Response to API 1163 and Its Impact on Pipeline Integrity Management

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Abstract. Knowing the accuracy and reliability of ILI measurements is important for determining optimum integrity rehabilitation project scope, re-inspection interval and the risk associated with the pipeline section examined. The recent (September 2005) introduction of API 1163 (title) highlights the importance of these metrics. Qualifying these metrics requires verification measurements with accuracies a level of magnitude higher than in-line-inspection. Lasersure^{SM} provides a process which uses in-the-ditch Laser Profilometry measurements which have an order of magnitude greater accuracy than the original ILI-MFL measurements, therefore are well suited to qualifying and potentially improve ILI results. The following paper outlines the Lasersure^{SM} process and the potential impact of this process on pipeline integrity management process.

Introduction

In-Line Inspection (ILI)

ILI (MFL) is commonly used by operators to determine the location and extent of metal loss (primarily) on their pipeline systems. MFL technology and its understanding have improved by leaps and bounds in the last decade or so, and has proven to be a valuable tool for operators. Despite the advances, significant uncertainty still exists regarding the accuracy of the data obtained from the MFL tools. Various factors such as the cleanliness of the pipe, chemical and physical properties of the steel, presence of localized residual stresses, variation of wall thickness, etc. all have a detrimental effect on the accuracy that can be expected from ILI.

ILI Tool vendors typically specify the accuracy and certainty associated with their data. In some cases, such metrics are defined for different geometrical categories as by the Pipeline Operator’s Forum and API 1163. In other cases, it is provided as an aggregate metric. The accuracy, thus defined, is typically of the order of +/- 10% with a certainty of 80% with respect to the depth measurement. In other words, the depth measurements from the MFL data would typically have an error, no greater than 10% of the wall thickness in 80% of the data points. This still leaves a huge amount of uncertainty that an operator has to account for while making critical decisions.

This uncertainty in the data has direct impact on the risk level that an operator associates with a pipeline system or the inspected section there-of. The economic impact on the integrity management program(s) can be huge, as operators have to make conservative estimates of the associated risk, subsequently driving up the number of digs in a rehabilitation project and/or shortening the re-assessment interval.

Laserscan^{SM}

Laserscan^{SM} is a service provided by RTD wherein the LPIT^{TM} tool uses laser profilometry for mapping the external surface of the pipe and thereby measuring with millimeter level resolution the extent of external corrosion as present on the pipe. As of now, it is a benchmark technology and has been proven to be very accurate and reliable in the field. It is capable of providing a high definition 3-dimensional map of the pipe surface in a digital format. Due to the nature of the dataset, the data from Laserscan^{SM} is ideally suited for detailed analysis and comparison.

API 1163

API 1163 (In-Line Inspection systems qualification standard) was introduced in August 2005 as an umbrella document defining the manner in which the ILI data was to be reported and qualified. While it does define the specifications for anomalies belonging to different geometrical categories, it does not offer a robust process for comparing the ILI data with the field measurements.

A metal loss defect, as measured in the field, usually comprises of multiple indications (each of the same or different geometrical shape) combined together using a pre-defined interaction criteria. Similarly, ILI data also undergoes a “clustering process”. To classify the indications into different geometrical categories, one has to use the un-clustered data.

Previous work

Several efforts have been made in the past to do correlation analysis between MFL data and field measurements. While considerable insight was gained in the process, most of these efforts were marred by a few common drawbacks. Some of these are as listed below:

- The field data was usually collected using manual methods, and therefore, was limited in definition and accuracy
- Manual measurements typically are prone to measurement and indexing error, making it difficult to match with the corresponding ILI anomalies
- Field data resolution is generally low, limiting the ability to match data points by geometrical shape.

