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ANALYSIS ON ERROR DISTRIBUTION OF IN-LINE INSPECTION IN OIL AND GAS PIPELINES

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Abstract: Nondestructive in-line inspections become more and more common for assessment of pipeline integrity and fitness for purpose procedure. A standard practice includes a validation of the inspection data by comparison with direct nondestructive test data in selected sites after excavation. The comparison usually is on the type and size of defect and flaws. Once the data is validated, it can be used to evaluate pipeline integrity directly by some deterministic model. Some probabilistic model can predict the defect growth better and hence the future of pipeline integrity with more accuracy. Generally, this kind of models depend on the distribution of the in-line inspection measurement error, therefore this work is focused on the analysis of error distributions through 6 sets of in-line inspection data and direct non-destructive field measurement data. The Kolmogorov-Smirnov test was employed for this analysis, and the distributions of Normal, Lognormal, Gamma, and Exponential were verified to obtain the best distribution. The final aim of the analysis is to offer evidence to develop a probabilistic model for prediction of corrosion rate.

Keywords: In-Line Inspection; Field Measurement; Lognormal distribution; Pits

HIGHLIGHTS

- Nondestructive in-line inspections data usually is on the type and size of defects.
- Comparison between inspection data and nondestuctive test data after excavation for a validation.
- Pipeline integrity can be predicted by probabilistic models.
- Probabilistic models need probabilistic distributions from the validation measurement error.

INTRODUCTION

Pipelines are considered the fastest, safest, and most economical means to transport hydrocarbons. To ensure safe transportation and distribution, pipelines are often buried exposed directly to corrosive soil [1, 2]. The main feature of the pipeline corrosion damage identified by various diagnostic tools is wall thickness losses due to general and pitting corrosion of the pipe steel. The wall damage of high-pressure gas or oil pipelines need to be controlled by their operators through integrity management [3, 4]. With the aging of pipeline infrastructure and the increasing economic and regulatory constraints, maintaining the integrity of pipelines becomes an area of increasing relevance for pipeline operators. Due to the complexity of most pipelines being buried, non-destructive testing (NDT) turns out to be the best method to evaluate the system. There is a wide variety of NDT's, among which the In-Line Inspection (ILI) stands out, the ILI have a regulatory framework to validate the obtained data. ILI assessment (NACE SP0102-2017 Standard) is a non-destructive technique often used to establish a clear perspective of the inner and outer condition of the pipe using magnetic (MFL) or ultrasonic tools (UT) to identify and measure metal loss. The results of an ILI inspection are of central importance to define a maintenance policy [5-8]. However, this detection process goes beyond a threshold, which determines whether a defect is detected or not [9]. The API 1163 method can be used to validate the ILI data [10]. The data validation process is comparing an ILI data set with previous ILI data and/or excavation data [11, 12]. The data of the ILI's tend to have a normal distribution, due to the Central Limit Theory in most cases, when the variables are independent and identically distributed [13]. Usually, the reporting precision regarding the depth measurement is around ±0.3 to ±0.6

mm for UT, and the confidence level is at 95% versus a level of 80% for MFL [14].

On the other hand, the corrosion rate has been studied with different models and theories, mainly with an electrochemical perspective, some in a deterministic way while others with a statistical and probabilistic approach [15]. Before the smart ILI technique appeared, the corrosion rate was used to be quantified by chemical and electrochemical analysis. The model developed by de Waard and Milliams [16] is the most frequently employed model in evaluating internal corrosion. Anderko model [17] has been developed to calculate the corrosion rates of carbon steels in the presence of CO_2, H_2S. The NORSOK model [18] is an empirical corrosion rate model for carbon steel in water at different temperatures, pH, CO_2 concentration, and wall shear stresses. Deterministic models have been used to predict the corrosion rate through basic calculations using two or more ILI data, which does not consider factors affecting localized corrosion [19]. Probability and statistics can be more adequate method to analyze ILI data [20]. Some researchers have studied corrosion using a probabilistic approach. Papavinasam's model [21] predicts internal pitting corrosion of oil and gas pipelines, the model accounts the statistical nature of the pitting corrosion and predicts the growth of internal pits based on the readily available operational parameters from the field. Caleyo et al. [22] carried out an analysis of the evolution of the underground pipeline's structural reliability.

