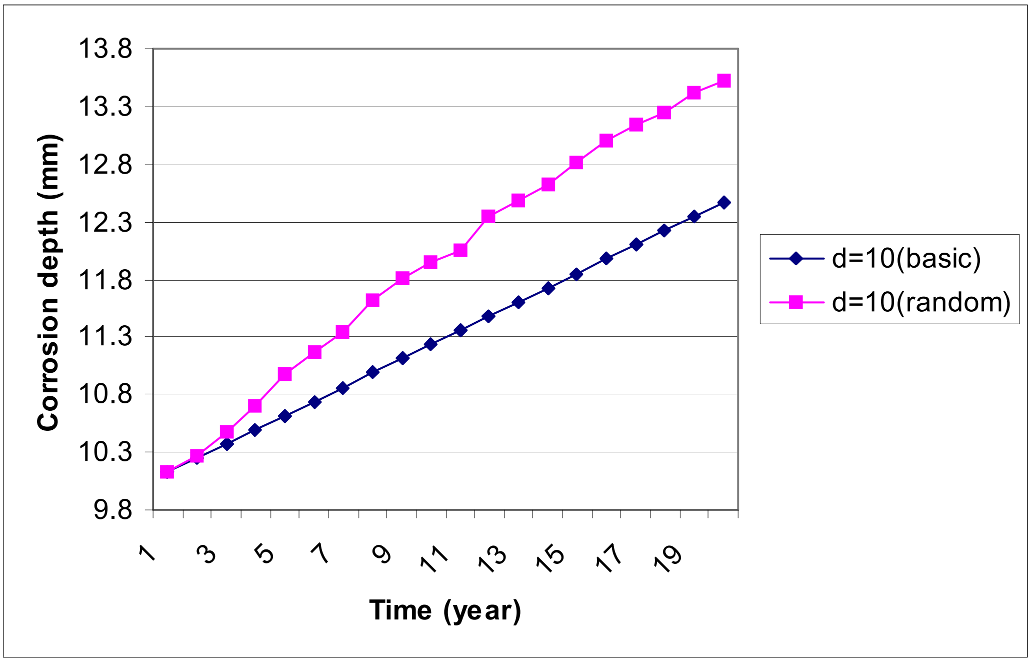

Figure 3.28: Linear prediction of corrosion defects by using basic and random linear models (d=10mm)

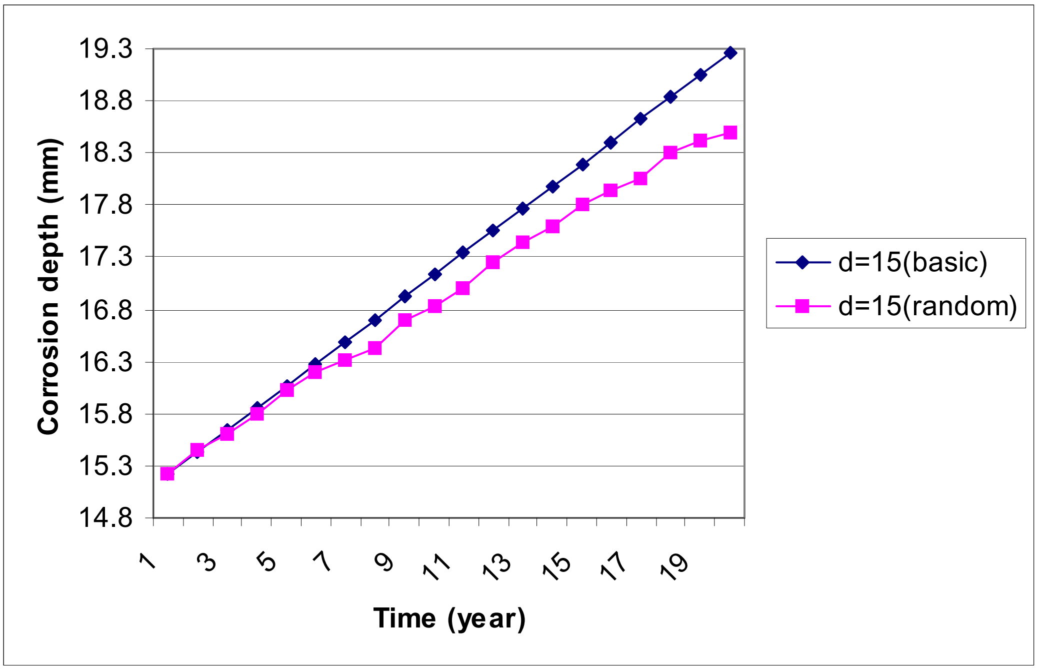

Figure 3.29: Linear prediction of corrosion defects by using basic and random linear models (d=15mm)

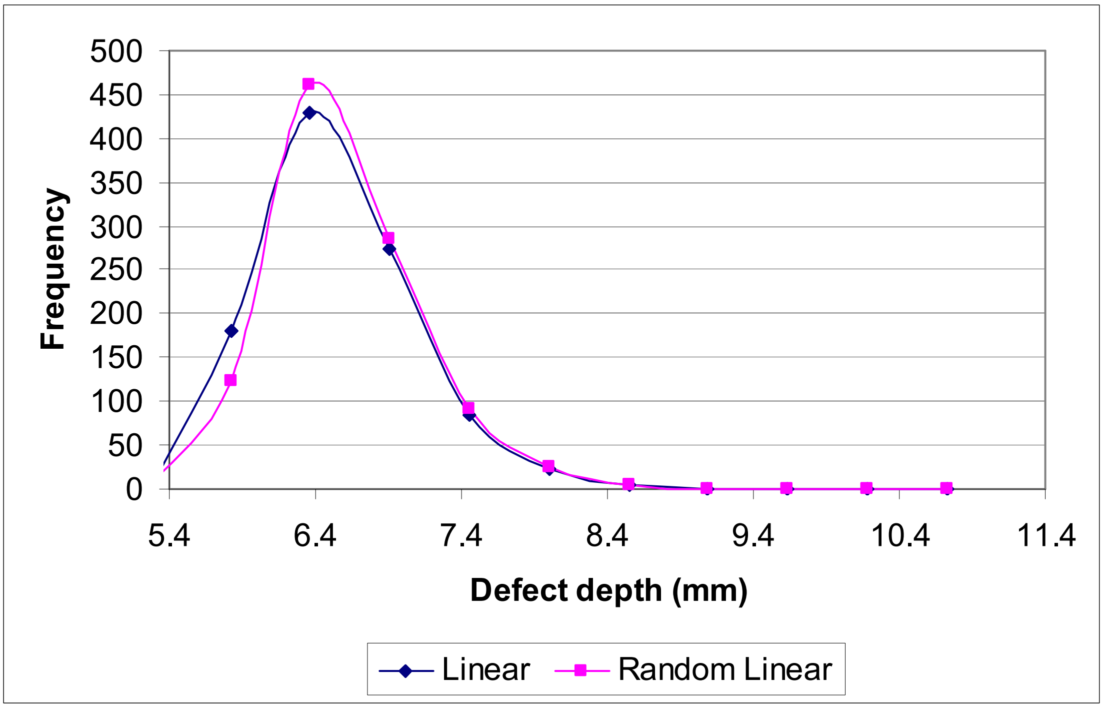

Figure 3.30: Comparison of predicted corrosion depth to actual depth in year 1995 using linear and random models (*Pipeline A*)

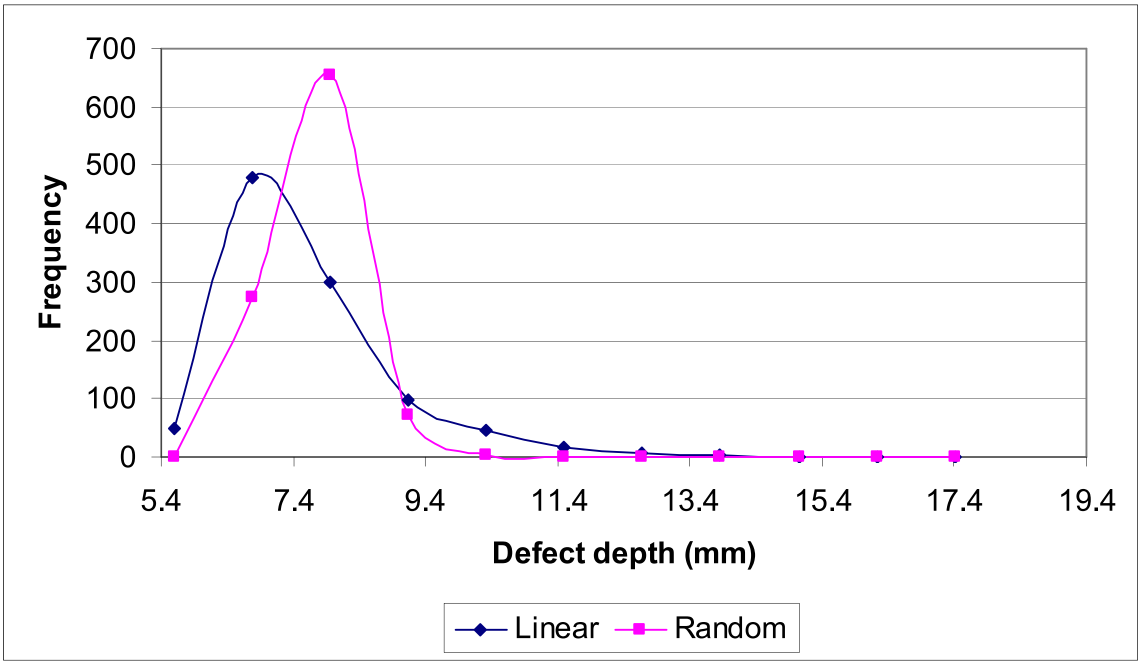

Figure 3.31: Comparison of predicted extreme corrosion depth to actual depth in year 2010 using linear and random models (*Pipeline A*)

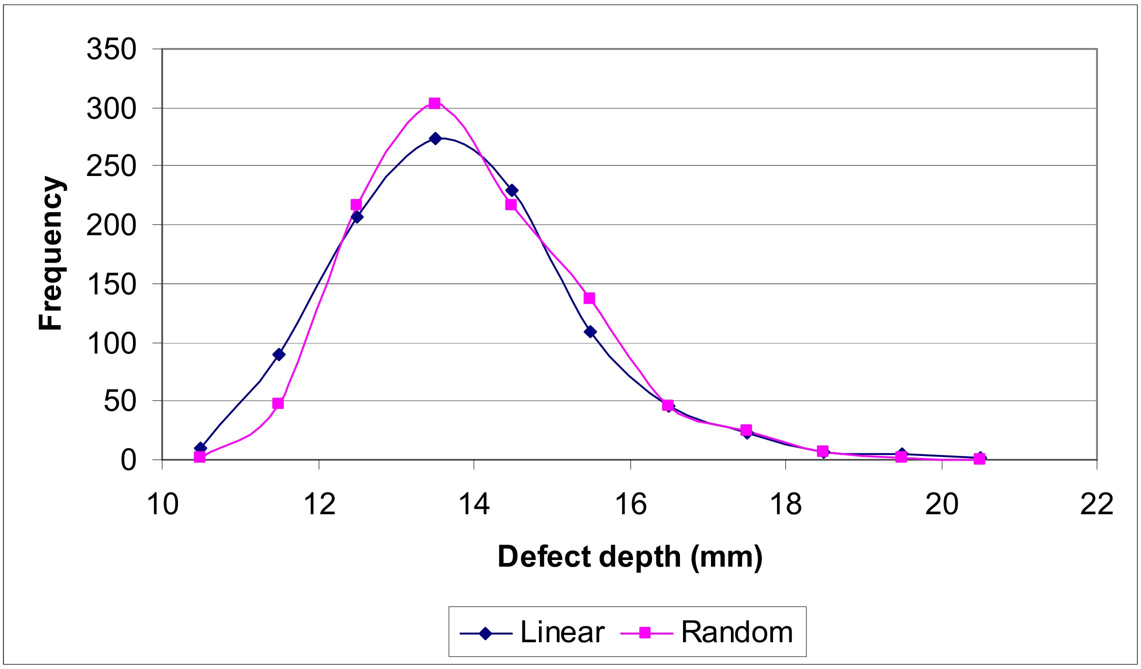

Figure 3.32: Comparison of predicted corrosion depth to actual depth in year 1995 using linear and random models (*Pipeline B*)

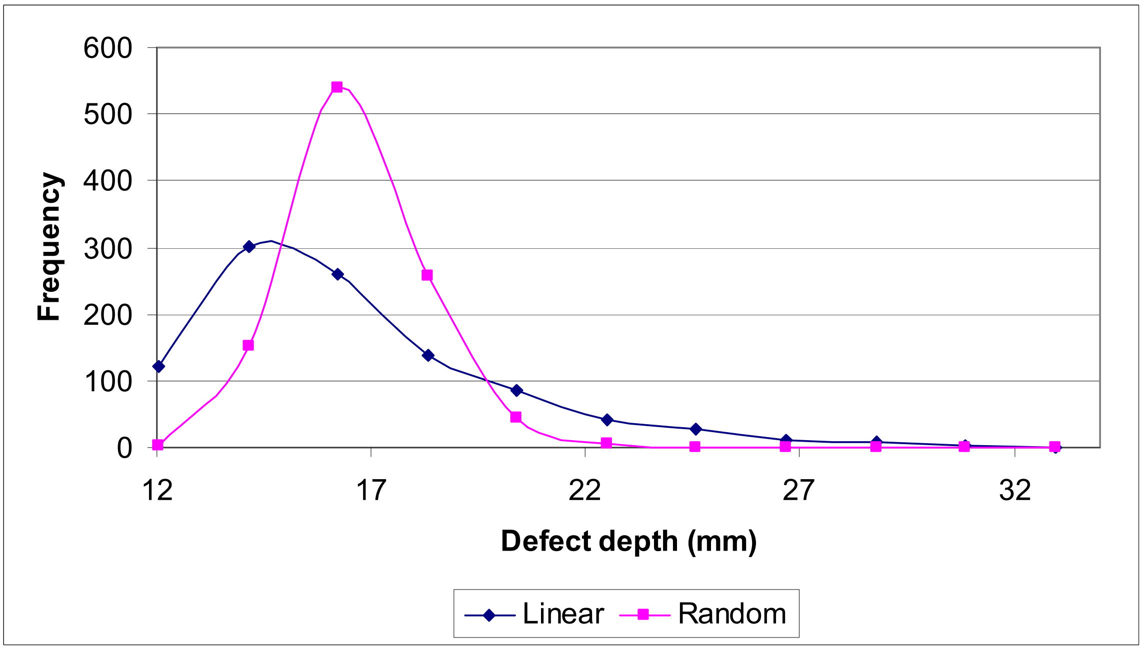

Figure 3.33: Comparison of predicted extreme corrosion depth to actual depth in year 2010 using linear and random models (*Pipeline B*)

3.7 Sources of Error of Pigging Data

The proposed methodology for pipeline assessment cannot accurately evaluate the integrity of the corroded pipeline unless good inspection data is obtained. Even though pigging inspection is the most sophisticated inspection technology at the present time, the accuracy of the data is still argued by the operators. The aim of this section is to discuss the error that can affect pigging data by looking at technical aspects such as pig velocity and data interpretation

In current practices most operators are interested only in identifying critical defects, and there is less emphasis on locating small defects. Small defects are equally important in the inspection report as these groups of small defects have a high possibility to grow extensively in the future. Furthermore, it is not impossible that these small defects would become more severe than the other extreme pits in the future owing to the random nature of the corrosion growth process.

