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ESTIMATION OF CORROSION RATES BY RUN COMPARISON: A STOCHASTIC SCORING METHODOLOGY

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ABSTRACT

Pipeline operators used to map and quantify corrosion damage along their aging pipeline systems by carrying out periodical in-line metal-loss inspections. Comparison with the data sets from subsequent runs of such inspections is one of the most reliable techniques to infer representative corrosion growth rates throughout the pipeline length, within the period between two inspections. Presently there are two distinct approaches to infer corrosion rates based on multiple in-line inspections: individual comparison of the detected defective areas (quantified by more than one inspection), and comparison between populations. The former usually requires a laborious matching process between the run-data sets, while the drawback of the latter is that it often fails to notice hot-spot areas. The object of this work is to present a new methodology which allows quick data comparison of two runs, while still maintaining local distinct characteristics of the corrosion process severity. There are three procedures that must be performed. Firstly, ILI metal-loss data set should be submitted to a filtering/adjustment process, taking into consideration the reporting threshold consistency; the possible existence of systematic bias and corrosion mechanisms similarity. Secondly, the average metal-loss growth rate between inspections should be determined based on the filtered populations. Thirdly, the defects reported by the latest inspection should have their corrosion growth rates individually determined as a function of the mean depth values of the whole population and in the defect neighborhood. The methodology allows quick and realistic damage-progression estimates, endeavoring to achieve more cost-effective and reliable strategies for the integrity management of aged corroded systems. Model robustness and general feasibility is demonstrated in a real case study.

NOMENCLATURE

- σ_i: standard deviation of depth metal-loss population in a defect neighborhood [mm];
- σ_{li}: standard deviation of depth metal-loss population in a defect neighborhood [mm];
- Δt_f: forecasting time interval [years];
- Δt_i: time interval between inspections [years];
- d_1: earlier inspection metal-loss depth average [mm];
- d_2: latest inspection metal-loss depth average [mm];
- d_{fi}: forecast defect depth [mm];
- d_i: pig-reported defect depth [mm];
- d_j: pig-reported defect depth [mm];
- d_{li}: metal-loss depth local average [mm];
- E_t: tool measurement error [mm];
- F_{si}: defect scoring factor for corrosion activity at defect vicinity;
- H_i: defect odometer [m];
- N: Population defects total number;
- N_1: Population 1 defects total number;
- N_2: Population 2 defects total number;
- n: vicinity parameter;
- R_{rc}: corrosion growth rate determined by run comparison [mm/year].

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INTRODUCTION

In the past few decades, many of the most catastrophic pipeline industry accidents have had as their root failure the mechanism diagnosed as corrosion. Presently, operators are able to rely upon several codes, standards and consolidated practices to assess the remaining strength in quantified corrosion metal-loss areas, ranging from the most simple and straightforward, such as ASME B-31G, to those more refined and time demanding, such as Finite Element analysis. Additionally, the market is now offering in-line inspection (ILI) technologies able to map and quantify, with reasonable accuracy, metal-loss damage distribution along pipelines, and the choice has grown considerably.

However, the definition of a proper pipeline integrity management strategy also requires damage progression forecasting. Indeed, growth rate estimation plays a fundamental role in the optimization of the re-inspection intervals and maintenance rehabilitation scope, and therefore has a direct effect on pipeline maintenance cost-effectiveness and operational reliability and safety.

The data-set comparison of subsequent ILI could provide solid ground for such estimates. Typically, corrosion rates are estimated by individual defect matching or by population comparison. The results achieved by the former could be quite accurate, especially when raw signal evaluation takes place, but the process applicability is rather limited, due to its characteristic of being time-demanding, while also requiring special computational tools and skilled people. On the other hand, ordinary procedures to perform run comparison by taking into account entire populations could be quickly carried out, but usually give rise to large errors in the resulting estimate.

This paper aims at presenting a straightforward scoring methodology which considerably enhances corrosion rate outputs from ILI population comparison. The work was developed based on the Principle of Local Corrosion Activity [1, 2] to take into account the neighborhood metal-loss characteristics of each defect individually. Methodology formulation could easily be put into practice on any commercial spreadsheet with basic statistic functions. A case study is presented in order to demonstrate that, despite its simplicity, the model's results are quite robust and realistic.

MODEL BACKGROUND

The difficulty in accurately measuring and predicting time dependent behavior of the parameters, which control the corrosion process in large structures such as pipelines, make it hard to accomplish effective forecasting of the metal-loss progression rates under operational conditions, by means of mechanistic approaches.

