MECHANIZE FEATURE-TO-FEATURE MATCHING SYSTEM UTILIZING REPEATED INSPECTION DATA

Mazura Mat Din[1], Norhazilan Mohd. Noor[2], and Md. Asri Ngadi[1]

[1]Faculty of Computer Science and Information Systems
Universiti Teknologi Malaysia
81310 Skudai, Johor
[2]Department of Structure and Material
Faculty of Civil Engineering
Universiti Teknologi Malaysia
81310 Skudai, Johor
Email: [1,2]{mazura,norhazilan,dr.asri}@utm.my

Abstract: The advances of computational methods and tools can greatly support other areas in doing tasks from the most tedious or repetitive to the most complex. In this paper, these advances were manipulated in civil structures maintenance specifically in pipeline corrosion assessment. This paper describes mechanize method developed to automatically detect and quantify important parameters for future prediction of corrosion growth using In-line inspection (ILI) data. The focal process in this system includes data conversion, data filtering, parameter tolerance or sizing configuration, matching, and data trimming. A sensitivity analysis using linear regression method was used to correlates defects from one inspection to the next. Issues and advantage gain from this mechanize system is threefold: Firstly, timeliness (manual matching procedure consumed a great deal of time). Secondly, accuracy and consistencies in data sampling (current implementation, different researcher obtain a different number of sample even though the method used in matching were the same), and finally, reduction of data matching error (manual matching was prone to human error due to the masses of inspection data to be match. Furthermore this method is impractical when facing the large amount of real inspection data).

Keywords: Mechanize matching system, repeated inspection data, sensitivity analysis

1. INTRODUCTION

A marine structure, e.g. pipeline, although simple in nature, has a complex range of continually changing, interacting events and operating conditions that must be carefully understood and managed. Based on The Health and Safety Executive (HSE) report (HSE, 2002), they outline some possible issues which confronted by structural analysis problem such as, most plant engineers and inspection personnel are facing a difficulty in understanding the analysis methods available due to the complexity of corrosion empirical models and statistical techniques. This leads them to conduct the assessment manually.

Although corrosion assessment procedure is a well research area, little attention has been paid on the early stage of assessment which leads to unavailability guidelines for data analysis in simplified form to suit the application on site. The non-existence standard to analyze the inspection data related to corrosion measurement, whilst the standard exists for statistical analysis of laboratory corrosion test data only. In such cases, most data were applied in multi-format form such as paper records, digital (spreadsheets), and databases.

As been suggested by Noor (Noor, 2006), the assessment procedure still carried out manually. For example the feature matching processes, a manual conduct of this process is a time consuming work and might be vulnerable to human error. The manual process in analyzing the corrosion means that the diagnosis and interpretation of the corrosion effects depends solely on the experience and the capability of the engineers and inspection personnel, as well as the reliability of the corrosion assessment growth. To compensate the shortcomings of the assessment methods noted previously, a mechanized matching procedure couple is believed to handle the timeliness and accuracies of the task involved. Instead of relying on experimental data, a large amount of inspection data from real structures will give a better insight and accurate information in corrosion assessment. Furthermore, the huge amount of real corrosion inspection data used will need a structured and intelligent processing; however, the technology is yet to be proven (Clausard, 2007).

The use of ILI data in accessing and predicting the remaining life of corrosion structures in traditional engineering and analysis, evolve around the use of complex deterministic approach (calculate an average value on every parameter which unable to eliminate the increases number of uncertainties that occur in inspection data). Furthermore, execution of this approach depended on many variables such as temperature, chemical substances, penetration rate, and partial pressure, which in some circumstances are difficult to measure correctly. This error prone process will lead to inaccurate assessment of the result. In worst cases, this information might not been recorded or vary significantly in different period of service. For example Melcers (Melcers, 1999) stated there's been a conflict whereby some variable that been recognized as a factor in laboratory testing but not in field of observation.

Engineers and inspection personnel of structure systems rely on the accurate interpretation and assessment of condition data for decision making regarding future maintenance. Although good inspection technology exists, the reliability of corrosion assessment is low due to the deterministic and subjective interpretation of inspection data. Managing this workload and transforming mountains of data into useful, practical information is a challenges we going to cater in this study.