The detection of corrosion length also has a significant bearing on the assessment results. Length accuracy is important since large errors in length can cause a significant error in estimating the severity of a defect. Nestleroth and Battelle [1999] have illustrated how this error could affect the estimated failure pressure. They concluded that, for a 30% deep and 26 centimetre long defect, a four centimetre error in length does not appreciably change the failure pressure. Therefore, an error in length will not significantly affect the calculated severity. However, for deeper defects, errors in length become increasingly important. For a 60% deep and 8 centimetre long defect, an error of four centimetre leads to a much larger error in the severity. Therefore, length accuracy is more important for short deep defects than for long shallow defects [Nestleroth and Battelle, 1998].

Even if the problem with the accuracy of detection can be overcome by increasing the tool accuracy, errors will still exist. With very high accuracy, difficulties arise, when several defects are in close proximity. Nestleroth and Battelle [1999] described how, in most inspection reports, many vendors will group individual defects together as a composite defect; that is, two or more defects are reported as a single defect. This practice can be very conservative, especially when several deep defects are grouped. Most assessment codes such as the DNV RP-F101, allows corrosion pits (short deep defects) to be treated as individual pits when their separation is relatively small. The pits can be treated as individual defect when the separation is greater than, for example, three times the wall thickness or two centimetres. Clearly, reporting four 4-centimetres long defects as one 16-centimetres long defect will cause serious errors in the final estimated severity [Nestleroth and Battelle, 1998].

Characterisation of accuracy is important in differentiating between defects, imperfections, pipeline components, and non-relevant indications, which cannot be ignored. “False calls” are indications that are classified as anomalies where no imperfection, defect, or critical defect exists. MFL tools, by their nature, receive signals from pipeline features and non-relevant conditions [Nestleroth and Battelle, 1998]. Occasionally, these indications are characterised as anomalies. Two common causes of false calls are metal objects near the pipeline and sleeve eccentricities. If these features are reported as imperfections or defects, costly excavations and remedial work may be performed, where none is needed.

Errors in inspection data are also associated with the speed of the in-line inspection tool. The MFL signal is not only proportional to the depth of the metal loss but is also influenced by speed of the pig [Tiratsoo, 1992]. Control of pig speed and velocity during inspection especially in low pressures gas pipelines, is difficult leading to the potential loss of inspection data [Smith, 1992]. The speed should be held within a certain ranges to ensure that high quality measurements can be made. For an MFL pig tool, the flux leakage fields are significantly influenced by tool velocity. High velocity may reduce the leakage field amplitude, changes the leading and trailing edges of the leakage field and decreases the base signal amplitude [Nestleroth and Battelle, 1998]. Detection of a corrosion defect with a shallow depth is affected more by the tool speed and velocity.

The other possibility of error is the different internal condition of the pipeline [Noor, 2002]. At the time of inspection the detection of corrosion defects might be different between two inspections if the cleaning routine is not carried out effectively. The waste of hydrocarbon products, such as wax when it becomes harder and thicker will cover the internal surface of pipelines. If the cleaning process is carried out only during the first inspection and not continuously in the second inspection, this will affect the measurement of corrosion depth and probably result in reduced measurement of defects compared with the previous inspection.

Lastly, the error in pigging data can also be related to the different inspection vendor to conduct inspection activities at different time for the same pipeline. Any replacement of inspection vendor might cause a change in many aspects, which are;

i. Change in instrumentation of the pipeline pigging tool
ii. Change in mathematical algorithm used to convert the electrical signal to defect size.
iii. Change in procedure used during pigging process.

The inspection tools used by different inspection consultants are often different in terms of tool construction, calibration and accuracy [Noor, 2002]. In addition, different techniques are used to convert the detected electrical signal to extract the corrosion dimension based on the speciality and engineering experience. In addition, the whole procedure of inspection may differ from one to another. The drastic change of these three items will cause a notable difference of data presentation. If two sets of data are collected from the same pipeline at different times by two different inspection consultants, the proposed matching procedure will not guarantee the number of matched data that can be detected. The accuracy of any assessment procedure is very dependent upon the accuracy of the pigging data.

3.8 Concluding Remarks

This chapter has demonstrated the investigation and analysis work on corrosion data of offshore pipelines. The proposed approaches include a discussion of data observation, feature-to-feature data matching procedure, statistical and probability analysis, correction methods and theoretical corrosion models. Thorough observation on the data prior to the data sampling work has effectively forewarned the existence of errors within the data, which might affect the corrosion growth rate value. Data matching procedure provides the best information on corrosion progress based on the metal loss evidence between inspections carried out at different time. All corrosion parameters have been treated statistically by their corresponding probability distribution to reduce the uncertainties that might be associated with inspection work and the environment. This probability distribution will be used later in the simulation of structure reliability subjected to corrosion attack. Several correction methods have been proposed to encounter the negative corrosion rates. Based on the comparison between measured and predicted data, it is obvious that the proposed correction method of the Exponential distribution is effective in minimising the effects of negative corrosion rate. However, if more data becomes available, better justification of the method accuracy can be done. Two theoretical-based corrosion models have been introduced to include the extreme growth of severe defects and the randomness of the corrosion progress. Figures 3.34 and 3.35 illustrate the step-by-step flow chart of the proposed analysis approaches on pigging data.

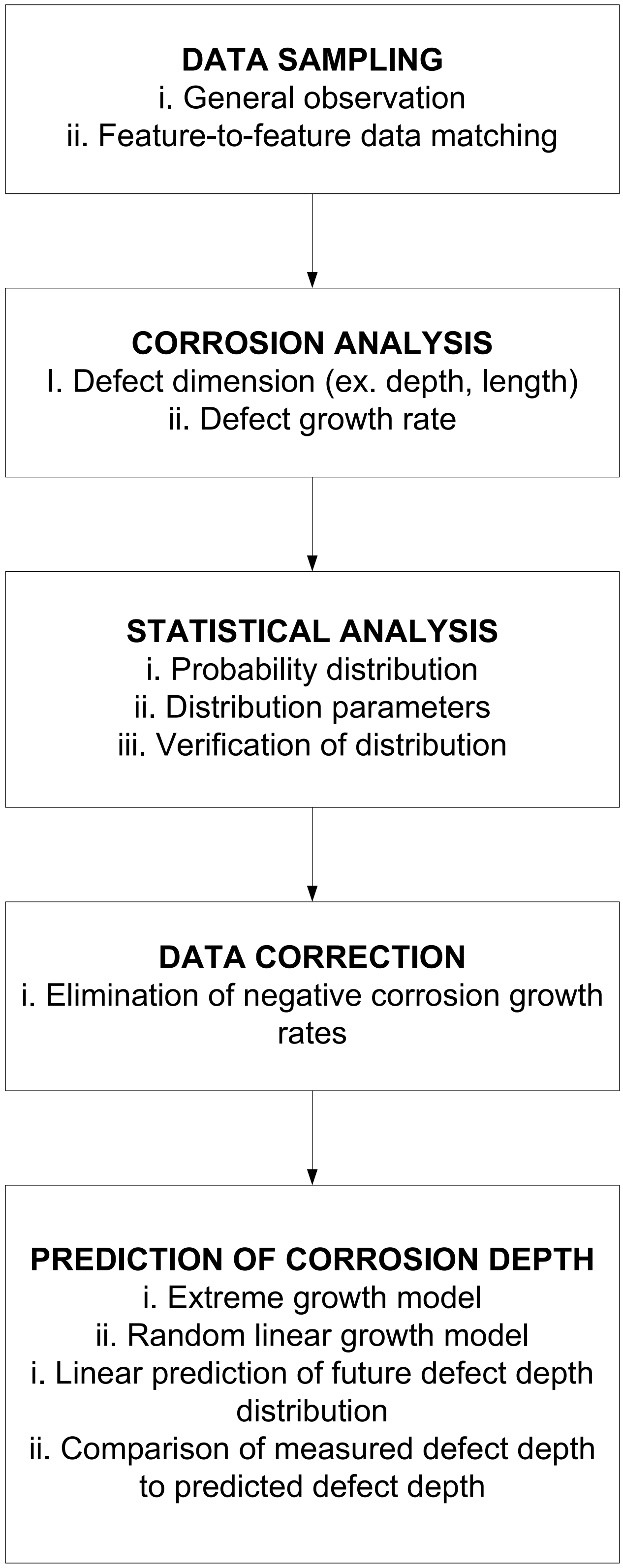

Figure 3.34: The proposed methodology of corrosion defect analysis of pipelines

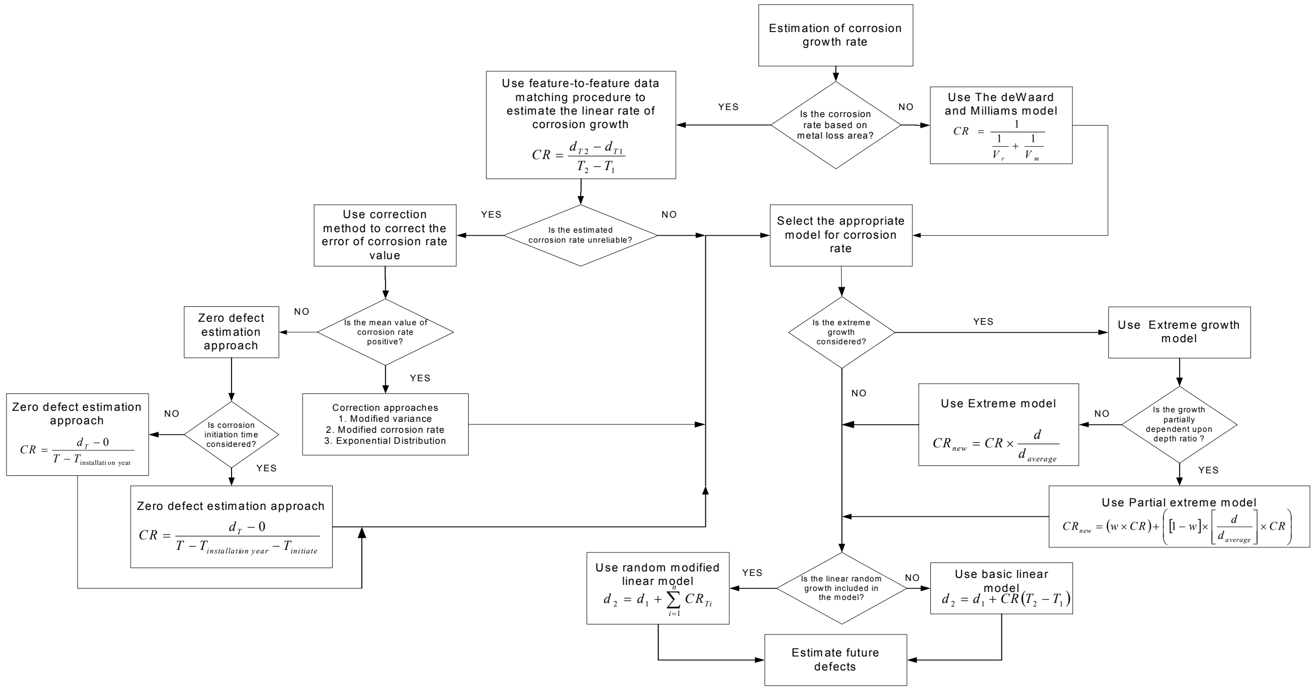

Figure 3.35: The flow chart of data assessment for corroding pipelines

CHAPTER 4 - ANALYSIS OF SEAWATER BALLAST TANK CORROSION DATA

4.0 Introduction

The analysis methodology presented in Chapter 4 is specified for repeated inspection data for which a data matching procedure was used to estimate the corrosion growth rate for each pipeline. However, this methodology cannot be applied when corrosion data are collected from a number of structures have been grouped altogether in one single database. It is not feasible to implement the data matching procedure when one cannot identify the subsequent inspection, even if there were one. This chapter describes how this so-called random data can be used to predict the corrosion growth statistically. Instead of estimating the corrosion growth rates by assuming the corrosion initiation time as proposed in earlier research work [Paik and Thayambali, 2002], an alternative approach is presented to estimate the corrosion progress without relying on the corrosion initiation time.

4.1 Corrosion of Ship Structures

Problems arising from corrosion are considered to be among the most important age related factors affecting structural degradation of ships in complex seawater environments. Seawater properties such as oxygen content, salinity, temperature, pH level, and chemistry can vary according to site location and water depth, making it difficult to predict the corrosion progress. Statistics for ship hulls show that 90% of ship failures are attributed to corrosion [Melchers, 1999a]. Localised corrosion especially pitting, is among the major types of physical defects found largely on ship structures. The areas of the ship most exposed to corrosion are wing ballast tanks, resulting from exposure of seawater, humidity and salty environment when empty.

The corrosion damage of steel structures in ships is influenced by many factors, including the corrosion protection system (coating and inhibitor) and various operational parameters. The operational parameters include maintenance, repair, percentage of time in ballast, frequency of tank cleaning, temperature profiles, use of heating coils, humidity conditions, water and sludge accumulation, microbial contamination, composition of inert gas, etc. To date, rigorous work to understand the effect of many of these factors and their interactions is lacking in the case of ship structures [Paik and Thayambali, 2002]. Moreover there are limited research and corrosion measurement data available for corrosion rates in tankers [Wang *et al*., 2003]. Discussions on corrosion wastage still remain largely qualitative rather than quantitative [Wang *et al*., 2003].

4.2 A Review of the Original Research Works

Paik and Thayambali [2001], Paik [2004] and Paik *et al*. [2004] have carried out an extensive study on corrosion data from seawater ballast tanks to model the deterministic time-dependent corrosion wastage mode. Measured data from the corrosion loss in structural members of seawater ballast tanks for ocean-going oil tankers and bulk carriers have been collected. Data for renewed structural members were excluded. A total of 1507 measurement points for seawater ballast tanks from the side and bottom shell plates were obtained and available for the study. The number of vessels involved in the data collection is unknown. Corrosion loss was measured mostly by the technique of ultrasonic thickness measurements. This implies that the measurements were made at several points within a single plating, and a representative value (e.g., average) of the measured corrosion loss was then determined to be the depth of corrosion. Table 4.1 indicates collected data of corrosion loss as a function of time (vessel age). It can be seen from Figure 4.1 that the distribution of corrosion loss is very scattered. The authors also surmised that the statistical frequency distribution of corrosion depth at a younger age tends to follow the normal distribution, while it follows a lognormal or exponential distribution for corrosion from an older stage.

In the analysis, three assumptions were made:

1. The annualized corrosion rate is constant so that the relationship between the corrosion depth and the ship age is linear.
2. The life of the coating is varied at 5, 7.5 and 10 years, because no information about the breakdown of coating is available (see Table 4.2).