Presented study

The present study is based on the premise that the MFL tool has a different level of measuring accuracy for anomalies belonging to different geometries. For the purpose of this study, the anomalies were classified into the following categories as defined by the Pipeline Operators Forum:

- Extended/General
- Pitting

- Pinholes
- Axial Grooves
- Axial Slots
- Circumferential Grooves
- Circumferential Slots

There are a few key characteristics that differentiate the study performed from the previous works in this direction. They are summarized as follows:

- The data points were matched on an individual pit basis
- The ILI data used was boxed data (prior to the application of interaction rules)
- The analysis was performed on data sets belonging to each geometrical category individually
- All data points were taken into consideration, including corrosion with very small depth measurements (>= 0.3mm)

Also, some assumptions were made to apply the process:

- It was assumed that the error in the LPIT^{TM} measurements was negligible
- It was assumed that the measurements from the ILI data were reliable enough to determine the geometrical category a particular indication belonged to.

Process

The process used in this study comprised the following steps:

1. Data Assimilation
2. Classification
3. Matching the data points
4. Data Extraction
5. Analysis
6. Validation

Data Assimilation:

The boxed data from a previous ILI (MFL) inspection was provided for this study by a major North American pipeline operator. The inspection was performed over three valve sections. In addition, Laserscan^{SM} service had been utilized during the rehabilitation project previously carried out by the operator. The data from all the locations inspected using the Laserscan^{SM} and the MFL data from the corresponding pipe segments was located.

Classification

Each MFL data point (indication) was then classified into one of the seven categories based on the ILI reported length and width using the criteria as defined in the POF document.

Matching the data points

The LPIT^{TM} data and the MFL data was then overlaid using a graphical tool designed for the purpose. Some key indications were used to determine if there was any location error in the data sets and data points that overlaid well were documented. Following is a snapshot of the utility used to match the data points (Figure 1). The blue indications are LPIT^{TM} indications and the red ones are MFL indications.

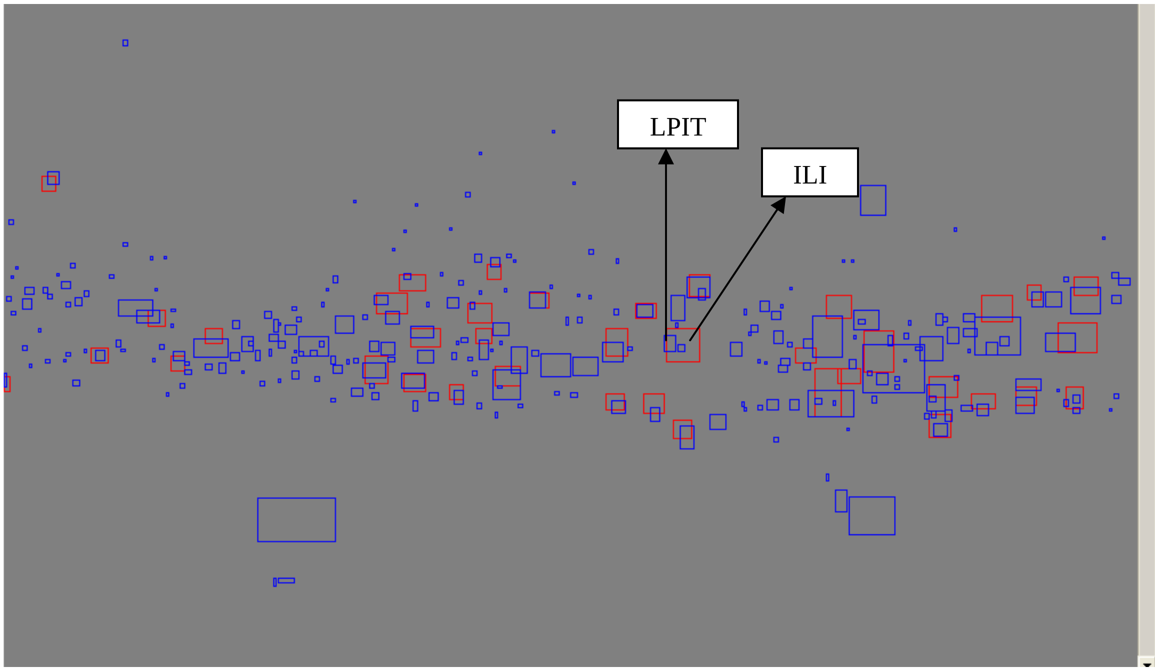


Figure 1: Data matching utility used to overlay the ILI and LPIT datasets

In cases where on indication in either datasets corresponded to multiple indications on the other, the boundary conditions were used to aggregate the multiple indications so as to get a one to one correlation.