To a structure maintenance engineer, gathering data is just the first step in the entire process of maintaining the condition and reliability of the assets. The next step is to take the various sources of data, review and combine them, interpret the data and taking action as appropriate. The absence of mechanize and analyzing standard for exploitation of corrosion inspection data may cause some difficulties (M. Kamrunnahar et al., 2005; Clouston and Smith, 2004; Yahaya, 1999; Clausard, 2006; Perich et al., 2003):

1. Often the operators focused the research on reliability assessment rather than the preceding data analysis which tend to affect the overall result of prediction.
2. Traditional analysis process do not provide sufficient information that can be used for reliability statistical and probabilistic analysis , while reliability method often suffers for inaccuracies caused by less important variables that didn't reflect an actual data.
3. The complexity and time consuming data analysis process tends to overburden the operators involved and may result in poor planning and maintenance scheduling.
4. The reliability assessment quantifies the degradation of the structural capacity (such as pipeline) and provide basis for making decision regarding the rehabilitation.

This paper will focus on utilizing corrosion growth analysis with the objective of mechanizing the feature-to-feature matching system for corrosion repeated ILI data. The term 'mechanize' refers to the consideration of using computing methods that can form a reliable basis for quantitative assessment of structural integrity which taking into account the availability of sufficient amount of inspection data. Furthermore the uncertainty and ambiguity in the data will be addressed through sensitivity analysis as been used in manual matching.

The paper is organized as follows: Section 2 discusses the corrosion growth model and related works. Datasets and case studies includes the types of inspection data and parameters involve was presented in Section 3. Section 4 detailing functions developed in matching system and its subsystems. Section 5 presents the experiment and results from the matching systems using sensitivity analysis. Finally we conclude our discussion in Section 6.

2. CORROSION GROWTH MODEL

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. Only selected model will be discuss in this section due to its applicability to the pipeline application.

2.1 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 (Yahaya and Noor, 2002). 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

2.2 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). 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 (°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.

2.3 Time-Dependent Corrosion Wastage Model

Paik (2004) developed a mathematical model with statistical characteristics which are mean, variance, and distribution of corrosion wastage as a function of time. This model will be useful for predicting the wastage of corrosion in seawater ballast tank structures of ships. The loss of plate thickness due to corrosion expressed as a function of the time (year) after the corrosion starts, namely

$$t_r = C_1 T_e^{C2}$$ Equation 2.2

$$r_r = C_1 C_2 T_e^{C2-1}$$ Equation 2.3

where,

t_r = corrosion depth (or loss of plate thickness due to corrosion) in mm

r_r = corrosion rate in mm/year,

T_e = T - T_c - T_t,

T = age of vessel in years

T_c = life of coating in years

T_t = duration of transition in years which may be pessimistically taken as $T_t = 0$.

C_1 & C_2 = coefficients to be determined by the statistical analysis of corrosion measurement data.

For corrosion of marine structures, some past studies indicate that the coefficient C_2 for marine structures may be typically in the range of 0.3 to 1.5. So, the statistical analysis of all gathered corrosion data will provide an 'average' (most probable) corrosion rate model. The author used the upper bound (severe) or lower bound (slight) statistical characteristic of the coefficient C_1. The author stated that the methodology presented is more general and can be applied to individual cases where sufficient data are available.

Many different models for corrosion growth assessment are used nowadays by engineers in the oil and gas industry. Some are described in the open literature, others are proprietary models. The latter are typically a variation of publicly available models or are uncertain empirical correlations based on practical experience. To date, the author have seen no such matching software been elaborate on the process involve in open literature or available academically. Among the software provided by the oil and gas company to run a comparison or matching between ILI data is NDT's Analysis Software PIXUS by NDT Systems and Services (Reber and Beller, 2005), inspection run comparison software (RUNCOM) by General Electric Company, and matching software by Morrison Scientific.

Morrison Scientific Inc. (MSI) developed the Goliath database comprising corrosion and corrosion rate data (Morrison *et al*, 2000a). The implementation of the Goliath database was for the management of corrosion data from in-line inspection and the corrosion-rate analysis results. Moreover, the Goliath database also contains related data such as pipeline dimension, inspection dates, and vendor-company information. Corrosion data was represented by a list of match data that associates one defect file to another defect in another file for the same pipelines. This massive compilation of in-line inspection corrosion data indicate the effort of using data matching procedure on multiple sets of corrosion data to estimate the likely corrosion growth rate for individual defects.