Stochastic modeling based on ILI data is better fitted to accommodate the inherent randomness of corrosion in pipelines. Accordingly, the principle of local corrosion activity states that a metal-loss defect could have its growth rate determined as a function of the average metal-loss damage in the adjoined region.

The concept of adjoined region or neighborhood (L_{ni}) is expressed by the vicinity parameter (n) and is characteristic to each location of each pipeline, being dependent on the defect population overall number as well as its local distribution. The vicinity parameter of a pipeline defect population should be determined in order to comply with the requirements expressed by Equations (1) and (2) below:

$$n >= 3 \qquad (1)$$

$$0.1 \leq \frac{\sum_{i=n+1}^{i=N-n}(H_{i+n} - H_{i-n})}{N - 2(n-1)} \leq 10 \qquad (2)$$

Simplistic assumptions[1]
- linear damage progression within the considered time intervals (between inspections and forecast period);
- all external corrosion active sites are associated with coat damage areas where the coat protection effectiveness is assumed to be null;
- new defect generation as well as stop growth rate is not considered.

CONSTRUCTING REPRESENTATIVE POPULATIONS

Regarding the construction of the populations to be assessed, special consideration should be given to tool measurement error significance, in order to guarantee relative significance of the ILI reported threshold. As a general rule, it is recommendable that depth values which do not comply with Equation (3) below should be dismissed.

$$d_i \geq \frac{2E_t}{1.28} \qquad (3)$$

Also, data population to be compared must have been collected by ILI tools of similar performance (technology, accuracy, peculiarities related to each run such as, line cleaning and flow regime) and they should both have been properly validated by field measurements. Possible bias should be identified and corrected. Depending on the adopted segmentation strategy, quality of data alignment could have a significant impact on model outputs.

A brief outline of segmentation strategy: the only mandatory segmentation procedure is the obvious partition of defects

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[1] Further details in references [1] and [2].

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located on the outside of the pipeline from those on the inside. Common segmentation based on axial distance is not particularly required, given the account of local corrosion activity. But, when it is previously known that different mechanisms are acting concomitantly and their attack severity is expected to be highly dissimilar, further population segmentation could be attempted, especially when those could give rise to distinct circumferential distributions.

Moreover, population segmentation could be also especially recommendable when coating material changes are involved (different degradation lags to be considered).
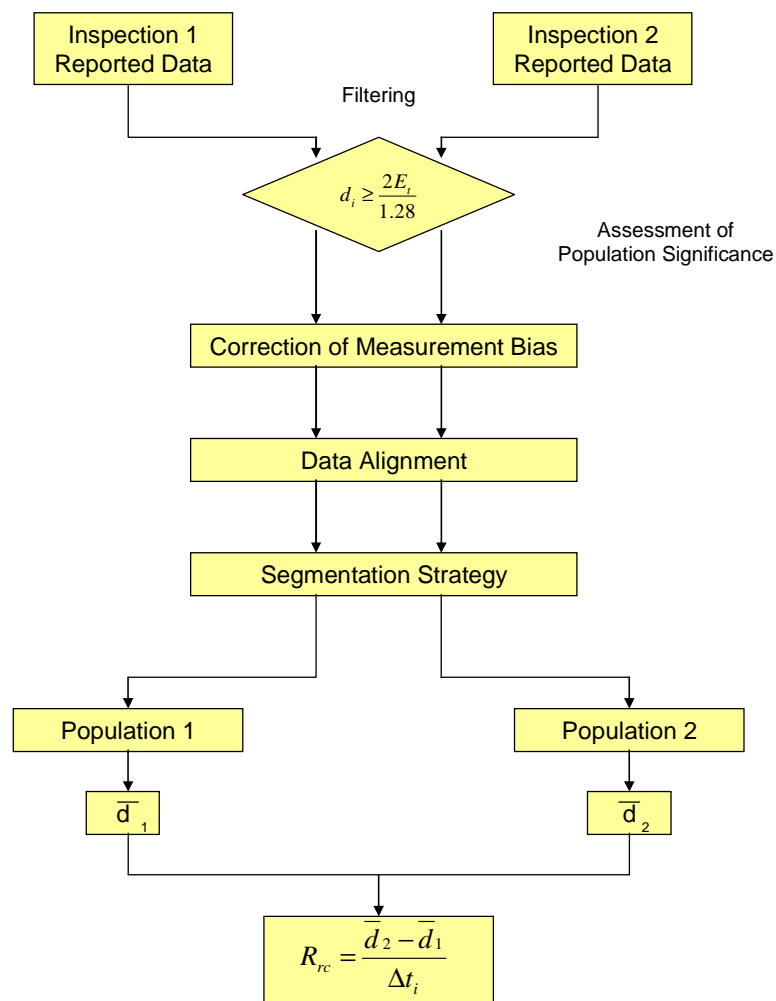
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┌─────────────────┐                      ┌─────────────────┐
│  Inspection 1   │                      │  Inspection 2   │
│  Reported Data  │                      │  Reported Data  │
└─────────────────┘      Filtering       └─────────────────┘
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$$d_i \geq \frac{2E_{t_i}}{1.28}$$