3. Corrosion starts immediately after the coating breakdown takes place.

The corrosion rate incorporating coating breakdown is estimated based on the following equation:

$$CR = \frac{t}{T - T_c} \qquad \text{Equation 4.1}$$

This study has estimated an extreme annualized of corrosion rate based on the 95 percentile and above band, while the averaged rate is based on the overall data (see Figure 4.2). Table 4.2 summaries the results for the mean and the COV of the annualized corrosion rates, while Figures 4.2 and 4.3 illustrate the mathematical models for the time-dependent corrosion wastage of the seawater ballast tank. The proposed assessment procedure is based on a deterministic analysis where a linear equation of the corrosion growth rate is used to predict the future growth of corrosion depth. Moreover, the corrosion initiation time has been assumed to simplify the estimation of corrosion growth rate due to the lack of information on the coating life value. Even though the proposed procedure is straightforward and seems practical for use on site, the corrosion data can still to be explored to optimize the findings. A statistical and probability approach can be used to enhance the corrosion modelling as presented in the next section.

Table 4.1: Summary of the computed results for the mean and the COV of annualized corrosion rate of bulk carrier's seawater ballast tank [Paik and Thayambali, 2001].

	Coating life assumed	**Mean**	**COV**
All corrosion data	5 years	0.0473	0.8388
	7.5 years	0.0621	0.9081
	10 years	0.0804	0.9031
95% and above band	5 years	0.1678	0.1678
	7.5 years	0.2212	0.2212
	10 years	0.2997	0.2997

Table 4.2: Gathered number of measured data set of thickness loss due to corrosion in seawater ballast tanks of bulk carriers [Paik and Thayambali, 2001].

Time (year)-middle class	Depth of corrosion, mm (middle class)							
	0.25	0.75	1.25	1.75	2.25	2.75	3.25	3.75
11.25	2	0	0	0	0	0	0	0
11.75	18	5	0	0	0	0	0	0
12.25	6	3	9	0	0	0	0	0
12.75	23	2	0	0	0	0	0	0
13.25	16	26	30	2	0	0	0	0
13.75	9	0	0	0	0	0	0	0
14.25	3	3	0	0	0	0	0	0
14.75	1	2	0	0	0	0	0	0
15.25	22	13	10	3	2	0	0	0
15.75	9	1	0	0	0	0	0	0
16.25	5	0	0	0	0	0	0	0
16.75	12	8	5	2	1	1	0	0
17.25	19	1	0	0	0	0	0	0
17.75	84	1	2	4	0	0	0	0
18.25	34	26	37	9	4	3	0	0
18.75	1	0	2	0	0	0	0	0
19.25	52	10	5	8	6	1	0	1
19.75	84	9	1	0	2	0	0	0
20.25	165	29	9	1	0	0	0	0
20.75	10	14	11	10	16	2	0	0
21.25	69	42	11	7	2	4	0	0
21.75	9	1	1	2	2	0	0	0
22.25	3	5	0	0	0	0	0	0
22.75	8	18	1	3	0	0	0	0
23.25	31	13	4	1	0	0	0	0
23.75	8	3	1	0	0	0	0	0
24.25	7	11	7	2	0	0	0	0
24.75	18	15	2	0	0	0	0	0
25.25	30	49	48	57	40	2	2	1
25.75	10	1	1	2	0	0	0	2
26.25	8	8	1	0	0	0	0	0
26.75	0	7	1	0	0	0	0	0

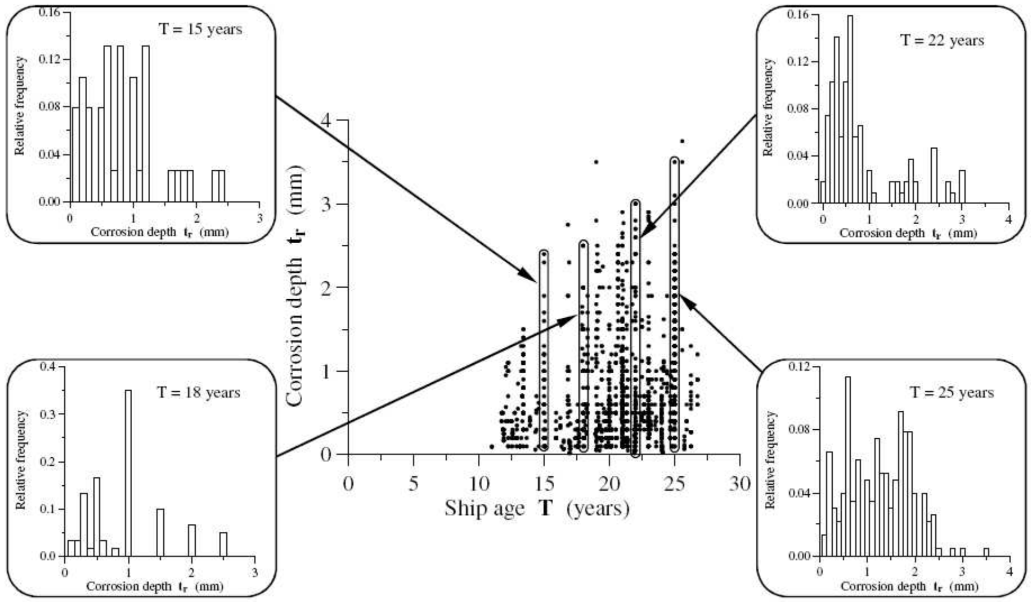

Figure 4.1: The corrosion depth versus the ship age from thickness measurements of seawater ballast tank structures [Paik and Thayambali, 2001].

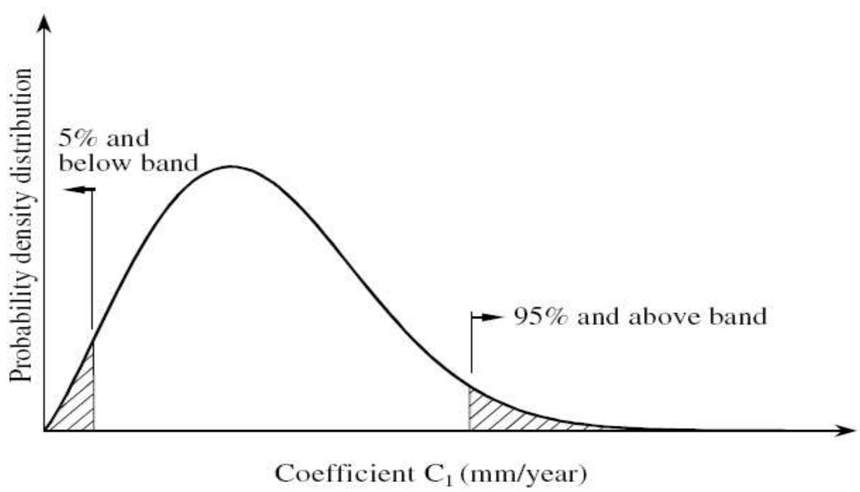

Figure 4.2: The 95 percentile and above band for developing the severe (upper bound) corrosion wastage model [Paik and Thayambali, 2001].

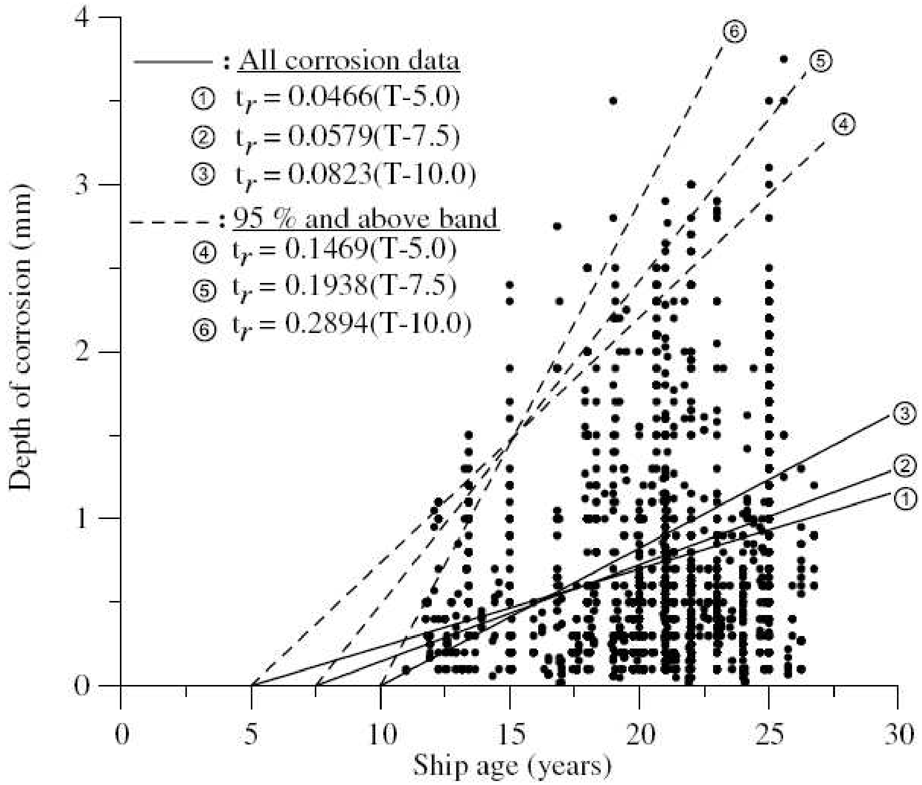

Figure 4.3 Comparison of annualized corrosion rate formulations, together with the measured corrosion data for seawater ballast tanks [Paik and Thayambali, 2001].

4.3 Alternative Approach

Unlike the pigging data analysed in the previous chapter, repeated inspection on vessels does not take place. The inspection and corrosion measurement activities were probably carried out once and randomly on different vessels. The data was then grouped according to the age of vessel and defect depth. Therefore, the estimation of corrosion growth rate is not possible for every single vessel and the feature-to-feature matching procedure is not possible in this case. The only way to estimate corrosion rate is by using the 'defect-free' method with the addition of corrosion initiation time. The proposed deterministic model is assumed valid for all vessels even though, in reality, each vessel involved in the sample has different factors that affect the corrosion progress. Based on this assumption, an enhancement of the deterministic model as proposed by Paik and Thayambali [2001], Paik [2004] and Paik *et al*. [2004] has been developed to incorporate the variation of the corrosion data.

The works by Paik and Thayambali [2001], Paik [2004] and Paik *et al*. [2004] have been revised with the introduction of a statistical model for a time-dependent corrosion process based on the same corrosion data. In this section, two statistical models are proposed with the intention of minimising the effects of uncertainties caused by the scattered corrosion data. The works cited in the literature did not consider the effect that possible uncertainties and errors related to imperfect measurement by inspection tools and the complex seawater environment might have on estimation of growth. The revision begins with the simulation procedure to extract artificial data from the grouped data following the unavailability of crude data for each single defect from the previous research.

4.3.1 Generating Artificial Data

As tabulated in Table 4.2, the exact number of defects in each class of vessel age has been individually generated using the Monte Carlo simulation. The uniform distribution is assumed to suit the range of corrosion depth best within each interval as it is small i.e. only 0.5mm wide. To validate the accuracy of the artificial data compared with the unknown actual data, a comparison of corrosion rate distribution has been carried out. The mean and average value of corrosion growth rate based on the artificial data is found to compare well with that predicted by the actual data. The comparison was based on the corrosion set estimated with 7.5 years of corrosion initiation time. Table 4.3 shows that the difference percentage between the growth statistics calculated from the data and from the simulation is less than 1% of the mean

Table 4.3: Comparison of Weibull moment values between actual and artificial data

Value	Artificial data	Actual data	%Δ
Mean	0.0627	0.0621	0.957
COV	0.9317	0.9081	2.533

4.3.2 Statistical Time-dependent model

An average value and standard deviation of corrosion depth is estimated individually for each set of vessel age. The graphs of average and standard deviation value have been plotted against vessel age to establish a relationship between the progress of averaged metal loss and the vessel age. The regression analysis was used to re-scale the data to time *t*=0. The interception of regression line at *t*=0 indicating zero corrosion initiation time was not considered, hence resulting a non-zero value of averaged corrosion depth in the beginning of vessel operation. Yet, this drawback can be resolved if more data can be collected especially from vessel age under 11 years. The regression line might approach zero interception with addition of new data. From Figures 4.4 and 4.5, it seems the averaged metal loss is scattered over the time but there is some indication of the increment of the averaged depth and standard deviation over time. The linear increment can be expressed as a function of time using the regression equations as follows:

$$d_{ave} = 0.0251.t_v + 0.1511 \qquad \text{Equation 4.2}$$

$$std_d = 0.0232.t_v - 0.037 \qquad \text{Equation 4.3}$$

where:

d_{ave} = linear regression model of defect depth average

std_d = linear regression model of defect depth standard deviation

t_v = age of vessel (year)

The linear regression equation is likely to contain some errors owing to the large scatters in the averaged corrosion depth for each class of vessel age. To minimise the errors, this deterministic equation will be combined with a probability distribution of corrosion depth representing all of the data. The next step is to construct a distribution for all the data by removing the effects of time. This distribution of the entire data was found to be best reproduced by the Weibull distribution based on linear fitting of the probability plot and verified by the Chi-square goodness-of-fit test. Figures 4.6 and 4.7 show the histogram and the Weibull probability plot of all the data respectively. The Weibull distribution function for all of the data can be expressed as follows:

$$f_{x_d}(x_d) = \frac{1.1(x_d)^{0.1}}{1.27^{1.1}} \exp\left[-\left(\frac{x_d}{1.27}\right)^{1.1}\right] \qquad \text{Equation 4.4}$$

where:

x_d = corrosion depth

The shape parameter for the Weibull distribution was found to be 1.1, and adequate accuracy was mentioned by approximating to an Exponential distribution. Statistically, when the shape parameter, β=1, the Weibull distribution is identical to the Exponential distribution. The function of the whole can be rewritten as follows:

$$f_{x_d}(x_d) = \lambda.\exp[-x_d\lambda] \qquad \text{Equation 4.5}$$

This distribution no longer represents the corrosion progress in time since this effect has been removed by gathering all of the data under one distribution. Nevertheless, λ has a direct relation to the mean value of corrosion depth as defined by Equation 4.6. This can then be incorporated into the Exponential function to produce a time-dependent distribution.

$$\lambda = \frac{1}{d_{ave}}$$ Equation 4.6

By inserting the linear regression equation into Equation 4.6, the new expression of the Exponential distribution parameters can be written as:

$$\lambda = \frac{1}{0.0251.t_v + 0.1511}$$ Equation 4.7

Equation 4.5 then can be rewritten as follows:

$$f_{x_d}(x_d) = \frac{1}{0.0251.t_v + 0.1511}.\exp\left[\frac{-x}{0.0251.t_v + 0.1511}\right]$$ Equation 4.8

This function now can be used to predict the distribution of corrosion depth at any point of time after the insertion of the linear function of averaged corrosion depth. However, there is a considerable doubt in the accuracy of this function for a number of reasons.

1. If the distribution of corrosion depth better suits the Weibull distribution when the shape parameters $\beta>1$, then the change of distribution shape from Weibull to Exponential for the sake of simplicity might affect the accuracy of the prediction even though the effect might be small.
2. The insertion of the regression equation into the distribution of corrosion depth might be difficult for a Weibull distribution since the mean value estimation required the distribution parameters unlike the Exponential distribution, which only requires an estimate of the averaged depth.
3. There is a significant increment of standard deviation value of corrosion depth in time as portrayed in Figure 4.5. The insertion of a linear function for the averaged corrosion depth might contribute to the increment of corrosion depth variation over time. The longer the prediction, the higher the variation of corrosion depth in the future which might mislead the assessment results.