Morrison Scientific Inc. (MSI) also carried out a validation study to assess the in-line inspection tool's capability in finding and sizing defects (Morrison *et al*, 2000b). The inspection data was provided by BJ Pipeline Inspection Services, Canada from pigging inspection activities using the high resolution Magnetic Flux Leakage (MFL) tool in a section of 27 kilometres of oil pipelines. The purpose of the pig run was to qualify the tool as a reliable means of metal loss inspection. The validation study was divided into the analysis of pigging data against field data and comparison of the new in-line inspection tools against existing technologies. As a result, the BJ MFL tool has been shown to size corrosion depth features with a small amount of error when compared with the field data with overall ± 80% confidence interval. The confidence interval for total prediction error varies from ± 12% to ± 17% for triplet data set, and from ± 19% to ± 22% for doublet data set.

Maintenance program planning for pipelines in the Alberta portion of the TransCanada System employed a corrosion growth modelling procedure using repeated in-line inspection (ILI) data (Worthingham *et al*, 2000). The corrosion rates were assessed by matching individual defects from multiple in-line inspections and statistically analysing the observed characteristics of every defect. Morrison Inc. has developed a method of matching anomalies and estimating corrosion rates for large numbers of corrosion defects. The process is managed by powerful pattern matching software which correlates the defects and accounts for odometer slippage, orientation differences, differing tool vendor, accuracy and sensitivity; and changes in corrosion shape and size. Manual checks are conducted throughout the process to ensure data accuracy. The quality of the growth modelling was accessed by comparing predicted penetrations and failure pressures to those measured in the field. The methodology of matching corrosion features between the different ILIs and estimating their severity at a future date was constructed and has been certified as an excellent proactive cost saving methodology with estimated future cost saving of US$ 10 million (Worthingham *et al*, 2000).

The same methodology was applied later on two different pipelines with only single inspection data named NPS20 and NPS36 (Worthingham et al., 2002). The method known as *One Run Growth* (*ORG*) uses a statistical analysis of the corrosion rates on one pipeline to predict corrosion severity on another pipeline. The author concludes *ORG* method provides a very good prediction of corrosion severity on pipelines with only one a single in-line inspection. The information of corrosion growth from other pipelines with multiple inspections was proven being useful to apply on other similar pipelines that had been inspected only once.

Noor, 2006 have proposed a solid framework for data investigation and analysis, which fully utilize the inspection dat. Detail analysis on inspection data for generic assessment method is not limited for pipeline only but extended to other structures as well by utilizing a common parameter in the data such as metal loss evidence in both structures without involving material and environmental properties. Details about the proposed framework are described in (Noor, 2006).

In current practice this process has been conducted manually based on expert approximation in sizing the accuracy of the data and to sample enough data to be analyse. Furthermore the manual matching is tedious process, error prone, and time consuming (Noor, 2006; Fenyvasi and Dumalski, 2004). A mechanize method were much needed in getting the more accurate and faster sampling (Fenyvesi and Dumalski, 2004; Clusard, 2006).The result from this system will be compared in term of its accuracies and timeliness with the manual method through its sensitivity analysis.

3. DATASETS AND CASE STUDIES

There are two methods in determining the corrosion rate based on ILI data (Desjardins, 2002). Our system was developed based on multiple inspections available. The following subsections describe the two methods:

3.1 Single Inspection

The estimation of corrosion rates from a single inspection requires a realistic corrosion growth model. The accuracy of that model is verified by its ability to accurately reproduce the condition of the pipeline as observed by the current in-line inspection. The model parameters are the:

- Condition of the pipeline at the time of construction (assumed to be defect free),
- Age of the pipeline,
- Current condition of the pipeline, (from the results of an ILI run),
- Corrosion rate (which is unknown).