Assessment of Population Significance

Correction of Measurement Bias

Data Alignment

Segmentation Strategy

Population 1

Population 2

$\overline{d}_1$

$\overline{d}_2$

$$R_{rc} = \frac{\overline{d}_2 - \overline{d}_1}{\Delta t_i}$$

Figure 1: Flowchart of the primary run comparison.

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2. MATHEMATICAL FRAMEWORK

1. Two sets of ILI reported depth values; named Population 1 and Population 2 (referred as former and latter inspections, respectively), should be "fitted" for analysis. The "fitting" procedure should incorporate data consistency checking, measurement bias assessment and correction, besides possible segmentation strategy (which could require data alignment). The average corrosion growth in the time interval between inspections (Δt_i) should be determined as the ratio of the difference between the population's arithmetic mean and Δt_i as expressed by Equation (4).

$$R_{rc} = \frac{\overline{d}_2 - \overline{d}_1}{\Delta t_i} \qquad (4)$$

Each individual depth measurement for Population 2 should be associated to a characteristic local depth Gaussian distribution, as defined by Equation [5a] and [5b].

$$\overline{d_{li}} = \frac{\left(\sum_{j=i-n}^{j=i+n} d_j\right)}{(2n+1)} \qquad (5a)$$

$$\sigma_{li} = \frac{\sqrt{\left(\sum_{j=i-n}^{j=i+n}(d_j - \overline{d}_{li})^2\right)}}{(n-1)} \qquad (5b)$$
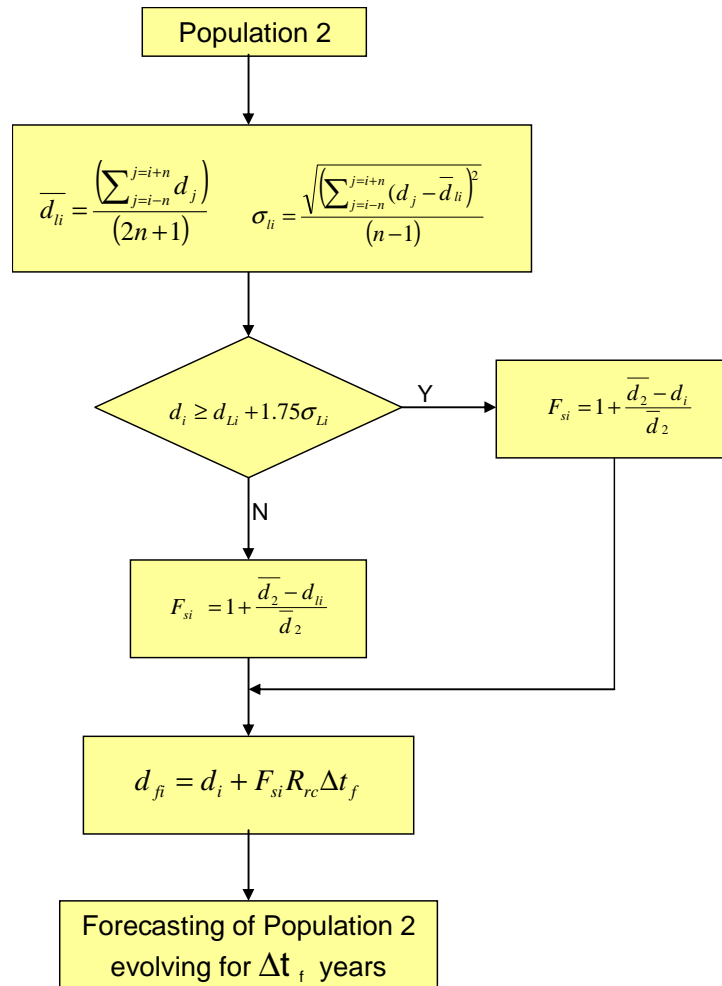

FIGURE 2: Flowchart of the process to forecast defects future population.