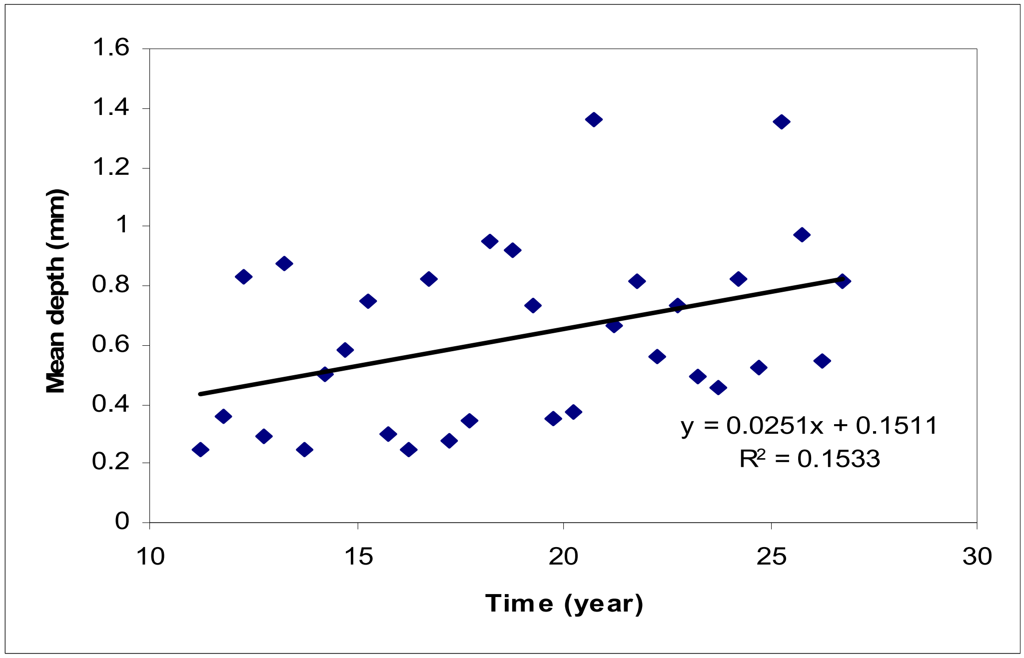

Figure 4.4: Linear regression analysis of mean value of defect depth and vessel age

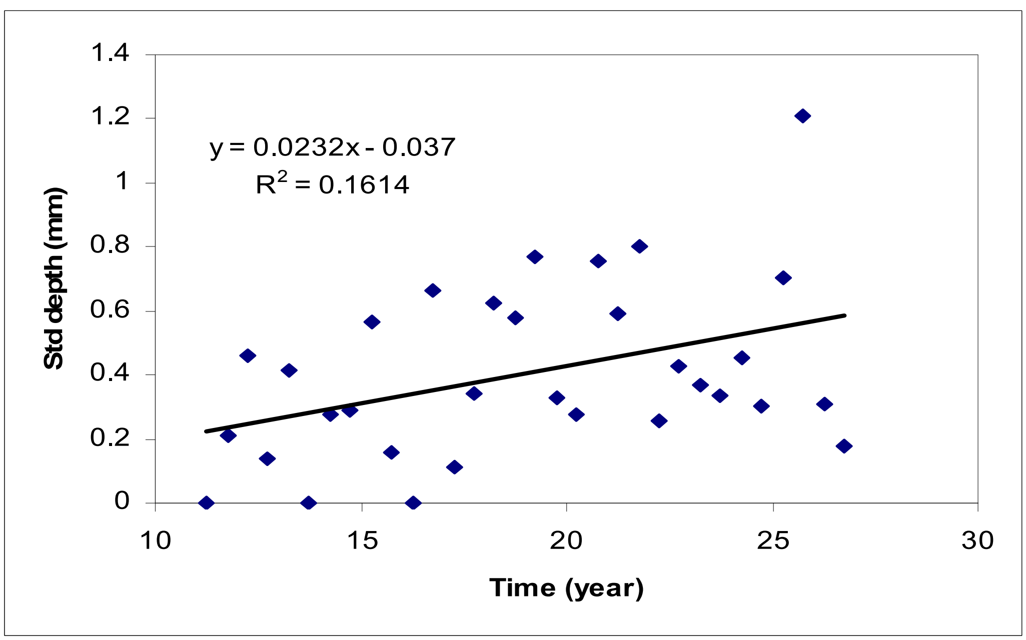

Figure 4.5: Linear regression analysis of *standard deviation* of defect depth and vessel age

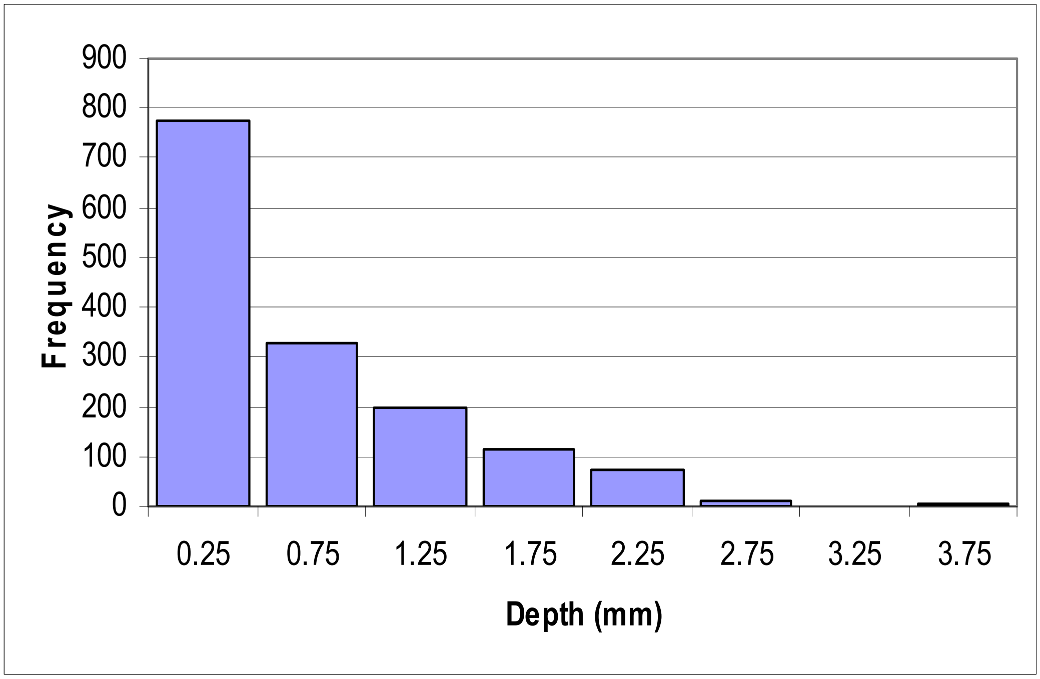

Figure 4.6: Histogram of the whole set of corrosion depth

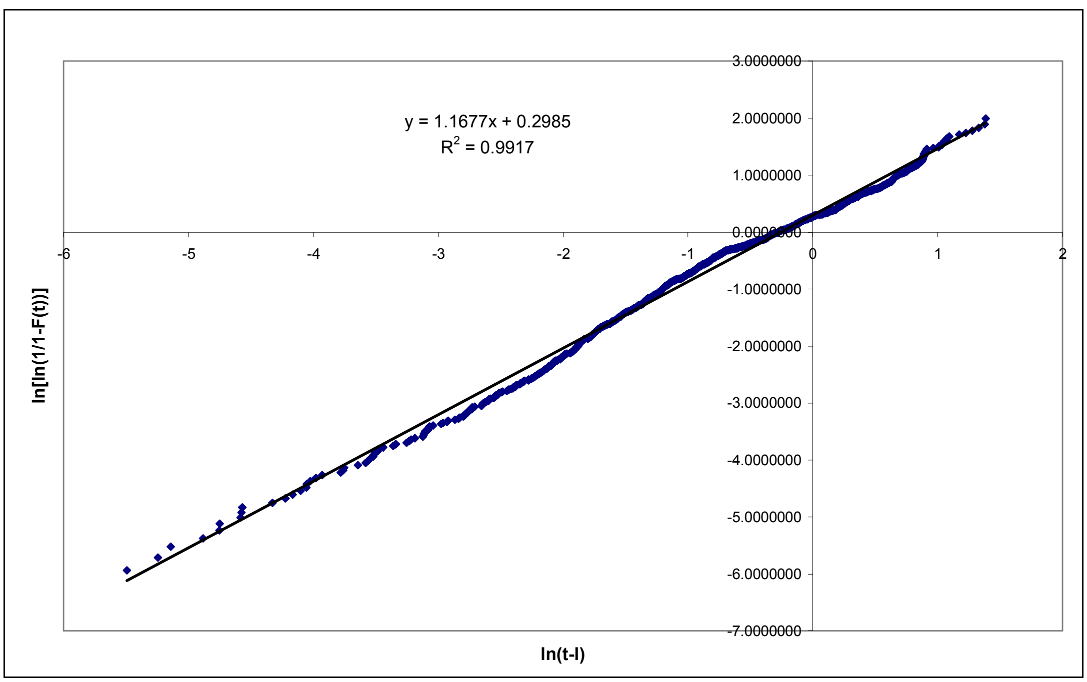

Figure 4.7: Weibull probability plot of measured data (actual)

4.3.3 Enhanced model

The previous proposed statistical model must be modified to provide corrosion depth distribution as a function of time when the Weibull distribution is found to be the best shape. The first step towards this enhancement is to normalise the corrosion depth data based on the predicted averaged corrosion depth for each class of vessel age; this can be estimated using Equation 4.9. The new corrosion depth can be expressed as:

$$x_{norm} = \frac{x_d}{d_{ave(t_v)}} \qquad \text{Equation 4.9}$$

where:

x_{norm} = normalised depth

The effect of this normalising procedure has changed the value and variation of corrosion depth since the averaged depth is different for each class of vessel age. Each single histogram of corrosion depth grouped by the vessel age now has a different size of class/bin. All of the data with the new class of depth value must to be rescaled and regrouped so that a new histogram of the whole data can be constructed. Table 4.4 shows the presentation of normalised depth with the new size of the class. The same procedure as that applied in section 4.3.2 is repeated. An average value and standard deviation of corrosion depth are estimated individually for each class of vessel age. The graphs of average and standard deviation value have been plotted against vessel age to develop a relationship between the progress of normalised average of metal loss and time (vessel age). From Figures 4.9 and 4.10, it may be deduced that the averaged metal loss is still scattered over the time. There is an indication of the increment of averaged depth; however the normalised standard deviation seems to be constant over time. The new normalised and regrouped data shows a better trend of constant variation of corrosion depth over time. The linear equation for the normalised average of corrosion depth over time is expressed as:

$$d_{ave} = 0.0064.t_v + 0.5144 \qquad \text{Equation 4.10}$$

The new Weibull distribution function can be written as follows:

$$f_x(x_d) = \frac{1.05(x_{norm})^{0.05}}{0.87^{1.05}} \exp\left[-\left(\frac{x_{norm}}{0.87}\right)^{1.05}\right] \qquad \text{Equation 4.11}$$

By inserting Equation 4.9 into Equation 4.11, the function can now be expressed as:

$$f_x(x_{norm}) = \frac{1.05\left(\frac{x_d}{d_{ave}(t_v)}\right)^{0.05}}{0.87^{1.05}} \exp\left[-\left(\frac{x_d}{0.87.d_{ave}(t_v)}\right)^{1.05}\right] \qquad \text{Equation 4.12}$$

and the time effect is added by inserting Equation 4.10 into Equation 4.13.

$$f_x(x_{norm}) = \frac{1.05\left(\frac{x_d}{0.0064.t + 0.5144}\right)^{0.05}}{0.87^{1.05}} \exp\left[-\left(\frac{x_d}{0.0056.t + 0.4475}\right)^{1.05}\right] \qquad \text{Equation 4.13}$$

The cumulative function then can be written as follows:

$$F(x_{norm}) = 1 - \exp\left[-\left(\frac{x_d}{0.0056.t_v + 0.4475}\right)^{1.05}\right] \qquad \text{Equation 4.14}$$

The Weibull function of normalised depth can now be used to predict the distribution of corrosion depth at any points of time. The location parameter, δ for both Exponential and Weibull distributions of corrosion depth was assumed as zero for any prediction time. This implies the smallest measurement of corrosion depth at any time will be zero. The Weibull distribution model is having a constant shape factor, β over time whereas the scale parameter, θ increases proportionally to the averaged normalised depth. This can be proven mathematically as follows.

The Weibull PDF function of normalised data is presented as follows;

$$f_x(x_{norm}) = \frac{\beta\left(\dfrac{x_d}{d_{ave}(t_v)}\right)^{\beta-1}}{\theta^\beta}\exp\left[-\left(\frac{\left(\dfrac{x_d}{d_{ave}(t_v)}\right)}{\theta}\right)^\beta\right] \qquad \text{Equation 4.15}$$

Equation 4.15 is rearranged to exclude the expression of linear regression model from the random value of corrosion depth, x_d.

$$f_x(x_{norm}) = \frac{\beta(x_d)^{\beta-1}}{(d_{ave}(t_v))^{\beta-1}.\theta^\beta}\exp\left[-\left(\frac{(x_d)}{d_{ave}(t_v).\theta}\right)^\beta\right] \qquad \text{Equation 4.16}$$

and

$$f_x(x_{norm}) = \frac{\beta(x_d)^{\beta-1}}{\left(\dfrac{[d_{ave}(t_v)]^\beta}{[d_{ave}(t_v)]}\right).\theta^\beta}\exp\left[-\left(\frac{(x_d)}{d_{ave}(t_v).\theta}\right)^\beta\right] \qquad \text{Equation 4.17}$$

Therefore, the final expression of Weibull function can be written as;

$$f_x(x_{norm}) = \frac{d_{ave}(t_v).\beta(x_d)^{\beta-1}}{(d_{ave}(t_v).\theta)^\beta}\exp\left[-\left(\frac{(x_d)}{d_{ave}(t_v).\theta}\right)^\beta\right] \qquad \text{Equation 4.18}$$

The new scale parameter, θ_{new} can be expressed as;

$$\theta_{new} = d_{ave}(t_v).\theta \qquad \text{Equation 4.19}$$

Equation 4.18 can be written in a simpler form as follows;

$$f_x(x_{norm}) = \frac{d_{ave}(t_v).\beta(x_d)^{\beta-1}}{(\theta_{new})^{\beta}} \exp\left[-\left(\frac{(x_d)}{\theta_{new}}\right)^{\beta}\right] \qquad \text{Equation 4.20}$$

Equation 4.20 shows that the new scale parameter, θ_{new} is proportional to the averaged depth which was derived from the linear regression model. The older the vessel, the deeper the averaged depth hence the larger the new scale parameter. The scale parameter then defines the mean and variance of the Weibull distribution (see Section 3.2.4 Chapter 3). As a conclusion, when corrosion progresses, the increment of averaged depth will affects the scale parameter hence changes the mean and variation of the Weibull distribution. However, the distribution shape defined by the shape parameter, β still remained the same, unaffected by the time of prediction. The change of the distribution variation is due to the inclusion of new defects growth every time corrosion prediction is made (see Figure 4.8).