The current condition of the pipeline, as represented by the model, includes the number of corrosion defects and the distribution of the corrosion depth based on the ILI data. Assumed corrosion rates are then utilized to simulate the growth of corrosion from the time of construction to inspection. This statistical analysis is an iterative approach whereby the model is continually rerun, with the assumed corrosion rate being adjusted, depending on whether the model underestimates or overestimates the observed severity of corrosion on the pipeline. The process terminates when it finds a corrosion rate that accurately models the current condition of the pipeline.

3.2 Multiple Inspections

When there are two or more in-line inspections available, individual defect growth rates can be determined with a high degree of confidence. Establishing corrosion rates from multiple in-line inspections is conceptually quite simple. The inspection results provide the location and size of each individual corrosion defect. Corrosion rates are then calculated from the change in defect size between two or more inspections. Determining the change in size however, presents the significant challenge of matching every defect from multiple ILI data sets. With high-resolution tools this can potentially necessitate matching hundreds of thousands of defects. In our study, we develop a method of matching anomalies and estimating corrosion rates for large numbers of corrosion defects. Parameters involved include absolute relative distance, corrosion orientation, and spool number. The pigging data for internal pipeline inspection used in this study are provided by various inspection vendors such as Petronas, Exxon Mobile, BP Amoco and Rosen.

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 1 and 2. In this study, because of the limited space, only an experiment and results from Pipeline B will be discussed.

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 analyzed (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 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. Because of the limited space, only data from Pipeline B will be thoroughly discuss in the experiments and results in this paper.

Table 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 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: 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

4. MECHANIZE MATCHING SYSTEM

The matching system developed follows the flowchart in Figure 1 below. The former datasets section shows the sampling that been derive and observed. The matching system will match the corresponding defects from different years based on three parameters namely defect relative distance, defect orientation, and defect location (spool number). The matching was done iteratively until a satisfied number of samples were achieved. The existence of distance error ascertained from observation stage 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 is allowed until the numbers of matched data are highly sufficient to produce a proper distribution. This was done in this system by specifying the sizing tolerance of the parameters. It was suggested that the number of matched data should be around 25% from the actual data or minimum numbers of 500 data to increase the reliability of corrosion growth estimate as mentioned by Yahaya and Wolfram (1999).

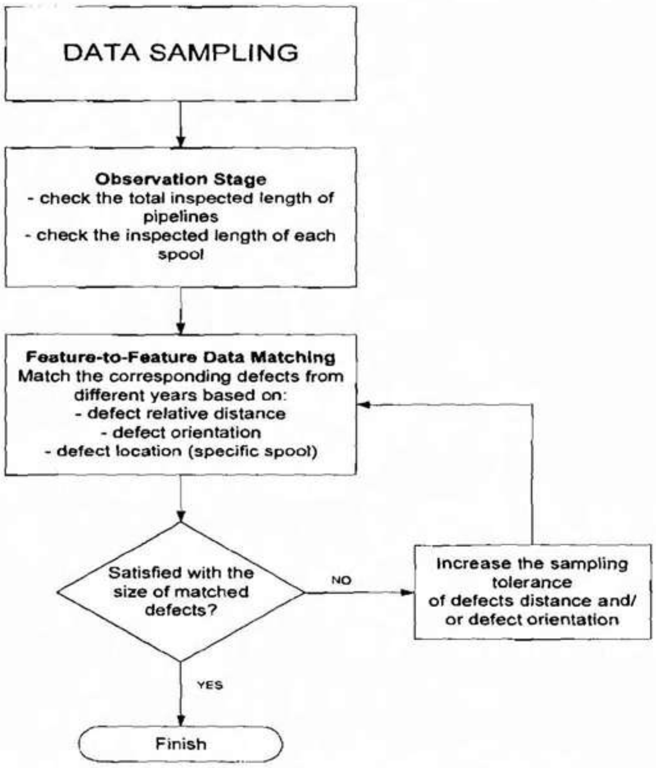

Figure 1: The flow chart of data sampling process

Our mechanize system consists of four main functions, namely filtering function, the tolerance configuration, matching function, and the data trimming function. The system was constructed using a .Net framework using C# language, and the SQL engine. Before the execution of this system, the data acquired in excel form was converted into .csv format in order to suites the database filtering requirements. The SQL engine was then used to filtered the data based on parameters mentioned before. The filtrations involved, selecting the match data and the unmatched data, and marking both data in separate worksheet.