3. Subsequently, a corrosion activity coefficient (F_{si}) should also be individually calculated by Equation (6a), in order to express the region's corrosion activity potential.

$$F_{si} = 1 + \frac{\overline{d_2} - d_{li}}{\overline{d_2}} \qquad (6a)$$

$$F_{si} = 1 + \frac{\overline{d_2} - d_i}{\overline{d_2}} \qquad (6b)$$

3a. Hot Spot Conditional Structure. The underestimation in hot spot regions should be prevented by modifying equation (6a) into (6b), when the conditional structure stated in Equation (7) is fulfilled:

$$d_i \geq d_{li} + 1.75\sigma_{Li} \qquad (7)$$

4. Finally, future defect depth should be determined by Equation (8).

$$d_{fi} = d_i + F_{si}R_{rc}\Delta t_f \qquad (8)$$

A broad outline of run comparison logic is depicted in the flowchart presented in Figure 2.

CASE STUDY

Background: The methodology described was applied to estimate the corrosion rate distribution in a 3.5 km segment of an oil production line with 16" diameter, 9.5 mm thickness, manufactured in API 5L X65. The pipeline had been used in the interconnection of onshore production fields of depleted reservoirs and the BSW content of the fluid conveyed ranged from 80-90%. In late 2007 and late 2009, the line underwent MFL ILI surveys. Both tool accuracy and performance were fairly similar but the reporting threshold was 10% in 2007, while in the 2009 inspection, only depths above 35% were reported. No attempt to identify and correct measurement bias has been carried out. Only the anomalies located in the internal pipeline surface have been considered in the analysis.

TABLE 1: Defect depth populations.

Inspection	Population	Number of defects	Threshold % wt	Average depth % wt
	1	12,833	32%	38.11
2007	1_o	33,833	10%	---
2009	2	12,833	35%	40.29

Table 1 gives some additional details regarding the internal defect populations reported in the 2007 and 2009 inspections, as well as their respective arithmetic means. Also, Figure 3 presents the axial distribution of defects with reported depths over 40%.

Procedure: as a consequence of the considerable difference between inspection reporting thresholds, the population of internal defects reported by the 2009 inspection (N_2) was almost a third of the 2007 (N_1) inspection. In order to deal with this problem the following procedure was adopted:

1. As a starting point, it was assumed that the N_2 deepest defects reported by the 2007 inspection were the same N_2 reported in 2009, those defects being labeled as Population 1';

2. A first approximation of the average corrosion rate in the period between the considered inspections (R'_{rc}) was determined by Equation (4), considering the Populations 2 and 1';

3. All defects originally reported by the 2007 inspection (Population 1_o) have had their future geometry forecast according to the procedure detailed in the flowchart of Figure 2;

4. Population 1 was then defined as being the N_2 defects which presented the deepest forecast depths for 2009;

5. A new R_{rc} value was calculated by Eq. (4), considering Populations 1 and 2;

6. Finally, Population 2 growth was forecast for a time interval of 3 years, resulting in the data set, labeled as Population 3.

Results: Figure 4 compares the defect depth histograms of 2007 and 2009 ILI measurements (Populations 1 and 2, respectively) with 2012 predicted population (Population 3). The steadiness of damage progression becomes much more evident when those populations are normalized by the Local Activity Principle as could be noted in Figure 5.