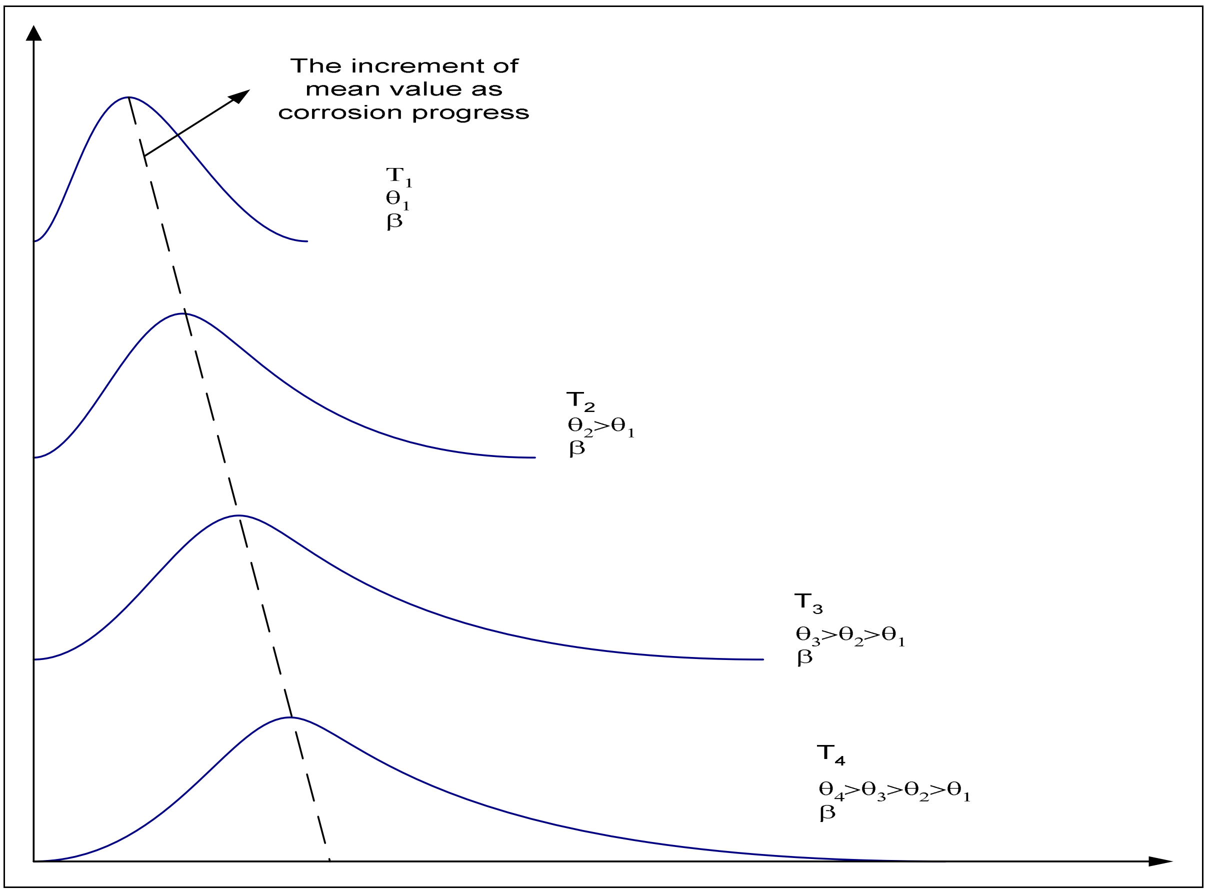

Figure 4.8: The increment of the Weibull scale parameter as corrosion progress for normalised data.

Table 4.4: Data of corrosion in seawater ballast tank (Rescaled and regrouped)

Age (year)	Depth of corrosion (mm)								
	0.625	**1.875**	**3.125**	**4.375**	**5.625**	**6.875**	**8.125**	**9.375**	**Total**
11.25	2	0	0	0	0	0	0	0	2
11.75	19	4	0	0	0	0	0	0	23
12.25	7	5	6	0	0	0	0	0	18
12.75	23	2	0	0	0	0	0	0	25
13.25	21	33	19	1	0	0	0	0	74
13.75	9	0	0	0	0	0	0	0	9
14.25	4	2	0	0	0	0	0	0	6
14.75	2	1	0	0	0	0	0	0	3
15.25	26	15	6	3	0	0	0	0	50
15.75	9	1	0	0	0	0	0	0	10
16.25	5	0	0	0	0	0	0	0	5
16.75	15	9	3	1	1	0	0	0	29
17.25	19	1	0	0	0	0	0	0	20
17.75	84	2	5	0	0	0	0	0	91
18.25	48	50	11	2	2	0	0	0	113
18.75	1	2	0	0	0	0	0	0	3
19.25	58	10	13	2	0	0	0	0	83
19.75	90	5	1	0	0	0	0	0	96
20.25	184	20	0	0	0	0	0	0	204
20.75	20	19	16	8	0	0	0	0	63
21.25	99	28	8	0	0	0	0	0	135
21.75	10	2	3	0	0	0	0	0	15
22.25	7	1	0	0	0	0	0	0	8
22.75	22	5	3	0	0	0	0	0	30
23.25	41	7	0	0	0	0	0	0	48
23.75	11	1	0	0	0	0	0	0	12
24.25	17	10	0	0	0	0	0	0	27
24.75	32	3	0	0	0	0	0	0	35
25.25	77	94	58	0	0	0	0	0	229
25.75	11	2	3	0	0	0	0	0	16
26.25	16	1	0	0	0	0	0	0	17
26.75	7	1	0	0	0	0	0	0	8
	996	**336**	**155**	**17**	**3**	**0**	**0**	**0**	**1507**

4.3.4 Prediction result

The Weibull function model was utilized to produce artificial corrosion data which later compared with the measured data in the same class of vessel age. The error of comparison between predicted and actual defect histogram is measured using Root-mean-square-error method (RMSE). Six sets of corrosion data histogram were generated using numerical simulation and inverse transformation method for every single group of vessel's age class. Since the predicted data is based on pseudo-random process, the selection and histogram comparison were repeated six times to get the averaged RMSE in order to minimise the error due to random selection. Overall, the comparison work on every single histogram of corrosion depth according to its vessel's age class yields range of RMSE between $\pm$0.4 to $\pm$28.8(refer Figure 4.12).The prediction results are enlarged by focusing on four histograms belongs to vessel's age class of 18-18.5 years, 19.5-20 years, 20-20.5 years, and 21-21.5 years old. These age classes were chosen due to the high number of data collected during onsite inspection. The generated data was compared with the measured data in the same class of vessel age. Based on the comparison of histogram shown in Figures 4.13 to 4.16, the prediction results yield error values between $\pm$ 4.47 to $\pm$ 14.84.

To visualize the relationship between RMSE values and vessel's age, the average RMSE values are plotted against time. The linear regression equation obtained from Figure 4.17 is likely to contain errors as there is a large spread in plotted data with value of correlation coefficient was estimated approximately at 0.02 indicating poor correlation between averaged RMSE and vessel age. Figures 4.18 and 4.19 however exhibit explicitly the increment of RMSE values as the number of data increases. Three groups of corrosion depth with the highest numbers of measurement of 229, 232 and 282 produce the highest RMSE values. Hence, indicates the diminution of prediction accuracy as the numbers of data increases.

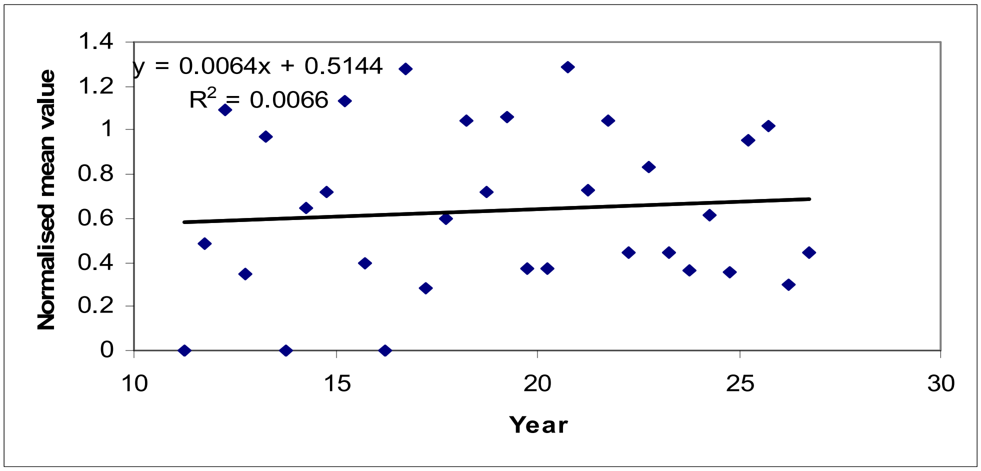

Figure 4.9: Linear regression analysis of mean depth and vessel age (rescaled data)

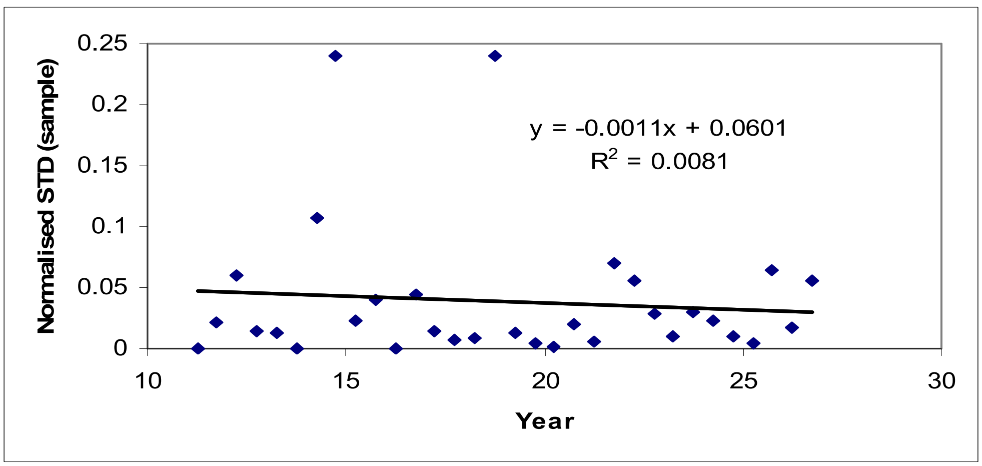

Figure 4.10: Regression analysis of *std* depth and vessel age (rescaled data)

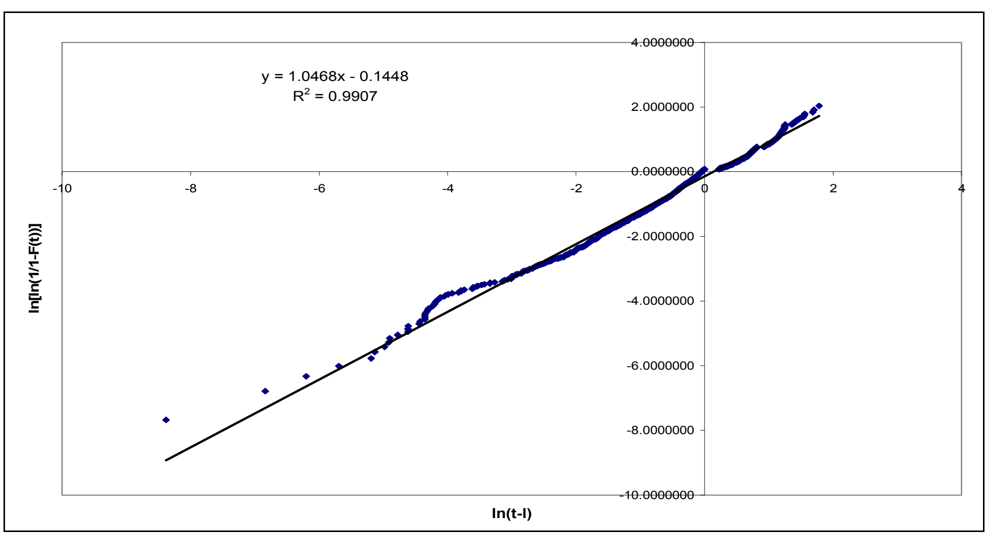

Figure 4.11: Weibull probability plot of rescaled data

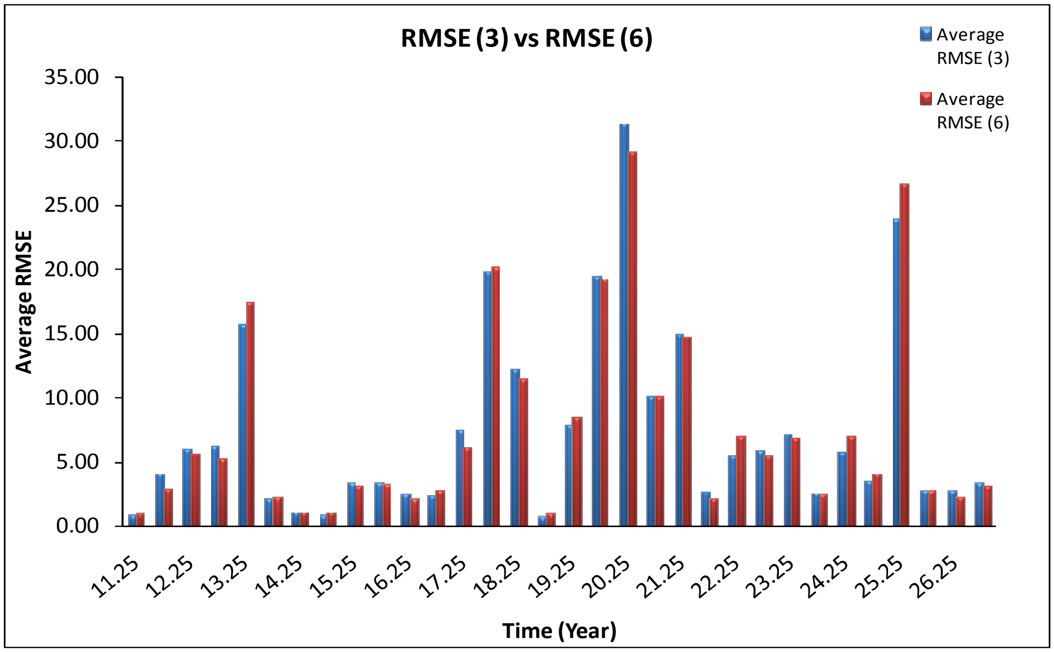

Figure 4.12: Average of RMSE (3 and 6 cycles of selection) from comparison works on artificial and actual data.