The major difference between manual matching and this mechanize system lies in the capabilities to derive a different set of data by just changing the sizing tolerance of its parameters. The sizing tolerance used in this system was assisted by expert opinion in this assessment as well as by previous sizing used in the same data, such as works by Noor, 2006, and Razak, 2008. Manual matching so far proved to produced an inconsistent sampling even though using the same data (for example Noor, 2006, produces a 617 sample of match data whereby Razak, 2008 produced a 473 sample). The sizing value of the parameters can be set up accordingly. Below is the snippet of the sizing value in bold numbers. The example od snippet below show that the value of 0.5 for relative distance parameter and 90 for orientation is set up in order for the matching to cluster the data based on that criteria.

```
<setting name="RelativeDistanceRange" serializeAs="String">
  <value>0.5</value>
</setting>
<setting name="OrientationRangeInMinutes" serializeAs="String">
  <value>90</value>
```

For ease of used, a console been developed and the mechanized matching can be executed by dragging two or more data files into the console. The matching process will took care all the possibilities of match data depending on the sizing parameters. The stochastic nature of the defect might produce a different number of sample for each year match (for example, spool 580 in year 90 produce two defect whereby the same spool in year 92 might produce 4 four defects). So, the trimming of the data has to be done for consistencies of data. Example of the console interfacing was shown in Figure 2, which shows a doublet matching (Year 90 and Year 92 data).

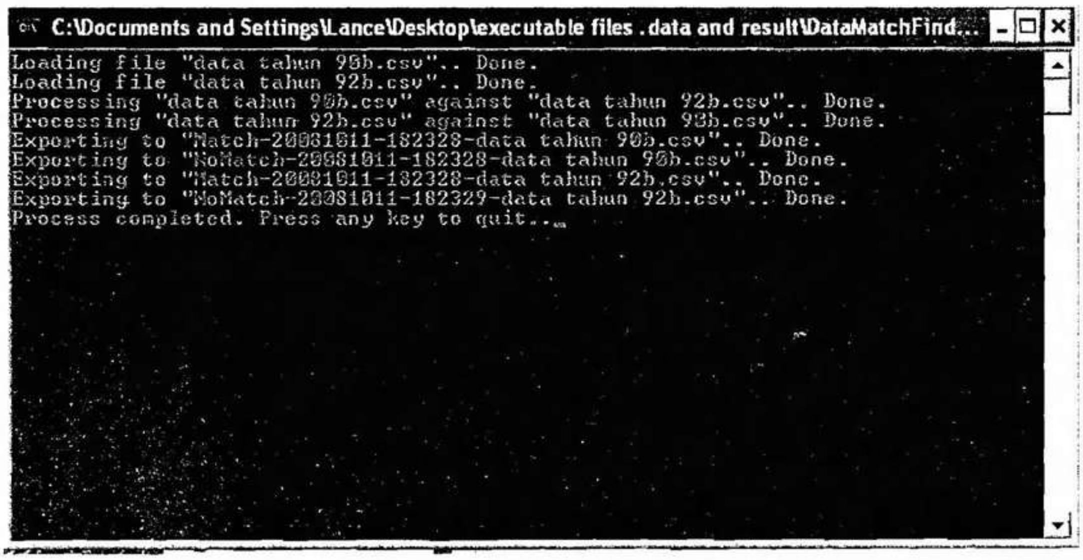

Figure 3: Console that shown a doublet matching

Finally, the trimming function will further compare the match data into its closest value, classify and grouped the match data into separate files depending on its spool number. This to make sure that the sample produced for each data set (in our case, sample for every year being match was equal) and enable the corrosion rate to be calculated based on observed changes in defect depths and lengths in the same spool.

5. EXPERIMENTS AND RESULTS

The experimentation setup was done following a simple mathematical sets union. For three inspections (Pipeline B data), we derive four matching scenarios, and for each scenarios, different sizing tolerance was applied in order to derive an optimize number of sample. The four scenarios and the sizing tolerance setting depicted in Table 4 shows the result from the execution of this system which produced the number of sample been matched. The result shows that the number of match data sampling becomes smaller when we reduce the sizing tolerance of the parameters. Furthermore, the result also shown that the matching data for consecutive years such as for scenarios 1 and 3 gives a large volume of match data compared to other scenarios. Based on previous research (Noor,2006; Yahaya and Wolfram, 1999), this problem was arise from measurement techniques and inspection devices used during the year of inspection.