As the pipeline industry is increasingly focusing on the reliability/risk-based pipeline integrity management practice [23-25], it is desirable to understand the probabilistic characteristics of measurement errors associated with ILI-reported defect dimensions [26]. If two or more ILI data sets and field measurements are available on the same pipeline, then the rate prediction model can be updated by using Bayesian theory [27-29]. The objective of this study is to analyze the measurement error associated to the ILI-detected pitting depths and lengths to offer distribution model and evidence for developing a probabilistic corrosion rate prediction model based on one set or more sets of ILI data.

METHODOLOGY

In probability theory, a normal distribution is a type of continuous probability distribution for a real-valued random variable. The general form of its probability density function is [30]:

$$f(x) = \frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{1}{2\sigma^2}(x-\mu)^2} \tag{1}$$

The normal distribution function has a parameter mean value μ and the standard deviation .

The lognormal distribution is used for a wide variety of applications. The distribution applies in cases where a natural log transformation results from a normal distribution. The continuous random variable X has a lognormal distribution if the random variable Y = ln(X) has a normal distribution with parameters λ and ξ. These parameters are related with the mean $\mu=\exp(\lambda+\frac{1}{2}\xi^2)$ and standard deviation $\sigma=\mu(e^{\xi^2}-1)^{1/2}$. The resulting probability density function of X is [30]:

$$f(x) = \frac{1}{\sqrt{2\pi\sigma x}} e^{-\frac{1}{2\sigma^2}(\ln(x)-\mu)^2} \tag{2}$$

A probabilistic model remains an abstraction until it has been related to observations of the physical phenomenon. These data yield numerical estimations of the model's parameters and provide an opportunity to verify the model by comparing the observations against model predictions. The former process is called *estimation*. The latter, comparative, process includes *verification*

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of the entire model, but more broadly it includes the search for *significance* in a batch of statistical data [30]. Having developed a model of the physical phenomenon leading to a proposed functional form (e.g., normal, lognormal) of the governing probability distribution. Subsequently, the parameters must be estimated and then the model can be validated. Both these processes, estimation and verification, require data for the resolution. No single sequence of observations in a finite number can be expected to give exact model parameter values, because the data itself is a product of the "randomness" which is characteristics of the phenomenon. One must be ready to accept a data-derived parameter value as an *estimate* of the true value, subject to an error of uncertainty but, not unquantifiable magnitude. A very common and most challenging problem is the assessment of *significance* in scattered statistical data. In this work, we concentrate on relatively simple model assumptions, test hypotheses, and treat the verification of the model or distribution. There are several ways of comparing the form of the model and the observed data, one of them is to plot each observation as a specific point side by side with the complete, continuous Cumulative Distribution Function (CDF) of the model. In practice, the comparison of cumulative curves can be simplified by scale changes, that is, through special plotting paper. It is so called *probability paper*. This probability paper provides properly scaled coordinates such that the cumulative distribution function of the probability plots as a straight line. In this paper, we considered normal, lognormal, exponential, and Gamma probability papers. To "test" a hypothesis is to conduct an experiment related to the state of nature. Based on the outcome of the experiment, to decide whether the hypothesis can be "accepted" or should be "rejected". To accept a hypothesis does not mean the same thing to all investigators or all situations. It does not mean, in a statistical experiment, that the hypothesis is "proved" in any rigorous sense, because the data in a sample give only incomplete information about a population and can easily be misleading [31].

A test of a hypothesis is a rule that assigns one of the inferences accept it or reject it to each foreseeable result of an experiment. The hypothesis to be tested is called the null hypothesis, and the set of other states of nature or models admitted as possible for a given experiment is called the alternate hypothesis. The null hypothesis will usually be denoted by H_0 and the alternative either by H_A or by H_1. Another way to verify that the data follows a distribution (e.g. normal, lognormal) is to subject the data to the Kolmogorov-Smirnov (K-S) test [31], which would indicate whether our hypothesis is to be accepted or rejected. On this work our null hypothesis is the data have a lognormal distribution, other researchers have also attempted to apply the distribution in their development of corrosion prediction models without a previous test [32], [33].

RESULTS AND DISCUSSION ON CASE STUDY

Six case studies, using ILI data and field measurements for corrosion defects in real pipelines, were carried out to establish the application of the model previously presented. From case 1 to case 4; the depths of pits were analyzed, and for the last two cases; the lengths of pits were studied.

CASE 1: A PIPELINE WITH 20" IN DIAMETER

A 78.4 km long pipeline has a nominal outside diameter of 508 mm (20 in) and a nominal wall thickness (WT) of 5.56 mm (0.21 in), which transports natural gas and was inspected three times in 2004, 2007, and 2009 respectively [34]. For this case, the 298 pits of field measurements and the three inspections using a MFL ILI tool were displayed in figure 1. The difference between the maximum and the minimum values were significantly large. Also, it should be noted that the ILI tool tend to understimate the depths of the corrosion defects.