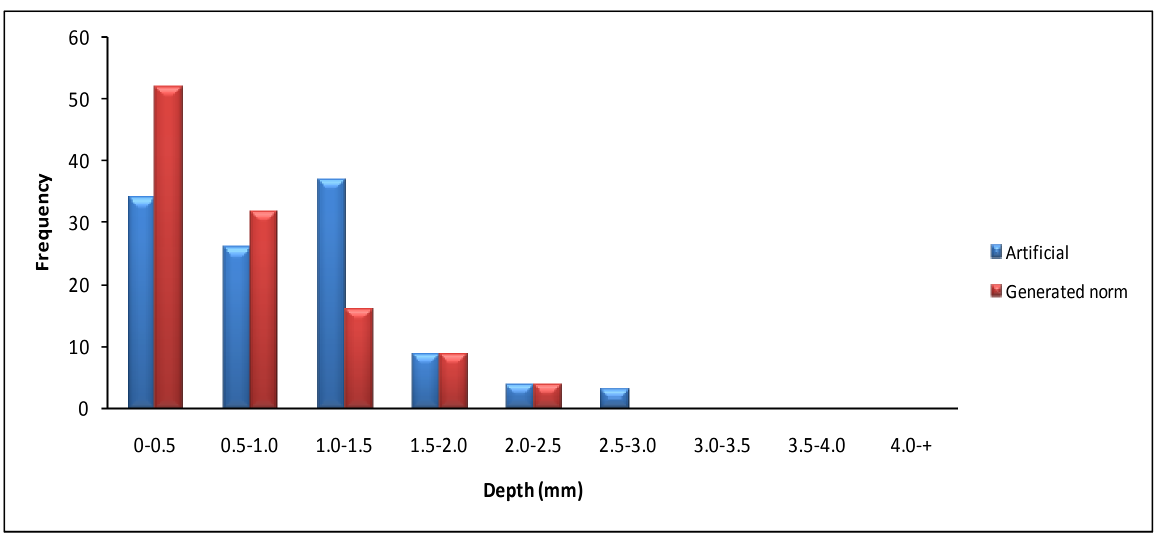

Figure 4.13: Comparison of predicted depth data to actual data for vessel age of 18-18.5 years old (RMSE of $\pm$11.62)

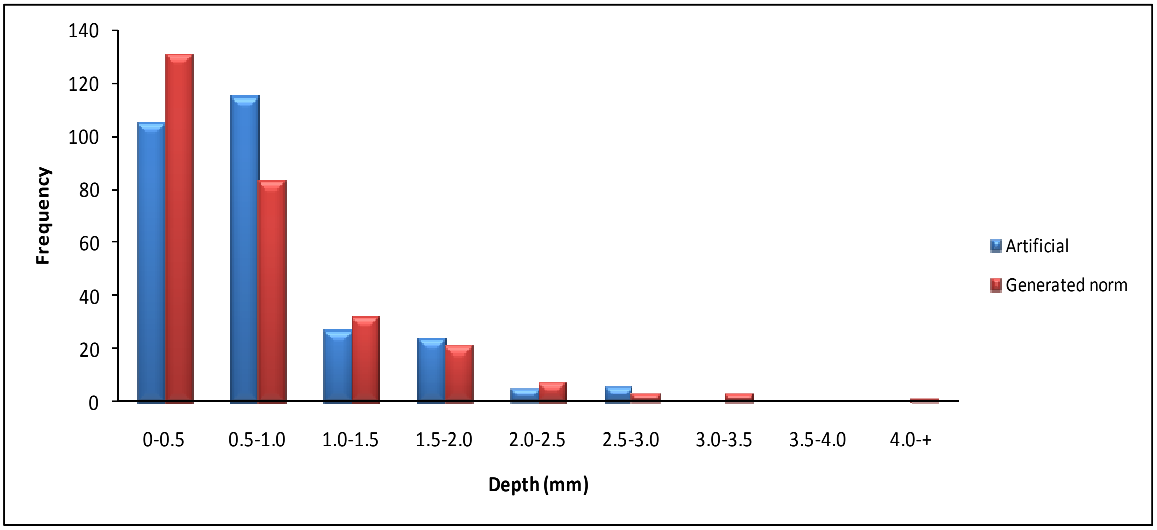

Figure 4.14: Comparison of predicted depth data to actual data for vessel age of 21-21.5 years old (RMSE of $\pm$14.84)

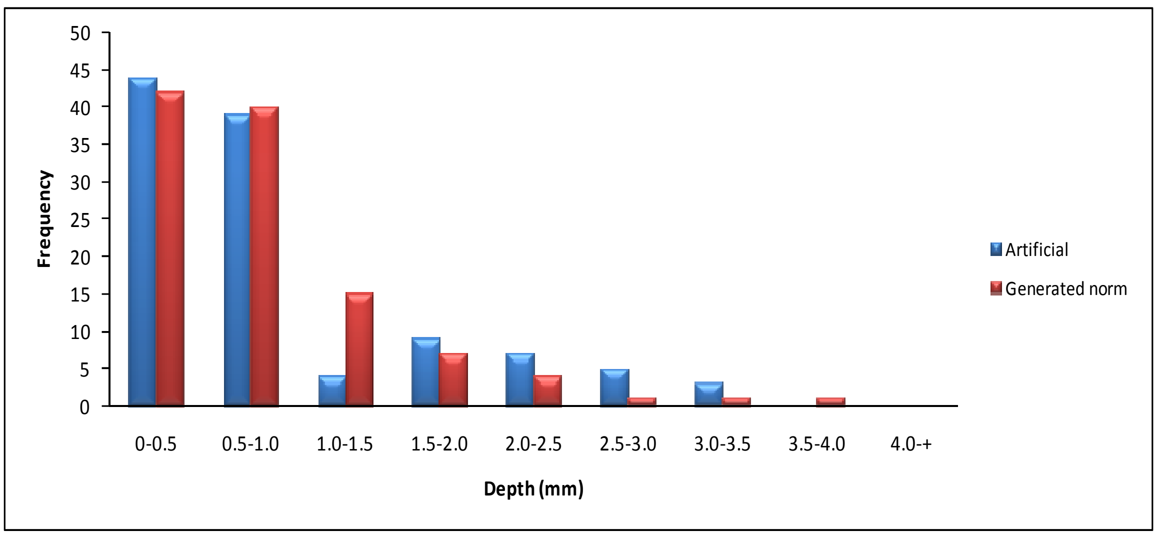

Figure 4.15: Comparison of predicted depth data to actual data for vessel age of 22-22.5 years old (RMSE of $\pm$4.47)

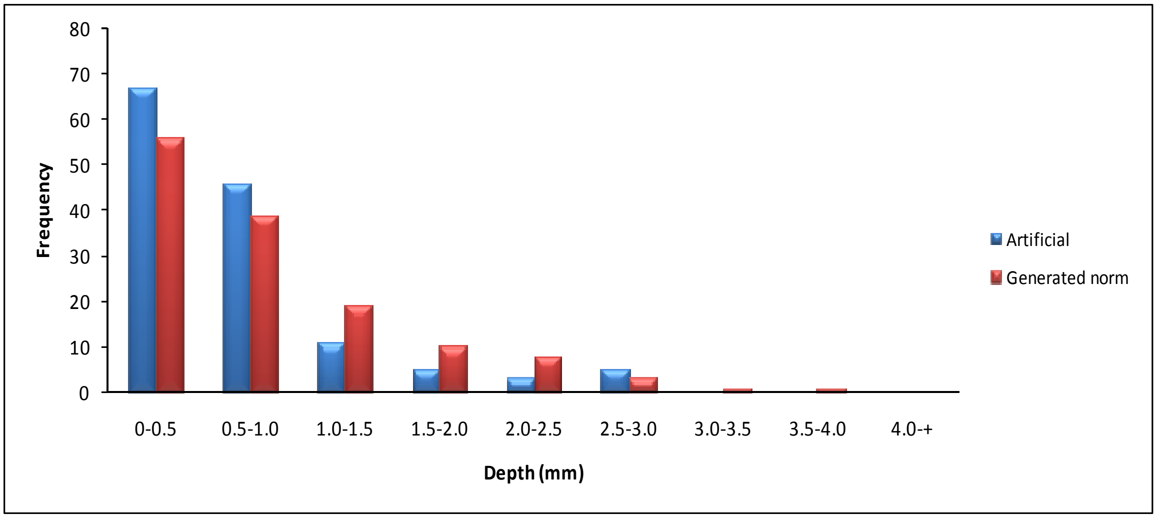

Figure 4.16: Comparison of predicted depth data to actual data for vessel age of 23-23.5 years old (RMSE of $\pm$6.07)

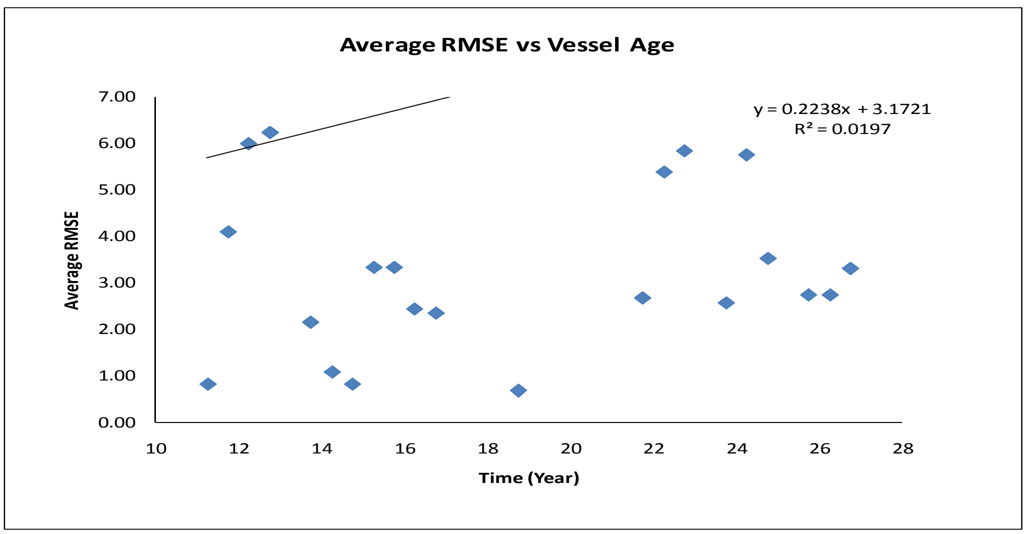

Figure 4.17: Correlation between RMSE and vessel age.

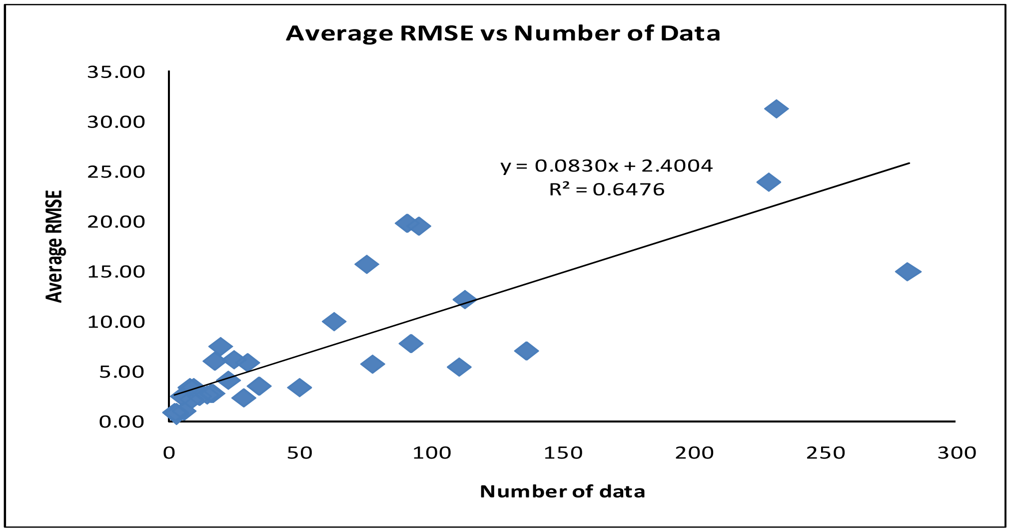

Figure 4.18: Correlation between RMSE and numbers of data.

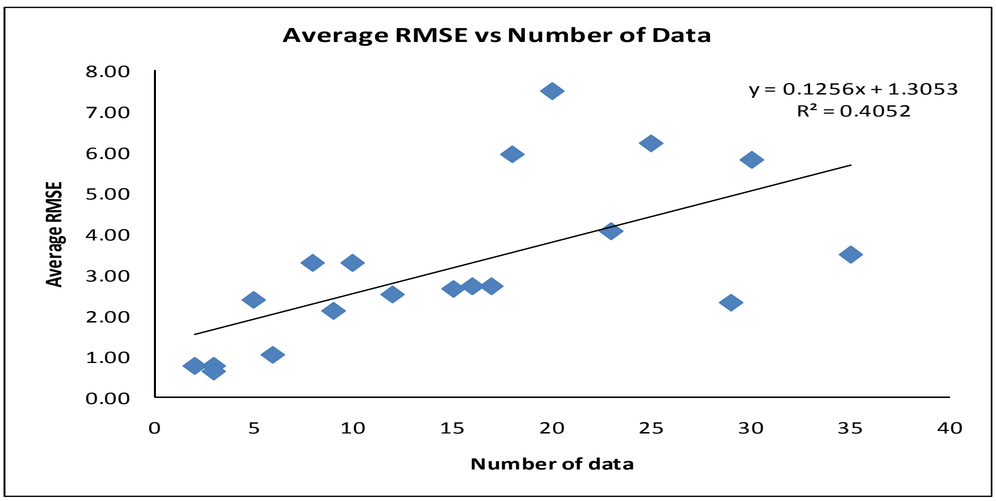

Figure 4.19: Correlation between RMSE and numbers of data below 40.

5.4 Concluding Remarks

This chapter has demonstrated an alternative approach to analysing corrosion data randomly collected from a large number of like assets (in this case vessel's ballast tanks). Rather than making an assumption on the time to the start of the corrosion process and then develop a linear model of corrosion rate, two corrosion depth models which are a function of time have been proposed. The new model can be used to predict the likely variation of corrosion depth at any point of time without having to estimate the corrosion growth rate for each single defect. Even though the value of correlation coefficient were not more than 0.16

indicating poor correlation between averaged depth and vessel age, the incorporation of probability model into the analysis methodology can improve the reliability of the prediction results as well as minimising the errors. Furthermore, the linear regression can be improved once more data from further inspections can becomes available, indicating the flexibility of the model. The provided information from the vessel inspections is full of uncertainties owing to the nature of marine corrosion. The proposed model intends to simplify the modelling process so the available data can be fully utilised for prediction purposes. If more information can be revealed, the prediction model could be improved to achieve a high accuracy of depth prediction at any point of time. High variability of corrosion wastage has been acknowledged by previous researchers [Loseth *et al*., 1994; Melchers, 1999a; Paik *et al*., 2003 and Wang *et al*., 2003]. Hence, statistical analysis on a collection of corrosion measurements seems to be one of the best options to express corrosion rates in seawater ballast tank. The proposed alternative assessment of corrosion data of vessel's seawater ballast tank is shown in Figure 4.20.