Table 4: Mechanize matching results

Scenarios	Relative Distance	Orienta-tion	Relative Distance	Orienta-tion	Relative Distance	Orienta-tion
	0.5	90	0.3	60	0.2	30
1. Year {1990, 1992}	1076		851		621	
2. Year {1990, 1995}	990		777		578	
3. Year {1992, 1995}	1888		1864		1819	
4. Year {1990, 1992,1995}	919		700		480	

The variation of sampling achieved proved that it simplify the engineer task in deriving the match sample from the large amount of inspection data. This variation can be further analyze using sensitivity analysis as been explained in the next section.

5.1 Sensitivity Analysis

Sensitivity analysis can be divided into two processes namely, the sampling tolerance and data correlation. The sampling tolerance was conducted in order to ascertain the quality of matching work on the pigging data in terms of relative distance and orientation. For example, in this process results from every spool in data matching process from each year will be calculated as follows: Average for Tolerance RD = (R90–R92 + R90-R95 + R92-R95)/3, where: RD – relative distance, R – result. The average value for the whole data based on distance and orientation parameters calculated will reflect the sampling tolerance. Small sampling tolerance with high numbers of matched data represents the low difficulty level in matching the data and vice versa. For scenario 4 in our case study using tolerance of 0.2 and 30 respectively for relative distance and orientation, the value of calculated average is 0.08337 which can be concluded as a low difficulty matching.

Apart from the sampling tolerance, the correlations between each corrosion related parameters can be identified using linear regression method. This process aims at identifying the relationship between defect depth and its length dimension. We use the scatter plot as depicted in Figure 4 to Figure 6 to visualize the correlation between defect depth and defect length for years of inspection been studies. From the distribution pattern it has been observed that, the defect distribution was reflecting a Weibull shape. So, based on this in order to predict its lifetime a Weibull formula can be used as a basis of studies. For further analysis either statistical or probabilistic methods, a standard deviation and average (mean) for every defect depth and length as well as its corrosion growth must be calculated.