Model Robustness: In order to assess the model output fitness, Population 1 (2007) evolution was projected towards 2009. The histogram of these predicted depths is compared with the histogram of 2009 ILI reported results in Figure 6. The match between them demonstrates the model robustness and its suitability for common pipeline fitness-for-purpose evaluations. The slight tendency to overestimate the frequencies of higher depths can almost be overcome by dismissing the hot spot conditional structure in the algorithm.
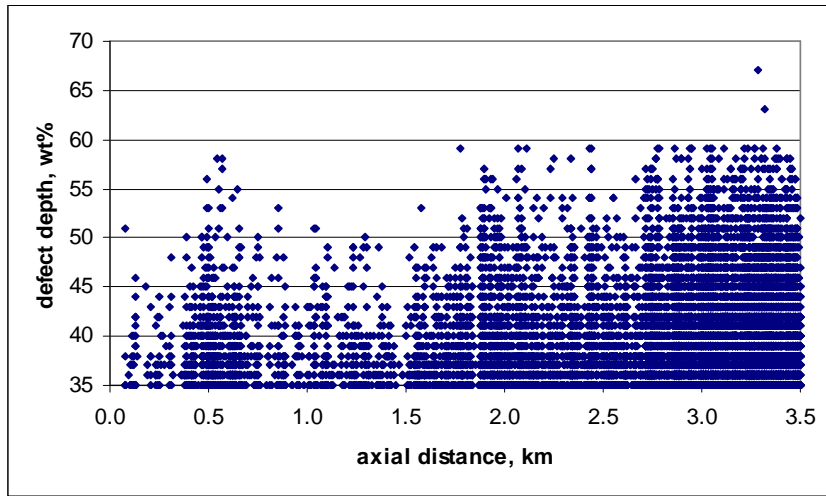
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FIGURE 3: Defects axial distribution in 2009.
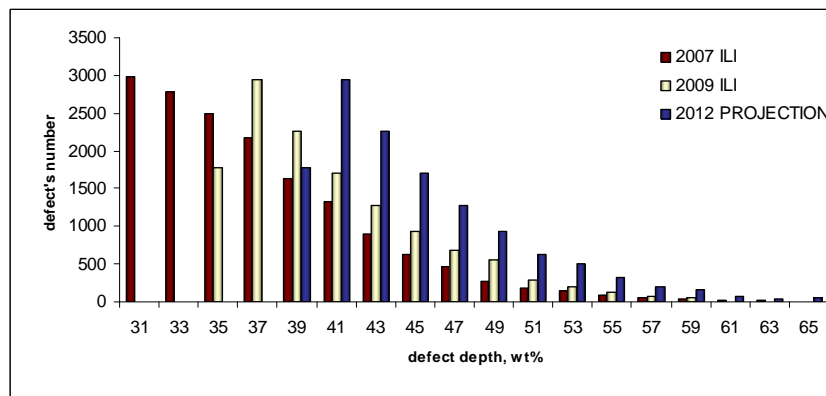

FIGURE 4: Histogram of defect depth populations.
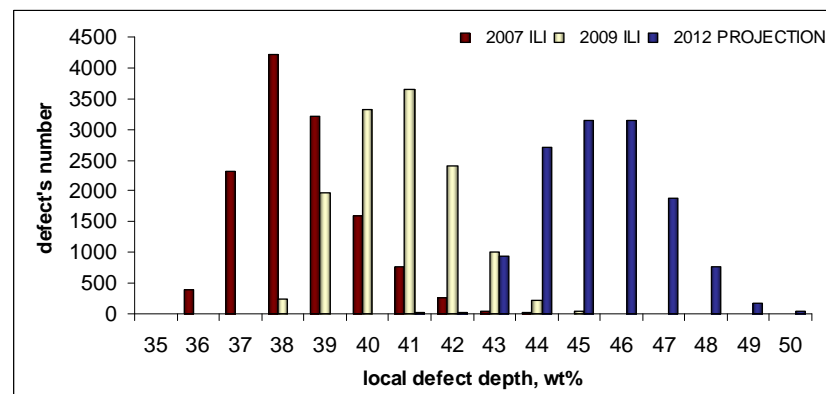

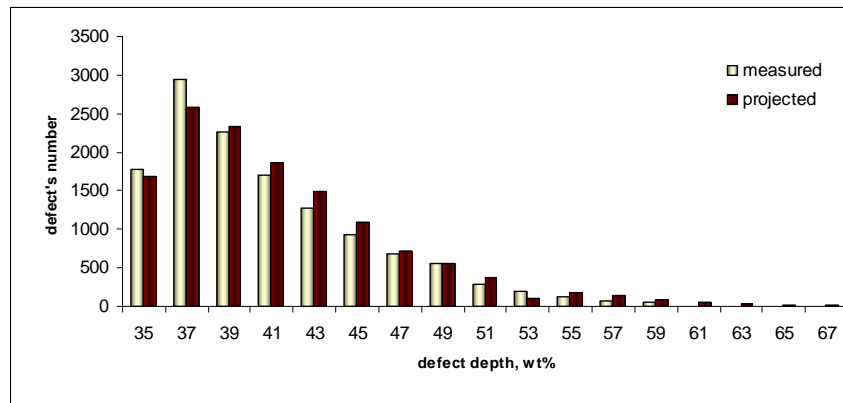**FIGURE 5:** Histograms of local defect depth.

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FIGURE 6: 2009 Histogram of defects depth.

CONCLUSION

A stochastic scoring methodology to estimate corrosion growth by ILI run comparison is presented. The model could easily be implemented in any mathematic commercial package and allows quick and reasonably accurate projections of the defect-depth population evolution throughout time.

Output reliability, however, is highly dependent on data consistency as much as the significance of the comparison procedure, and so the differences in the tool technologies, performances and reporting thresholds should be carefully evaluated and assessed. Also, it is assumed that significant tool measurement bias had been previously identified and properly treated.

ACKNOWLEDGMENTS

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