Data Extraction

The data from the matching data points was then accumulated and verified to ensure consistency. The parameters for consideration (Length and Depths) for these indications were extracted from the pool of data and arranged in a comparable format. Some of these matching data points were set aside as a control group at random for validation purposes.

Analysis

Statistical analysis was performed on these data sets. To streamline the process, and due to the limited amount of data available, the analysis was performed for two of the geometrical categories, viz. General corrosion and pitting. Within these categories, both parameters of interest (Depth and Length) were evaluated to determine the error and any evident bias in the positive or negative direction. Figure 2 shows the potential impact an error in length measurement can have.

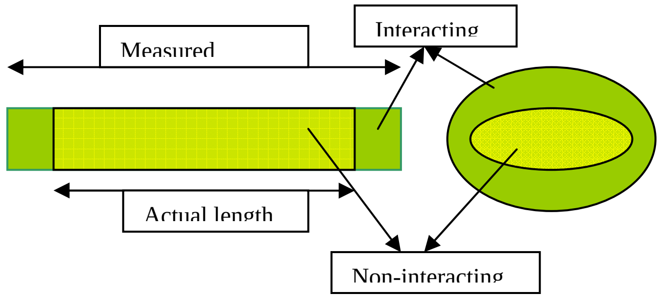


Figure 2: Anomalies clustered due to error in length measurement

Validation

Once the bias (or relation) was determined, a correction factor was calculated and applied to the MFL data points from the control data set. These corrected measurements were then compared against the LPIT™ measurements to determine if there was any improvement in the accuracy. The results are as provided in the following sections.

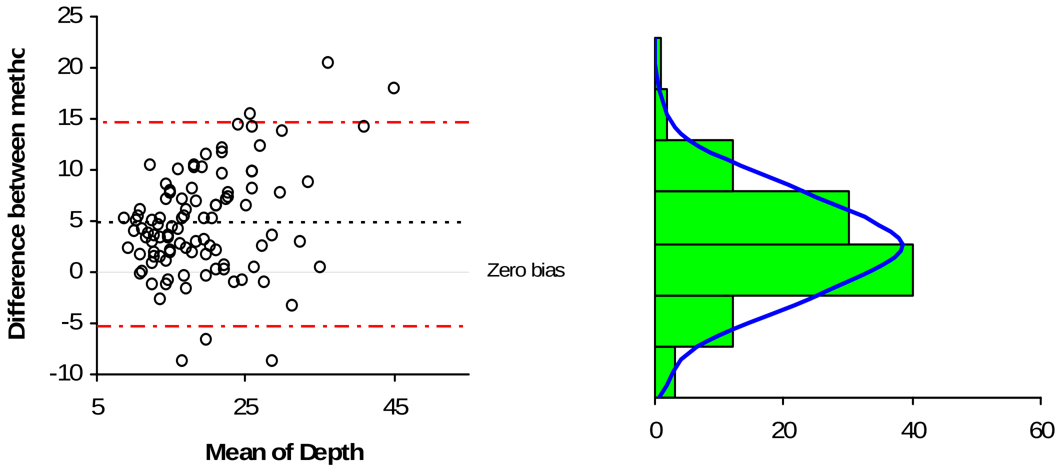
Data Analysis

The data considered for the purpose of this study was taken from 6 different excavation locations. Data extraction provided us with 138 indications belonging to the pitting corrosion category and 59 indications belonging to the general corrosion category. 38 indications from the pitting corrosion data set and 20 indications from the general corrosion data set were randomly set aside as the control group for validation purposes. The Laserscan℠ measurements were used as the reference data set to calculate the error in depth as well as length measurements for each data point.
Different standard statistical techniques were utilized to measure the bias, if any, in the ILI data using the Depth and Length as the parameters of interest. They are:

1. Paired t-test [1]
2. Wilcoxon signed ranks test [2]
3. Passing-Bablok method [3]

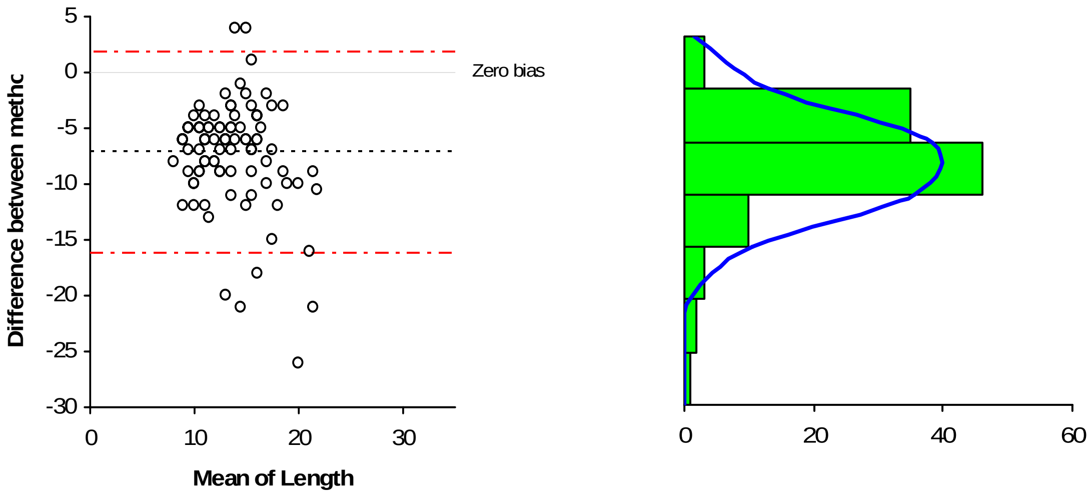
The two data sets, ILI and Laserscan℠, were treated as paired data, as it was assumed that since both measurements are for the same anomaly, values in one data set would change with the other [4][5][6]. As is shown in Figure 3, the bias plots [4] for both the depth and length measurements show a clear bias. The depth measurements reported by ILI seem to be almost consistently less than the corresponding LPIT™ measurements for both pitting and general corrosion.

a)



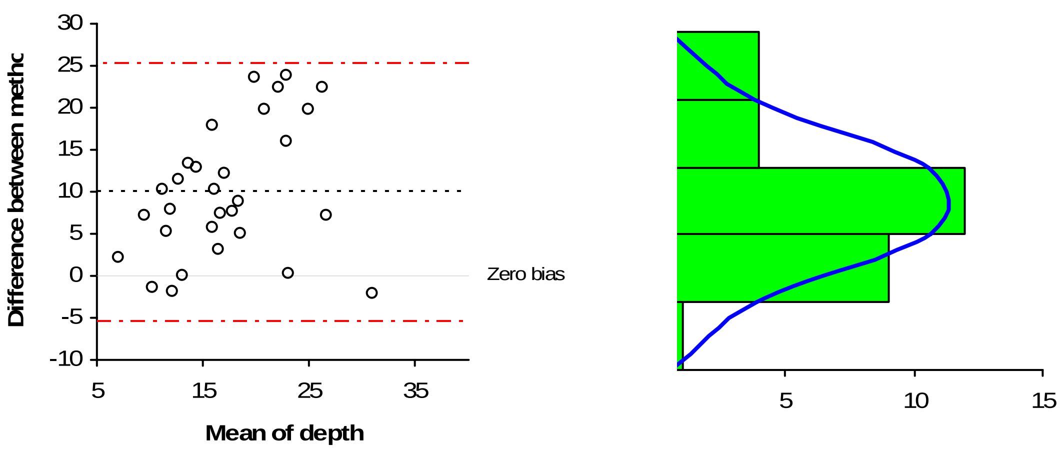
Difference between methc
Mean of Depth
Zero bias
25
20
15
10
5
0
-5
-10
5
25
45
0
20
40
60

b)



Difference between methc
Mean of Length
Zero bias
5
0
-5
-10
-15
-20
-25
-30
0
10
20
30
0
20
40
60

c)



Difference between methc
Mean of depth
Zero bias
30
25
20
15
10
5
0
-5
-10
5
15
25
35
5
10
15

d)