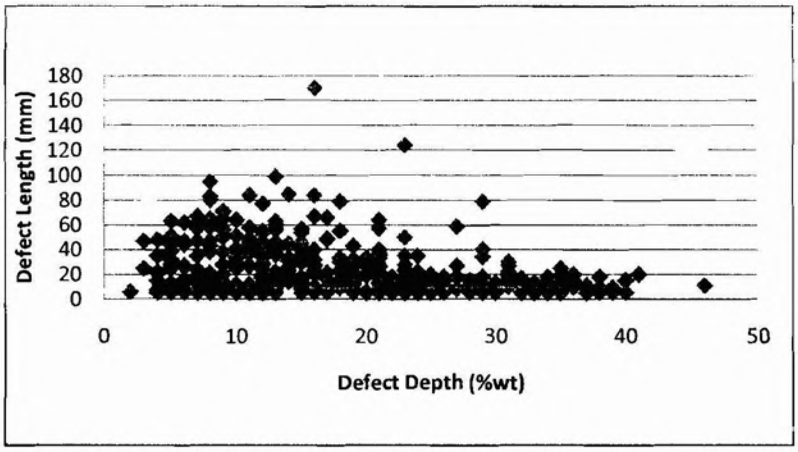

Figure 4: Defect length plotted against defect depth of 1990 data

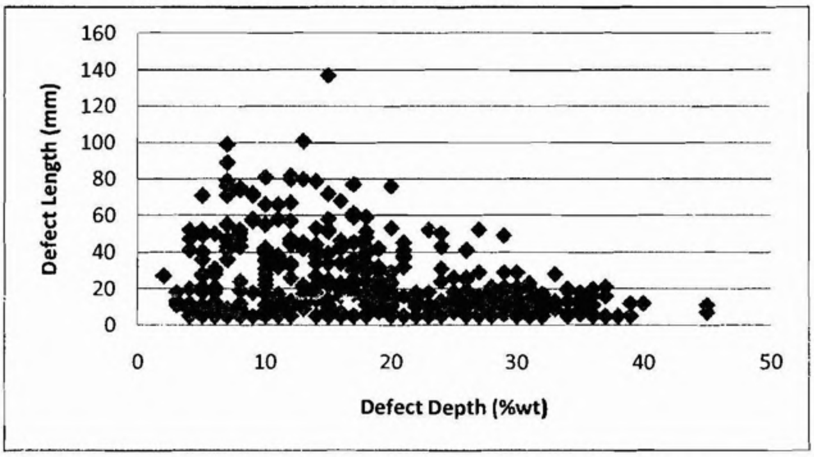

Figure 5: Defect length plotted against defect depth of 1992 data

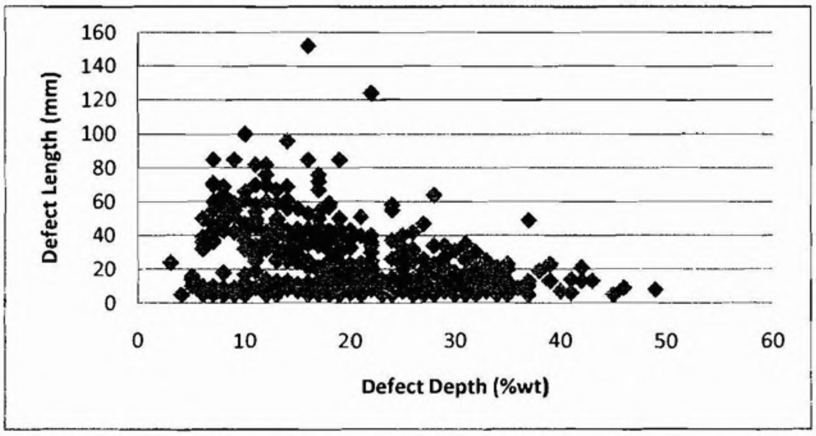

Figure 6: Defect length plotted against defect depth of 1995 data

The standard deviation was derived as follows:

$$s = \sqrt{(\sum x^2 - ((\sum x)^2/n)) / (n-1)}$$ Equation 5.1

where:

x = sum of defect depth, length, corrosion rate for depth, and corrosion rate for length

n = number of matching data sample; i.e. 480

Because of the limitation of space in this paper, the results of mean and standard deviation for matching data for scenario 4 with sizing tolerance of 0.2 and 30 only was summarized in Table 5 and Table 6.

Table 5: Average and Standard Deviation of Corrosion Depth and Corrosion Length

Set of data	CORROSION DEPTH			CORROSION LENGTH		
	1990(d_{B90})	1992(d_{B92})	1995(d_{B95})	1990(l_{B90})	1992(l_{B92})	1995(l_{B95})
Average (mm)	3.552	3.402	4.011	21.613	22.510	23.819
Standard Deviation (mm)	1.978	2.066	1.836	19.824	19.609	20.013

Table 6: Average and Standard Deviation of Corrosion Growth Rate for Defect Depth and Corrosion Growth Rate for Defect Length

Set of data	CORROSION DEPTH			CORROSION LENGTH		
	1990-1992 (CRD_{B90-92})	1990-1995 (CRD_{B90-95})	1992-1995 (CRD_{B92-95})	1990-1992 (CRL_{B90-92})	1990-1995 (CRL_{B90-95})	1992-1995 (CRL_{B92-95})
Average (mm)	-0.039	0.182	0.094	0.616	0.544	0.404
Standard Deviation (mm)	0.912	0.471	0.620	7.947	3.821	5.003

The result shows that the sensitivity analysis done on the mechanize data were as good on data acquired through manual process, but can be achieved in lesser time and consistent accuracy. The whole data can be manipulated by changing the parameters in involved in corrosion growth assessment. Form each run, the analysis can be performed until it reach the most optimize/appropriate level of confidence in growth rates and corrosion severity prediction by incorporating the error associated with inspection tools into all observation and calculations.