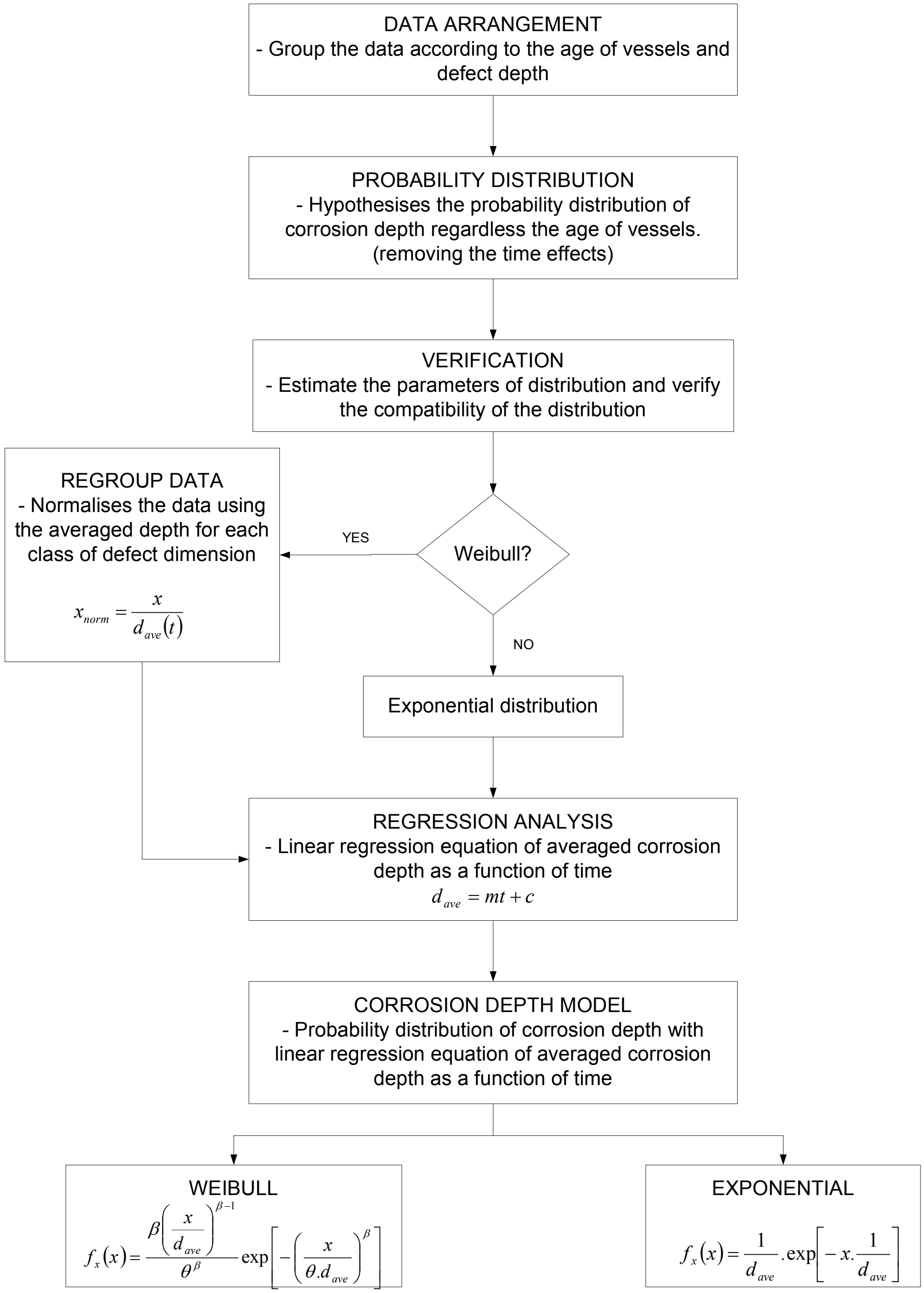

Figure 4.20: Flow chart of a development of corrosion depth distribution with defect depth as a function of time.

CHAPTER 5 - DISCUSSION

5.0 Overview

This chapter discusses the proposed concept of a generic assessment procedure for corrosion data and its application on structure reliability. The assessments of both the pipelines and vessel's seawater ballast tanks have been combined to produce a generic assessment guideline. A discussion of issues related to the assessment of corrosion data and the application of the techniques to structure reliability evaluation has been included to emphasise and strengthen the justification of the research work.

5.1 Summary of Generic Assessment Procedure of Corrosion Data And Structure Reliability

The proposed generic procedure of corrosion data assessment consists of four stages: data identification, statistical and probability analysis, data prediction and structure assessment. The generic term is used specifically to emphasise the flexibility of this procedure for implementation on different types of structures that suffer from localised corrosion attack, regardless of the types of inspection tools used for data collection. As long as the dimension of a corrosion pit can be measured by the inspection tool, the proposed generic assessment procedure is suitable for use to evaluate and predict the future growth of corrosion defects and the remaining life-time of the structures. Figures 5.1 and 5.2 depict the flow charts of the proposed generic assessment procedure.

5.1.1 Stage I: Data identification

There are two types of inspection data sets: single set and multiple set. Each set needs a different approach to extract fully the information regarding the corrosion growth parameters.

5.1.1.1 Single Set of Corrosion Data

For single set of corrosion data, estimating the corrosion growth rate value using a linear model based on metal loss evidence is possible only if information on the corrosion protection system (internal coating) is available. Without this information, an assumption must be made as to whether the corrosion started to grow immediately after the structure was placed into service or, alternatively, if corrosion initiation was delayed owing to the protection from the coating system. Then, the simple linear model can be used to estimate the corrosion growth rate value for each single defect. This simple method will produce only positive growth value; hence no correction method to deal with unreliable growth value is required.

The other way to use single set data in predicting the future growth is by analysing the probability distribution of corrosion depth which the defect depth is modelled as a function of time (see Chapter 4). The time variation along with the distribution can then be used to predict if the averaged corrosion depth is increasing with time, and the probabilistic distribution of corrosion depth at any point of time or structure age can be also be defined. This method has been tailored for grouped data obtained from a large number of structures. All single sets of data are grouped together as one sample of corrosion depth. This sample can then be grouped by the dimension of depth and the structure age. A deterministic linear model of corrosion depth (averaged depth) as a function of time is then combined with the appropriate probability distribution of corrosion depth to predict the future distribution of defect depth at any point of time in the life of the structure.

5.1.1.2 Multiple Set of Corrosion Data

Multiple set of corrosion data from the same structure will enable the estimation of corrosion growth rate using a linear model based on evidence from the measurement of metal loss volume of the individual defects detected in two, or more, inspections. This can be achieved by matching the corresponding defect from previous inspection with that from the next inspection. The linear estimation of corrosion growth rate does not require any variables related to the operational condition, structure material and environmental properties which are considered to have an effect on corrosion growth rate as proven through extensive laboratory work by previous researchers. The advantage of having multiple sets of corrosion data apart from the simple linear estimation of corrosion growth rate is that it provides an opportunity to evaluate the quality of inspection data. Multiple sets of data allow the development of correction methods and theoretical models related to linear growth of corrosion, and provide a good platform for comparison of data prediction so that the accuracy can be verified (see Chapter 3).

5.1.2 Stage II : Data Sampling

The main aim of this second stage is to provide a group of matched data for statistical and probabilistic analysis purposes. This stage requires at least two sets of corrosion data, collected between two different times of inspection activities from the same structure to estimate the corrosion growth rate. The data sampling procedures can also be used as an initial step to determine the likelihood of errors by estimating the sampling tolerance to quantify the difficulty during data matching.

5.1.2.1 Data 'Feature-To-Feature' Matching Procedure

Corrosion dimensions, including depth and axial length can be used to estimate the corrosion growth rate. Therefore, the availability of two sets of corrosion data or more is important to model the corrosion growth rate based on the metal loss evidence. The feature-to-feature data matching procedure can be accomplished by sampling the corrosion dimension based on the distance and orientation/position in the structure (see Section 3.2.1.2). During the sampling process, factors resulting from possible errors within the data caused by imperfect measurement by the inspection tools should be considered. It has been noticed that negative growth is possible owing to both imperfect measurements by the inspection tool as well as human error. As a result, finding the absolute location of the same defect from two inspections will be almost impossible without having an acceptable sampling tolerance. The data matching process has to be done iteratively in order to obtain as many amounts of matched data as possible, by increasing the sampling tolerance until a sufficient amount of matched data can be achieved. Yahaya and Wolfram [1999] have suggested that the amounts of matched data should be around 25% from the actual data, or alternatively a minimum numbers of 500 data points to improve the reliability of the corrosion growth estimate.

5.1.2.2 Data Grouping

If corrosion data was collected from huge number of similar structures, all single set of data can be combined and grouped by the depth measurement and the age of structure to produce one large sample of corrosion depth. The main intention of combining all sets of data from different structures as demonstrated by analysis on the vessel's ballast tank is to develop a probability distribution of corrosion depth for the whole set by removing the effects of time (see Section 4.3). Then, data from each class of structure age can be used to develop a linear regression equation representing the averaged depth as a function of time. The regression equation is then combined with the corrosion depth distribution to estimate the likely distribution of corrosion depth at any point of time. The requirement of corrosion initiation time for linear estimation of corrosion growth rate is not necessary for grouped data. Instead, the future growth of defect depth can be predicted directly without estimating the corrosion growth rate value since the corrosion depth distribution is modelled as a function of time.

5.1.3 Stage III: Statistical and Probability Investigation

The next stage is the implementation of the statistical and probabilistic techniques to analyse the corrosion properties and growth rate. Expected findings from this stage are the statistical parameter represented in the form of a probability distribution to cater for the variation of each corrosion-related parameter (corrosion rate and corrosion depth).

5.1.3.1 Sampling Tolerance

In order to characterise the sampling tolerance on corrosion data, analysis of the difference in relative distance and orientation has been performed to evaluate the difficulty of the matching the data (see Section 3.2.2.1). Each set of the matched data between two inspections can be characterised by estimating the relative difference between two located defects which are believed to be the same defect. The relative distances are called the sampling distance. This distance can provide information about the quality of the matching procedure. This in turn can help to illustrate the accessibility of the matched data. If the number of matched data is low (for example less than 25% of overall data) due to distance error, sampling distance can be increased to increase the amount of matched data but with a greater chance of mismatch.

5.1.3.2 Corrosion Properties Analysis

The information on defect depth, length and growth rate for both dimensions is very important for assessing the reliability of a corroded structure. It is also necessary to determine the correlation between defect depth and length if the length parameter is thought to affect the structure performance, such as in offshore pipelines. If there is a strong correlation between defect depth and length, the projection of corrosion length in the future can be carried out using the same growth rate as that found for corrosion depth. If little or no correlation exists, the prediction of corrosion length has to be carried out independently using a different corrosion growth rate value. In this study, it was assumed that the defect length growth was independent of depth growth; hence the corrosion growth distribution of defect length was developed separately from the distribution for defect depth. This is based on the correlation analysis which shows a very weak relationship between the growth of defect length and depth.

5.1.3.3 Correction Methods

The averaged value of corrosion growth rate can give an early indication of the error severity due to imperfect measurement by inspection tools or human error during data sampling. If the average of corrosion growth rate indicates a negative value or positive value with a large standard deviation which extends the possible growth rates into high negative values, the data might be considered to be unreliable for prediction purposes unless an appropriate correction method is applied to minimise the error. Therefore, four types of correction methods have been proposed and developed to correct and reduce the embedded error within the corrosion data (see Section 3.4). The Z-score method can be used to reduce the amount of negative growth rate when this is assumed to be normally distributed (see Section 3.4.1.1). However, the Normal distribution is a poor choice when there is a relatively small amount of negative growth rate, and for this case the Exponential distribution is proposed to remove the negative growth value (see Section 3.4.2). A more complicated technique is the "modified corrosion rate method" designed for multiple sets of data. This method will produce a correction factor, so one set of corrosion data which is assumed to be flawed can be corrected (see Section 3.4.1.2). The corrected data may then be used with its corresponding set to re-estimate the corrosion growth rate. It is worth mentioning that although the proposed correction methods are relatively crude, they have been shown to provide a reasonable means of handling the negative growth effects for future data prediction.

5.1.3.4 Determination of Distribution Parameters

Reliability analysis requires data in the form of a probability distribution. For that reason, the corrosion dimension and corrosion growth rate have to be represented by an appropriate distribution. A hypothesis of the best type of distribution to represent the corrosion data is derived by observing the shape of the histogram of the corrosion data. From this hypothesis, the distribution parameter is computed using probability plotting. Chi-square goodness of fit test and probability plot have been used to test whether the corrosion data can be fitted under the proposed distribution.

5.4 The Accuracy Of Assessment

The generic assessment procedure offers reasonable simplicity of approach in comparison with the complexity of the current methods of corrosion assessment which are based on identifying specific types of corrosion within individual structures. The current mechanical and empirical corrosion models are sometime too complex in that many parameters related to material and environmental conditions are required to estimate the corrosion growth rate. The accuracy of these models could be jeopardised by its very complexity and the unknown variability of the required parameters. Based on this hypothesis, the generic assessment procedure as proposed certainly reduces complexity and is designed to minimise the uncertainties arising from variations in operational condition, structure material, and environmental properties. However, its simplicity might trigger other sources of uncertainty owing to the assumption of a linear estimation of corrosion growth rate. The application of statistical methods has been applied to minimise the effect of linear estimation on the accuracy of prediction.

The accuracy of the prediction of future data and remaining structural lifetime by this generic assessment procedure can be measured and justified only once new data becomes available. Therefore, it is of important that plant engineers or inspection personnel make a continuous assessment by comparing the previous prediction of structure reliability with the current condition of the structure. At some stage, once the assessment work can cover most of the sources of the uncertainty, the highest accuracy of data prediction and future structure reliability evaluation can be achieved.

5.5 Linear Growth Model

One of the disadvantages of using a linear growth model in corrosion assessment is the uncertainty of corrosion growth throughout the duration of the projection. The longer the projection, the more uncertainty that is involved. The linear model has some serious limitations that can cause significant error of prediction if not applied properly. For example, it is not able to include the probable physical effects to corrosion rates following the alteration of electrochemical factors inside the structure [Yahaya, 1999]. Moreover, extreme changes in the corrosion caused by unforeseeable circumstances cannot be predicted [Yahaya, 1999]. These factors do affect significantly the accuracy of a linear prediction. As a result, a random linear model has been proposed specifically to include the random changes of corrosion growth rate because of the factors discussed previously. It is hoped that the random changes of corrosion growth rate selection throughout the projection period will minimise the uncertainties, especially for a long term projection. The inclusion of the random linear model will increase the random nature of corrosion growth and make the prediction more flexible. Since it is not possible to know if the corrosion growth is increasing or decreasing with time without detailed knowledge of operational condition, the random linear model seems to be a reasonable option to cover the uncertainties.

Previous researchers asserted that the deepest defects are bound to grow at a very high rate, and hence become the most likely site to fail. The correlation analysis shows that the corrosion defects grow at a random rate regardless of the dimension of the pit in contrast to this commonly held assumption (see Section 3.2.2.4). The engineers or inspection personnel are given the option to include this common assumption in the reliability assessment. An extreme linear growth model has been proposed to allow a random defect, with a depth greater than the averaged value, to grow faster than a shallower, non severe, defect. The growth rate depends on the ratio between the random defect depth and its averaged value, and also the random growth rate. The structure reliability assessment based on the simulation results show an early exceedance of limit state failure if the extreme growth model is included in the simulation. The simulation results, based on extreme growth and non-extreme growth linear model, would give a reasonable time frame of possibility of two failure events, hence increasing the awareness of the future condition of the structure under corrosion attack by taking into account different aspects regarding the nature of corrosion growth.