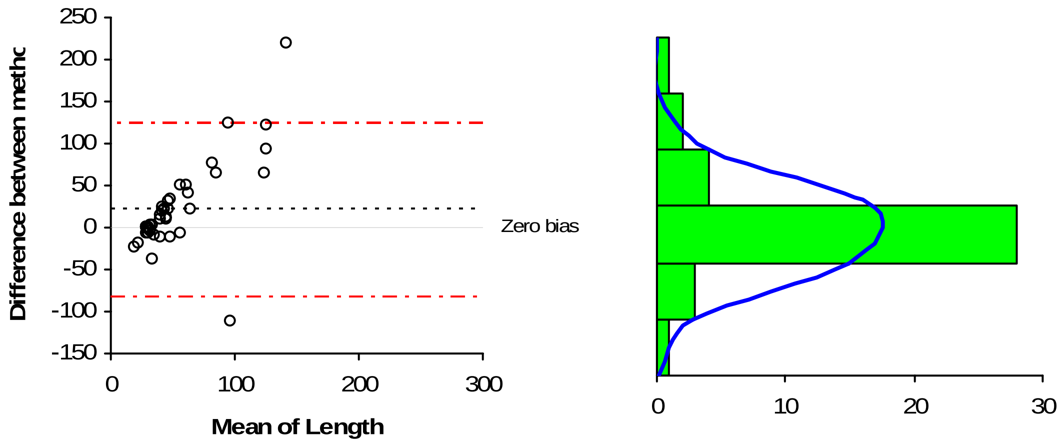
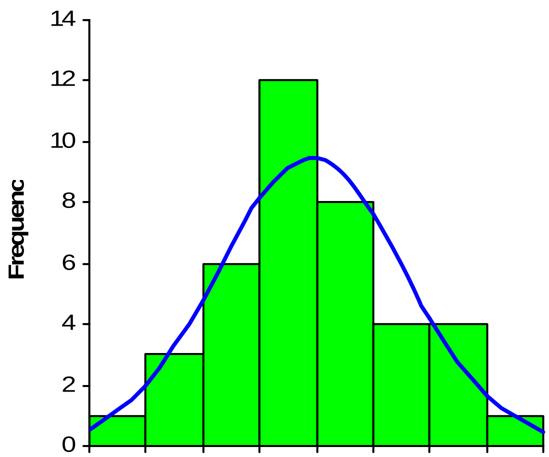


Figure 3: Bias plots showing that a bias is present in both length and depth measurements. (a) and (b) are Bias plots for Depth and Length respectively for Pitting Corrosion. (c) and (d) are bias plots for Depth and Length for General corrosion category

The calculations for Depth

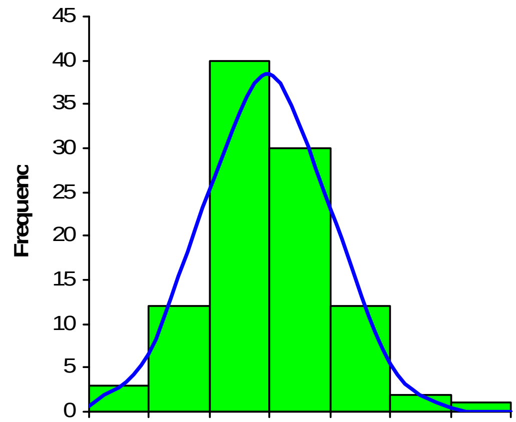
The error in depth measurement (LPIT^{TM} – ILI) seemed to follow the normal distribution. This was verified using the kolmogorov-smirnov test at a significance level of 0.05 (Figure 4).

(a)



	Coefficient	P
Kolmogorov-Smirnov	0.6261	> 0.15
Skewness	0.3370	0.3540
Kurtosis	-0.3670	0.7007

(b)



	Coefficient	P
Kolmogorov-Smirnov	0.6586	> 0.15
Skewness	0.2638	0.2653
Kurtosis	0.7096	0.1579

Figure 4: Results from Kolmogorov-Smirnov test demonstrating that the error does follow a normal distribution. (a) and (b) are histograms for Error in Depth for Pitting and General Corrosion respectively.