6. CONCLUSION

As in line inspection technology advances and tool resolution and accuracy increases, the traditional methods of dealing with ILI data are quickly becoming unfeasible, both from economic and a practical point of view. Corrosion growth analysis provides a proactive method of analyzing large quantities of ILI data, prioritizing pipeline repair programs, and optimizing reinspection intervals. Manual method and mechanize method in feature-to-feature matching process for multiple inspection data is described. By comparison, the development of the mechanize system was fulfill the advantages as been described earlier in the paper. The variation of the matched data sampling was achieved and can be further analyzed to gain an optimize value for further evaluation. The implementation of this system is strongly believed to greatly assist a pipeline operator to utilize their tremendous amount of inspection data to a useful decision-making for future planning and maintenance of pipeline structure. The proposed approach can also be applied to minimize the overall cost of inspection and repair of existing pipeline.

ACKNOWLEDGEMENTS

The author gratefully acknowledges the financial support for this study provided by Universiti Teknologi Malaysia.

REFERENCES

Clausard, C., (2006), Pipeline Integrity Management Strategy for Aging Offshore Pipelines, MACAW Engineering Limited, UK

Clausard, C.,(2007), Integrity Management Strategy for Ageing Pipelines, MACAW Engineering Limited, UK

Clouston, S., Smith, J., (2004), Realise the Value of Pipeline Data Management Across the Enterprise by Exploiting Legacy Database, PII Pipeline Solutions, Cramlington, UK.

de Waard C., Lotz U. and Milliams D.E. (1991), Predictive Model for CO_2 Corrosion Engineering in Wet Natural Gas Pipeline, Corrosion Engineering, 47(12). pp 976-985.

Desjardins G. (2002a), Improved Data Quality Opens Way for Predicting Corrosion Growth and Severity, Pipeline and Gas Journal, December 2002, pp. 28-33

Fenyvasi, L. Dumalski, S.,(2004), Determining Corrosion Growth Accurately and Reliably, PISTech Paper, BJ Services.

HSE (2002), Guidelines for Use of Statistic for Analysis of Sample Inspection of Corrosion, Health and Safety Executive, Research Report 016.

KamrunNahar, M., and Urquidi-Macdonald, M., (2005), Data Mining of Expei imental Corrosion Data Using Neural Network', 208th Electrochemical society Meeting, Penn State University.

Melchers R.E. (1999), Corrosion Modelling for Steel Structures, Journal of Constructional Steel Research, **52**, pp. 3-19.

Morrison T., Bhatia A. and Desjardins G. (2000a), Development and Remote Access of an In-Line Inspection and Corrosion Growth Database. Calgary, Alberta, Canada: IPC00-0051, International Pipeline Conference. October 1-5. 1-6.

Morrison T., Mangat N., Desjardins G, and Bhatia A. (2000b), Validation of an In-Line Inspection Metal Loss Tool, ASME Pipeline Technology, **V**, pp.839-842.

Nestleroth J. B., Battelle B.T. A. (1999), Magnetic Flux Leakage (MFL) Technology for Natural Gas Pipeline Inspection. USA: A Report for the Gas Research Institute (GRI),

Noor, N.M (2006), A Generic Assessment Approach to the Analysis of Corrosion Data and its Application to Reliability Assessment, Heriot-Watt University, Phd Thesis

Paik J.K, Thayambali A.K., Park Y.I. (2004), A Time-dependent Corrosion Wastage Model for Seawater Ballast Tank Structures of Ships, Corrosion Science, Vol.46, Issue 2, pp.471-486

Paik J.K. and Thayamballi A.K. (2002), Ultimate Strength of Ageing Ships, Journal Engineering for the Maritime Environment, Vol. 216, pp. 57-77.

Perich, W., van Oostendorp, D.L., Puente, P., Strike, N.D., (2003), Integrated Data Approach To Pipeline Integrity Management, Pipeline & Gas Journal, pp. 28-30.

Worthingham R., Morrison T. and Desjardins G. (2000), Comparison of Estimates from a Growth Model 5 Years after the Previous Inspection, ASME Pipeline International, pp.895-900.

Yahaya N. (1999), The Use of Inspection Data in the Structural Assessment of Corroding Pipelines, Heriot-Watt University, Edinburgh: PhD Thesis

Yahaya N. and Noor, H.M.,(2002), Comparison Between Deterministic and Probabilistic Approach in Predicting the Remaining Strength of Corroded Pipelines, 2nd World Engineering Congress, Sarawak, Malaysia, July 2002.