The figure 2 (a), (b), (c) and (d) presented all the probability papers of the four differents probabilistic distributions for this case. It can be observed that the best fit is the lognormal distribution. What follows is to calculate through K-S test whether the lognormal distribution is the best fit for the data of case 1 with 95% of confidency level. The model was applied and the probability paper with test parameters and results is shown in figure 2(b) for the lognormal distribution, the results showed that the lognormal distribution was accepted, and the distribution has mean value of 1.70931 and standard deviation of 2.5323 and the minimum rate was 0.10585, and the maximum rate was 30.1576.

CASE 2: A PIPELINE WITH 18² IN DIAMETER

A 110 km long pipeline transports crude oil. The diameter of the pipeline is 457.2 mm (18 in), and the wall thickness is 6.35 mm (0.25 in). The inspection was carried out in 2010, the pipeline has between 35 and 42 years of service [35]. 40 pits data detected with an UT tool was used and are shown in figure 3. Here the UT tool underestimated the corrosion defects in the pipeline. In figure 4(a), (b), (c) and (d), the four probabilistic papers are plotted, and it showed that the data might have a lognormal or a Gamma distribution.

The outcome of the K-S test for the 40 pits, figure 4(b) demonstrates that the data prefer a lognormal distribution with a mean value of, a minimum value of 0.14575 and a maximum value of 10.27581 and almost all values are in the range except for one data point.

CASE 3: A PIPELINE WITH 28² IN DIAMETER

A segment of a 145 km long high-pressure gas pipeline, with an outside diameter of 711mm (28 in) and nominal wall thickness of 10.5 mm (0.41 in) [3] was analysed and the model was applied to 18 pits. The dimension of 18 pits is between 17 and 79 %WT for the field measurement and between 24 and 72 %WT for the ILI measurement as shown in figure 5, the minimum value of the dataset is 0.3832 and the maximum value is 39.2162, while the mean is 3.00012. According to the figure 5 the tool correctly detected most of the corrosion defects. a MFL tool was used for the ILI.

In figure 6(a), (b), (c) and (d), the four probabilistic papers are presented, the figure 6(b) displayed that even though there are 5 pits out of the minimum and maximum range, it still has a lognormal distribution.

CASE 4: A PIPELINE WITH 36² IN DIAMETER

The oil pipeline has an external diameter of 914 mm (36 in) and wall thickness of 11 mm (0.43 in). During the inspection a total of 42 internal pits were detected, localized, and sized [14]. The minimum, maximum and mean values are 0.0235, 12.442 and 1.6338, respectively for the dataset. Again, the MFL tool underestimated the corrosion defects in field, this affects to the probabilistic models due to the errors in measures. Not even the larger pits are well measured, this can be seen in figure 7. Three distributions may fit the dataset as shown in figure 8 (a), (b), (c) and (d).

The figure 8(b) shows that the data has a lognormal distribution where almost all the pits are within range through the K-S test.

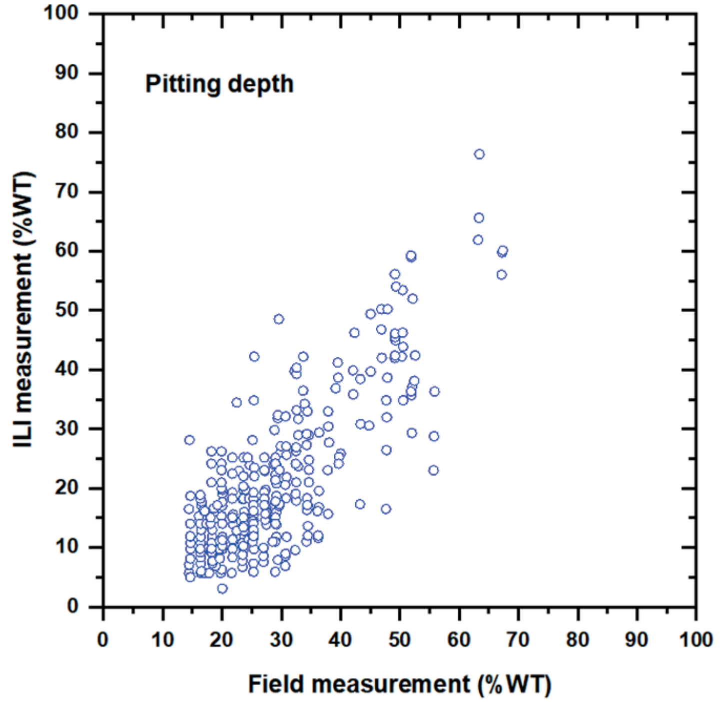

Fig. 1. Field and ILI measurement pitting depth for case 1.