Now, assuming normality, an estimation of the bias (assuming a constant bias) was performed at a significance level of 0.05. Since the mean error was found to be positive, the estimated bias was added to the depth measurements in the control group for validation and the results compared to the uncorrected error. The results are as provided in Table 1.

Similar calculations, when carried out on the control data for general corrosion, revealed a similar phenomenon. The SSE for uncorrected measurements was found to be 1346, while the SSE for corrected measurements was found to be 744. The data, when subjected to the non-parametric wilcoxon signed ranks test revealed results almost identical to the results presented.

Further investigation of the data seemed to indicate that the magnitude of the error seemed to be a function of the reported depth measurement itself. This trend is quite evident in the following charts (Figure 5)

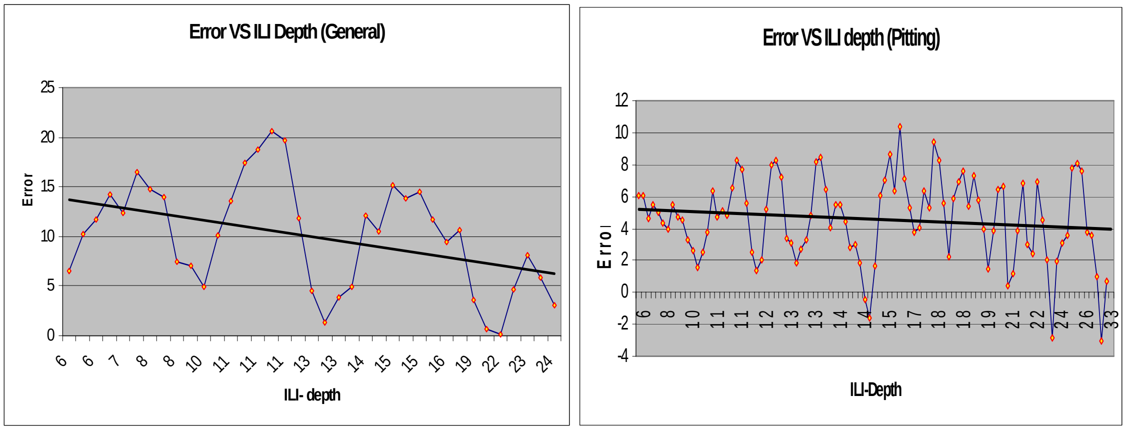


Figure 5: Plots showing that the magnitude of error could be a function of the measured value

This indicated that the bias in the data might be proportionate to the depth. Therefore, the data was then subjected to the Passing-Bablok comparison test. The test was carried out at a confidence level of 95%.The results from the tests are as follows (Figure 6):

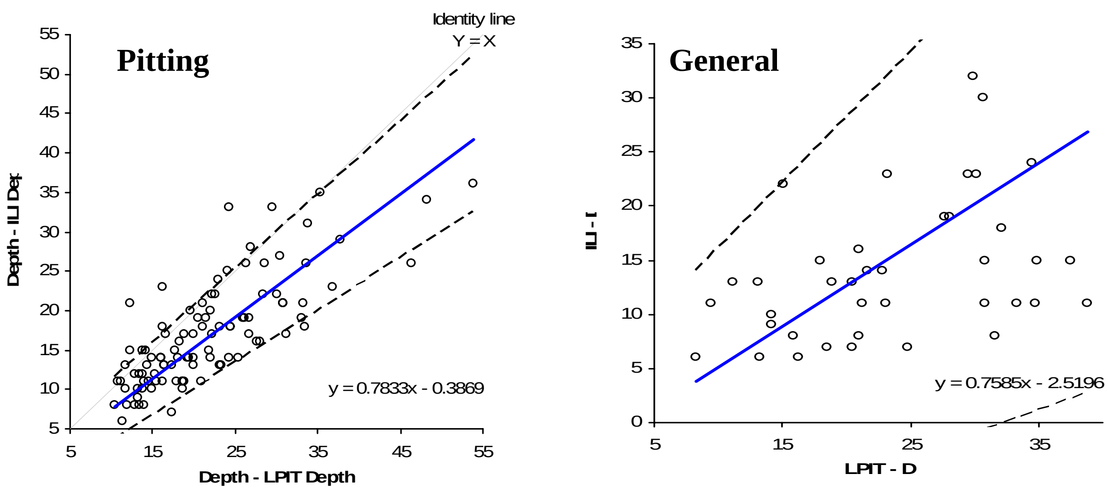


Figure 6: Results from Passing-Bablok regression reflecting the proportionate bias

Subsequently, the control data was corrected using the respective correction model. The results showed marked improvement over the uncorrected data. The results are as provided in Table 1.

