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Improving Inspection Data Quality in Pipeline Corrosion Assessment

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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 improved the quality of In-line inspection (ILI) data by automatically detect and quantify important parameters for future prediction of corrosion growth. 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: timeliness, accuracy and consistencies in data sampling.

Keywords: Mechanize matching system, ILI data, sensitivity analysis

1. Introduction

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.

The absence of mechanize and analyzing standard for exploitation of corrosion inspection data may cause some difficulties [1-5]:

- Often the operators focused the research on reliability assessment rather than the preceding data analysis which tend to affect the overall result of prediction.
- 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.
- The complexity and time consuming data analysis process tends to overburden the operators involved and may result in poor planning and maintenance scheduling.
- 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. 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.

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2. Corrosion Growth Model

There are theoretical and empirical models available to estimate the rate of corrosion growth. An empirical model such as deWaard and Milliams equation [6] 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 linear model will be discuss in this section due to its applicability to the pipeline in this study.

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 [7]. The linear equation is performed as below:

$$CR = \frac{dT2 - dT1}{T2 - T1} \tag{1}$$

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

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 application 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 [5], inspection run comparison software (RUNCOM) by General Electric Company, and matching software by Morrison Scientific [7]. 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. The manual matching is tedious process, error prone, and time consuming [8-9]. A mechanize method were much needed in getting the more accurate and faster sampling [9][4].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 namely; single inspection and multiple inspections [10-11]. Our application was developed based on multiple inspections available. 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. 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.

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	1990/92/ 95	1990/92/ 95	1990/92/ 95
Year of installation	1977	1977	1967
No. of data (all sets)	7734	7009	6639

Table 2: A Typical Presentation of Pigging Data

Spool Length (m)	Relative distance (m)	Absolute distance (m)	*d% wt*	*l* (mm)	*W* (mm)	O'clock
11.6	6.6	1016.5	18	32	42	6.00
11.5	11.5	1033.0	19	46	64	5.30
11.8	10.6	1043.6	12	18	55	5.30
11.7	1	1045.8	13	28	83	5.30

where:
d%wt : Maximum depth of corrosion in terms of percentage
l : Longitudinal extent of corrosion
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)
W: Extent of corrosion around pipe circumference weld
Absolute distance: Distance of corrosion from start of pipeline

4. Mechanize Matching Application

The matching application developed follows the flowchart as depicted in Figure 1. 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 [3].

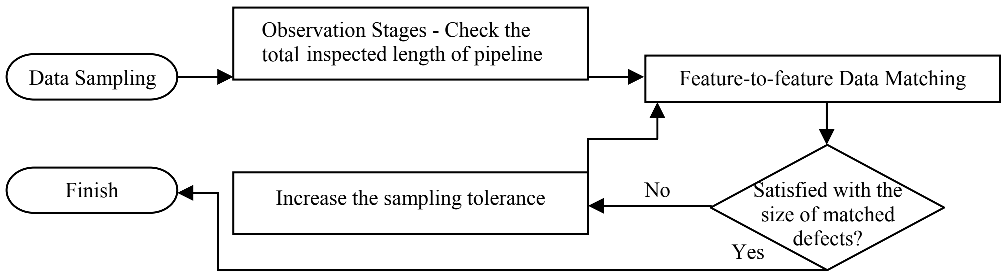

Fig.1: The Flow Chart of Data Sampling Process

Our application 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 application 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 [8] and [12]. Manual matching so far proved to produced an inconsistent sampling even though using the same data (e.g. [8], produces a 617 sample of match data whereby [12] produced a 473 sample). The sizing value of the parameters can be set up accordingly. The matching process will look at 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 defects whereby the same spool in year 92 might produce four defects). So, the trimming of the data has to be done for consistencies of data.

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 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 3 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 [10][3], this problem was arise from measurement techniques and inspection devices used during the year of inspection.

Table 3: Mechanize Matching Result

Scenarios	RD	O	RD	O	RD	O
	0.5	90	0.3	60	0.2	30
Year {90, 92}	1076		851		621	
Year {90, 95}	990		777		578	
Year {92,95}	1888		1864		1819	
Year {90, 92, 95}	919		700		480	

(RD : Relative Distance; O: Orientation

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 in order to prove its quality has been explained next.

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 (2)

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. Based on these data, the defect distribution was reflecting a Weibull shape. So, 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. 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 4.

Table 4: Average and Standard Deviation of Corrosion Growth Rate and Corrosion Depth and Length for Defect depth and Defect Length

Set of data	CORROSION DEPTH			CORROSION LENGTH			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})*	*1990 (d_{B90})*	*1992 (d_{B92})*	*1995 (d_{B95})*	*1990 (l_{B90})*	*1992 (l_{B92})*	*1995 (l_{B95})*
Average (mm)	-0.039	0.182	0.094	0.616	0.544	0.404	3.552	3.402	4.011	21.613	22.510	23.819
Standard Deviation (mm)	0.912	0.471	0.620	7.947	3.821	5.003	1.978	2.066	1.836	19.824	19.609	20.013

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 re-inspection 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.

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