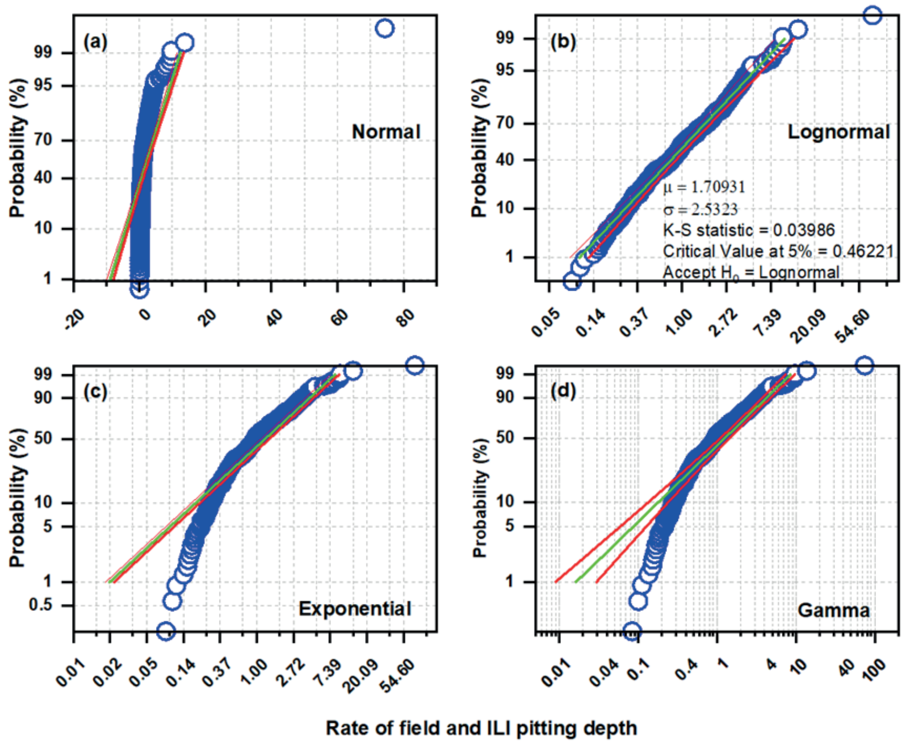

Fig. 2. Probability paper of field and ILI measurement pitting depth rate for case 1: (a) Normal, (b) Lognormal, (c) Exponential, and (d) Gamma.

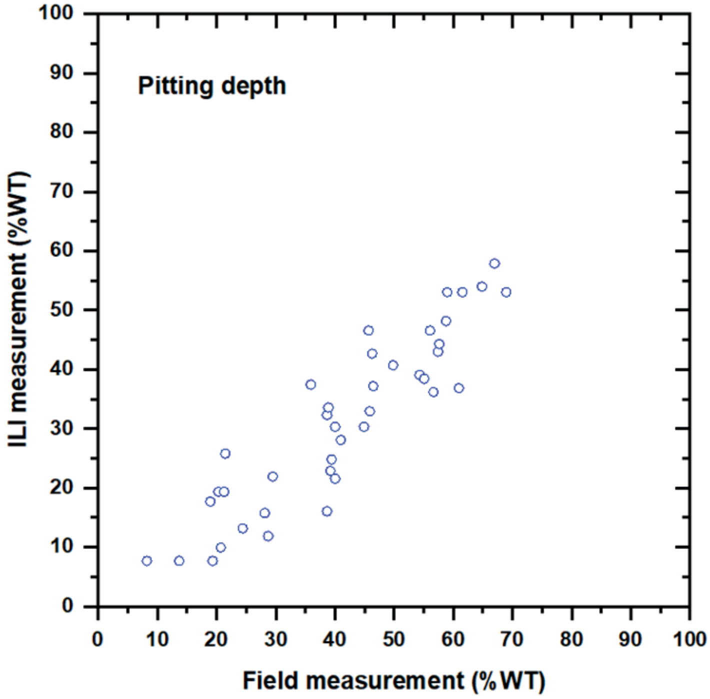

Fig. 3. Field and ILI measurement pitting depth for case 2.