One thing to be noted here is that while the sum squared error seems to be lower for the non-parametric wilcoxon-bablok method, the absolute maximum error was found to be more in the parametric case. In other words, using a constant bias would cause the outliers to be even more pronounced.

The calculations for Length

The MFL tool reports depth as a relative measurement as a percentage of the wall thickness. This normalizes the data and therefore, the scatter doesn't seem as pronounced. Since the length measurements are absolute (mm), the effect of outliers on the analysis is quite pronounced. To reduce this, the analysis for length was carried out using percentage length, defined as the ratio of the lengths reported by LPIT^{TM} versus that by ILI times 100. The same calculations, when carried out for length, yielded results as shown in Table 2.

As is obvious from these results, the improvement in length is not nearly as significant as for depth, although some improvement can be achieved. The reduced improvement can partly be attributed to the fact that the deviation from true measurement (error) is much larger for length than for depth.

Conclusion

The following key conclusions can be derived from this exercise:

- There is statistically significant bias in both depth and length measurements in the MFL data.
- The bias is different for different geometrical categories. While the process, as defined in this paper was completed on pitting and general corrosion, it can also be applied to calculate the ILI tool performance for different geometries of anomalies.
- While conventional (parametric) statistics does provide means for calculating these biases, these techniques typically assume that the data belongs to a particular distribution and therefore, when a sample does not conform to the given distribution, the error in the outliers is magnified causing larger maximum absolute errors.
- Non-parametric techniques seem to be more adequate as they are more resilient to outliers in the data set.
- These correction factors can be applied to boxed data and the data clustered again by applying the respective interaction criteria to provide more accurate data to the operators, thereby reducing the overall uncertainty and subsequently, risk.
- Development and subsequent application of such a process can assist operators in establishing qualified re-assessment intervals owing to higher certainty in the data.
- Methods such as bootstrapping and/or Bayesian techniques should be explored to determine if they can provide further improvement in results.

References

[1] Statistical methods for assessing agreements between two methods of clinical measurement. Bland J.M., Altman D.G.

[2] Individual comparisons by ranking methods. Wilcoxon F. (1945)

[3] A general regression procedure for method transformation. Passing H., Bablok W

[4] Principles and procedures of exploratory data analysis. Behrens, J. T. (1997).

[5] *NIST/SEMATECH e-Handbook of Statistical Methods*, http://www.itl.nist.gov/div898/handbook.

[6] Essentials of Statistical Inference (Cambridge Series in Statistical and Probabilistic Mathematics) 2005.

Table 1: Pitting corrosion

	Corrected Depth			Corrected Length		
	Uncorrected depth	Using constant bias	Using Passing Bablock	Uncorrected Length	Using constant bias	Using Passing Bablock
Mean Error	5.78	1.93	0.22	-37.34	-0.55	-37.62
Standard Deviation	5.00	5.00	5.46	68.36	50.05	64.67
Max Error	19.37	15.52	13.40	233.33	144.05	226.22
Sum squared error	2193.77	1066.87	1104.82	225889.27	92698.66	208516.21

Table 2: General corrosion

	Corrected Depth			Corrected Length		
	Uncorrected depth	Using constant bias	Using Passing Bablock	Uncorrected Length	Using constant bias	Using Passing Bablock
Mean Error	8.28	1.39	-1.27	-7.67	-5.16	4.74
Standard Deviation	9.54	9.54	10.72	41.95	40.23	23.43
Max Error	27.78	20.89	20.96	112.00	104.55	39.44
Sum squared error	1345.57	745.81	934.02	14605.00	13189.95	4595.61