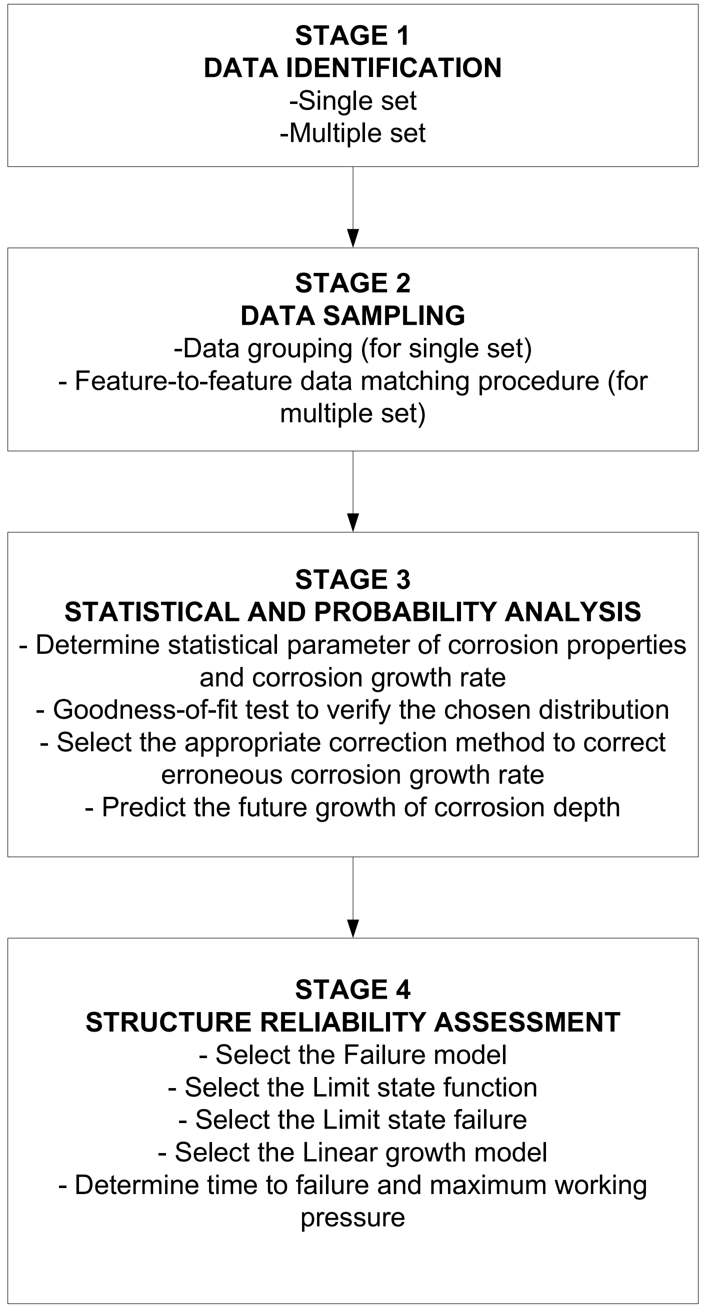

Figure 5.1: General illustration of the proposed assessment procedure for corrosion data and structure reliability analysis.

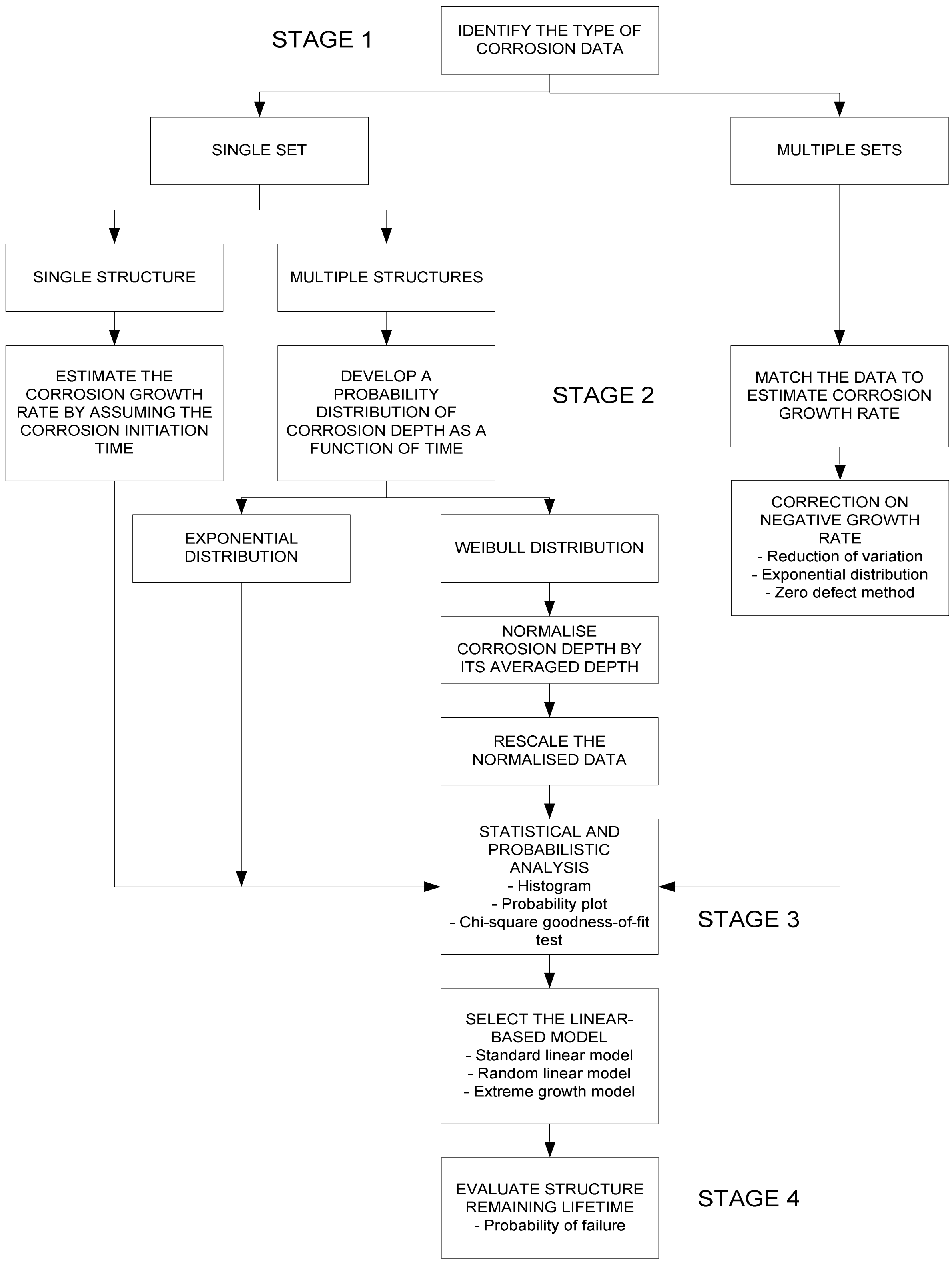

Figure 5.2: Detail illustration of the component of generic assessment procedure for corrosion data and structure reliability analysis.

CHAPTER 6 – CONCLUSIONS

6.1 Conclusions

It can be concluded that the proposed research work has been successfully accomplished. The final findings from the research work have sufficiently fulfilled the aim of this research in developing a generic assessment approach to the analysis of corrosion data and structure reliability. The achievements from this research work can be summarised according to each research objectives.

6.1.1 Analysis of inspection data using statistical methods to extract information about corrosion behaviour.

Thorough investigations on pipelines and vessel's ballast tank data of corrosion defects were carried out to demonstrate how inspection data can be utilised fully to improve the understanding of corrosion progress. Statistical analysis was deployed to determine the most appropriate distribution for the key parameters of corrosion dimension and corrosion growth rate. The analyses of the corrosion data from offshore oil pipelines and vessel's seawater ballast tanks were carried out separately because of the difference in the data collection method. The findings from this section are concluded as follows:

1. The pigging data from the internal monitoring of pipeline structures represents the case for which repeated inspection data are available which allows the feature-to-feature data matching procedure to estimate the corrosion growth rate. The data matching procedure has been proven to be practical and allows estimation of the corrosion growth rate for each single paired defect. When the normal analysis yields negative growth rate, several correction approaches have been shown to improve the reliability of corrosion interpretation.

2. The vessel's seawater ballast tank inspection data represent the case where only a single database is available, hence data matching is not an option to estimate corrosion growth rate. This corrosion database consists of a large amount of data collected through random inspection involving a great number of vessels, and this requires different analysis technique. A technique for predicting the future growth of defects in the vessel's seawater ballast tanks was developed based on a combination

of probability distribution for the defect depth and linear regression equation of averaged depth as a function of time. This new approach enables the prediction of future corrosion depth of the whole database without having to rely on the coating resistance value to estimate the onset of corrosion. This represents an alternative solution when a large amount of data from several inspections is grouped together in one database as if the data represent a single structure.

3. Both the above approaches have been developed to provide an alternative solution to the engineer and inspection personnel so that the available corrosion data can be fully utilised for structural assessment purposes. The proposed analysis approaches can be applied to (i) a multiple set of data from repeated inspection or (ii) a single set of data, either from a single structure or grouped data from a great number of structures compiled in one single database.

6.1.2 The development of a generic corrosion-related model with suitable data correction methods.

The primary aim of the part of work was to show that a model of the corrosion data that was based solely on metal loss evidence and which eliminated the dependency of the model on explicit information on material and environmental properties could be formulated. The uncertainties associated with the inspection data, arising from various sources was exemplified by the appearance of apparent times of negative corrosion growth rate, a physically unrealistic case. The specific conclusions on this part are as follows;

1. *Pipelines B* and *C* were each found to have a negative average corrosion growth rate for defect depth. The negative rate was expected prior to data analysis. Sources of errors were noticed early during the observation stage where *Pipeline B* data indicated a ‘missing’ 6km of total inspected pipelines length in year 1990 compared with the inspections in years 1992 and 1995. This has resulted in high sampling tolerance required to obtain sufficient matched data based on 1990 set. The errors are possibly caused by imperfect dimension measurement by pig tools or by human error during data interpretation and data matching.

2. Several correction methods were proposed and developed to correct the existing error and increase the reliability of the pigging data. The reduction variation techniques of modified variance and modified corrosion rate methods were used to reduce the standard deviation of the Normal distribution of the corrosion growth rate. The Exponential distribution was proposed as an alternative correction method since the Normal distribution is a poor choice for corrosion growth rate due to the existence of negative value for growth rate. The proposed correction methods are simple yet practical for improving the reliability of corrosion information. This work has shown how the correction methods can be used for flawed inspection data so that structure assessment is still possible. Since the cost of inspection and maintenance work is very high, it is necessary for the engineer not to neglect any single inspection data just because the information obtained from the data is apparently not reliable. More can still be done by way of improving the data interpretation as demonstrated by this research work.

3. A time interval-based error theory was proposed to represent the relationship between the frequency of inspection and the quality of the corrosion data. If the structure operator conducted inspections within a short time interval (say every two years instead of every five years), the corrosion progress might not be identified because of the slow progress of defect growth. Any prediction of future growth based on data from repeated inspection within a short time interval might be flawed, especially when such a prediction was made based on a linear model. Therefore, it is of importance for structure operator to schedule the frequency of inspection work satisfactorily. The inspection should not be carried out within a short time interval, nor should it be done too frequently to reduce the total operational cost and uncertainties. Nevertheless, they must be balanced against the failure cost of the structure. If too long a time passes before the next inspection this might be too late to secure and improve structure remaining life time especially when new data indicates more extreme defects which have great potential to leads to structure failure.

4. Two linear-based corrosion growth models were proposed to deal with the random nature of corrosion. The random linear model was introduced to minimise the uncertainty due to the changing of physical nature of corrosion throughout the

operational period of the structures. The extreme growth model was proposed to allow extreme defects to grow faster than non extreme defects in the simulation if the depth measurement is higher than the averaged depth of defect sample. This is to satisfy the theory of the rapid growth of severe corrosion defects. The accuracy of both models in predicting the future defect depth was not extensively investigated throughout the research due to limited inspection data. Nevertheless, these models can be verified if new data can become available in the future. The issues of the simplicity of the conventional linear prediction for corrosion growth have been addressed by the introduction of both models. The simplicity of the linear model does not warrant for high accuracy of the prediction results due to the random nature of the corrosion progress. This research has enhanced the application of the linear model by improving the flexibility of the linear model. The new models can be used to reflect the random growth of defects and take into account the possibility of a greater growth rate for severe defect.

5. For the vessel's seawater ballast tank structure, a new method of predicting future corrosion depth without relying on the corrosion initiation time was developed. The technique allows the prediction of future depth to be carried out without estimating the corrosion onset. A deterministic equation of averaged corrosion depth as a function of time is combined with a probability distribution of corrosion depth derived from the whole data as one sample. The proposed analysis technique was specifically tailored to apply to data collected from a number of structures which are grouped together as one large sample. The proposed correction methods and corrosion related models were developed independently of operational conditions, materials, and environmental properties to make it as a general and simple application yet practical on corrosion data.

6.2 CONTRIBUTION

1. The proposed generic assessment approach can be applied to two common sampling methods. A feature-to-feature matching procedure is intended for repeated inspections of data. A new data sampling technique specifically designed for single inspection data where the issues of unknown corrosion initiation time can be resolved has also been developed. The generic method has an improved flexibility for practical use compared to the existing assessment methods.

2. The issues of negative growth rate obtained from the data feature-to-feature matching procedure have been addressed by the development of several correction methods. This reflects the importance of utilizing fully the inspection data regardless of the quality, since the inspection activities contribute significantly to the total cost of the structure.

3. The linear growth model has become a widespread method to predict future corrosion growth, especially when there is not enough information gathered on site to model the actual corrosion growth form. This research has demonstrated how the reliability of a linear model, whose accuracy is frequently questionable, can be improved to address the issues of corrosion randomness and differential growth of severe defects.

4. Overall, the proposed data sampling techniques, correction approaches and alternative linear models have been specially designed for use on corrosion measurement from different types of structures, regardless of the types of inspection tools used during on site inspections. The proposed approach offers a generalised assessment of corrosion data which is more practical than current methods. It also provides great flexibility due to the range of different choices for data sampling, correction methods, and linear models offered. This will assist the decision-making based on the assessment of inspection data for structure reliability analysis

6.3 Further Work

Further research can be carried out to enhance the final findings. Therefore, several suggestions can be made for the research work in the future.

1. It is suggested that a computer programme is developed to automatically match the corrosion data from repeated inspections as a part of the assessment procedure. The manual data matching procedure as practiced by this research is a time-consuming work and might be vulnerable to human error. Even though repeated sampling would minimise the effect of human error, the automatic data matching by using computer software could speed up the sampling process.

2. Only pitting corrosion was considered in the analysis. Therefore, the effects of other forms of corrosion especially uniform corrosion largely found in concrete reinforced steel structures can be further studied to improve the generality of the proposed assessment approach of corrosion data and structure reliability. The proposed data sampling and correction approaches in theory can be applied to uniform corrosion data assessed by the area of metal loss.

3. The research work can be enhanced by emphasising on the optimisation problem where the expected lifetime costs can be minimised with a constraint on the minimum acceptable reliability level. The study of pipeline costing for inspection and maintenance can be carried out to specify the frequency of inspection in the future and the right type of inspection device to be used, whether high or low resolution. Moreover, the effects of the time interval between inspections (inspection frequency) can be studied extensively to determine the relationship between data reliability and time interval between inspections in terms of structure failure cost.

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