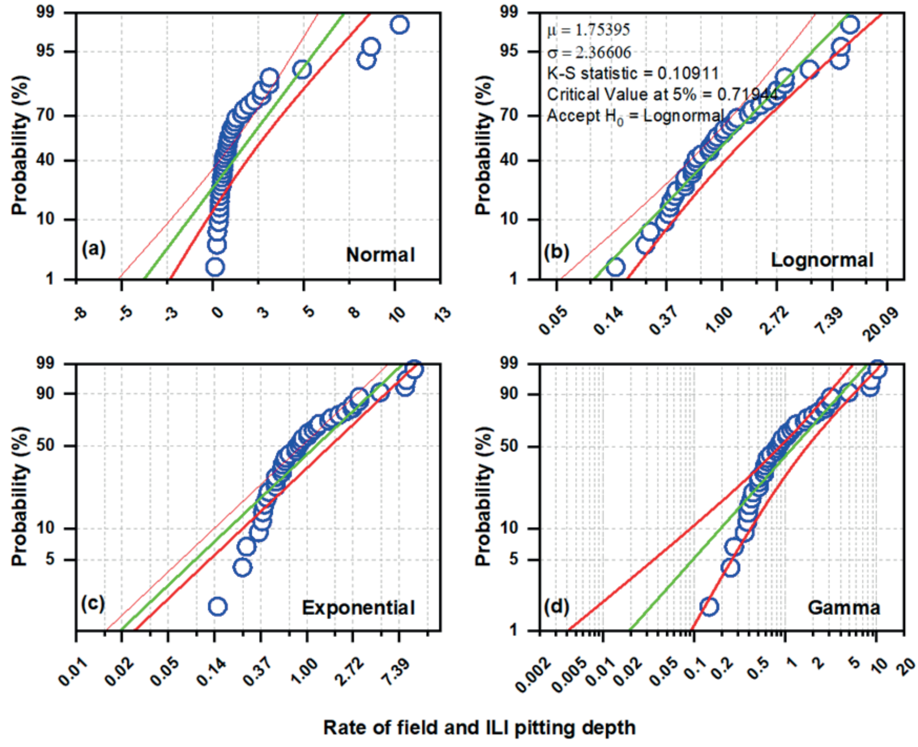

Fig. 4. Probability paper of field and ILI measurement pitting depth rate for case 2: (a) Normal, (b) Lognormal, (c) Exponential, and (d) Gamma.

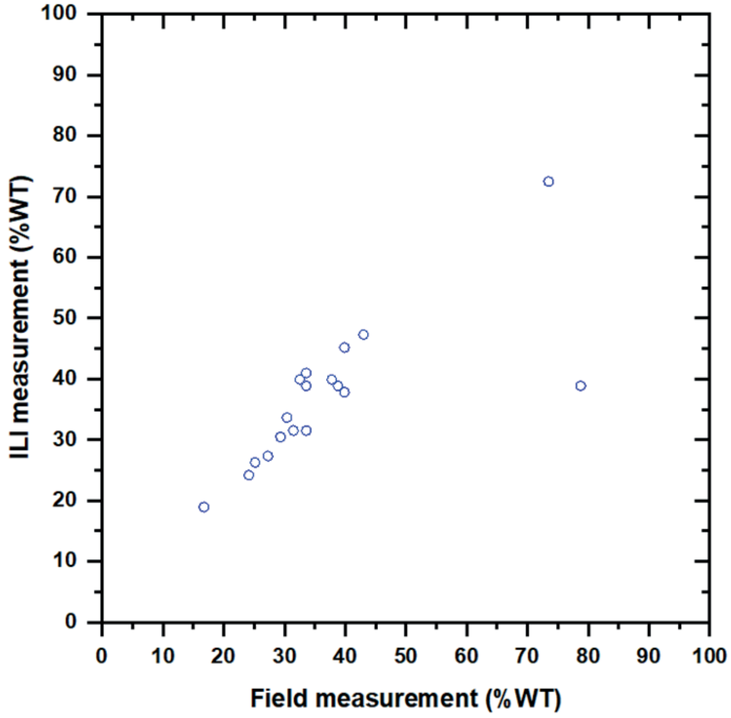

Fig. 5. Field and ILI measurement pitting depth for case 3.

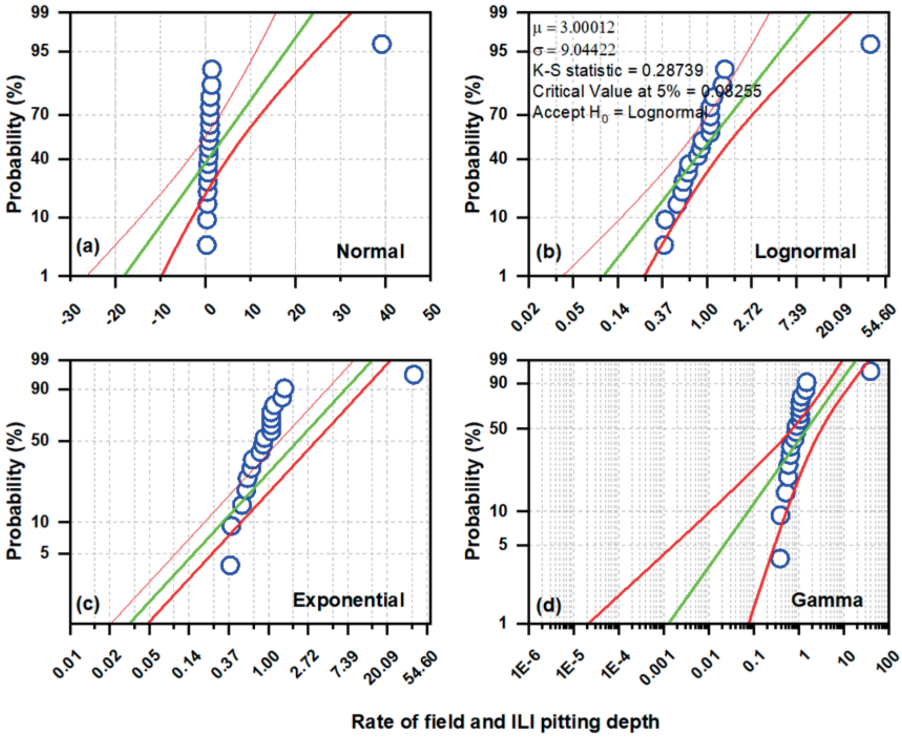

Fig. 6. Probability paper of field and ILI measurement pitting depth rate for case 3: (a) Normal, (b) Lognormal, (c) Exponential, and (d) Gamma.

CASE 5: A PIPELINE WITH 30² IN DIAMETER

The natural gas pipeline has an external diameter of 762 mm (30 in) and wall thickness of 12.7 mm (0.5 in) [26]. The ILI found 199 defects as shown in figure 9. The minimum value was 0.0495, the maximum was 11.937, and the mean was 1.6301. The ILI tool overestimated the corrosion defects up to 11 times its actual size.

In figure 10(a), (b), (c) and (d), the four probabilistic papers are presented. The figure 10(b) shows the Kolmogorov-Smirnov test result, which demonstrates that the distribution was lognormal for the case number 5 for pitting length.

CASE 6: A PIPELINE WITH 28² IN DIAMETER

The pipeline is the same as in case 3, instead of pitting depths, the pitting lengths were analyzed [3]. The 18 pits are shown in figure 11 where the pitting lengths are in mm. The values for the case were as follows: minimum 0.3113, maximum 13.9991 and the mean 2.1317.

In figure 12(a), (b), (c) and (d), the four probabilistic papers are presented. For the case, the distribution accepted by the K-S test is a lognormal as shown in figure 12(b).

The null hypothesis presented in this work was the lognormal distribution as a main probabilistic distribution, considering that data sets might not have a proper distribution or might have one or more distributions due to the number of items in those data sets, this work presented the null hypothesis is accepted in the six studied cases graphically and doing calculations with the K-S test.

To summarize, table 1 shows the different statistical values for the 6 studied cases. In the table it can be found that the different values for depth (case 1-4) and length rate (case 5 and 6). The p-value changes according to the pitting number and numerical values.

As we mentioned above, a probabilistic model may be applied to these data sets to predict the damage evolution of the pitting depth and length. Related to it, the following probabilistic model can be proposed.

The measurement error in ILI's can be defined as the difference between the actual and measured pitting dimension as such depth, which we will denote as ε, assuming data from ILI has a normal probability density function. Therefore, it can be defined the pitting depth as a random variable $D_1(t_1)$ of the ith corrosion defect in inspection t_1[36].

$$\boldsymbol{D_1(t_1) = d_{m_1}(t_1) + \varepsilon} \tag{3}$$

Given the probability density function of the measurement error and according to the probability theory, the normalized probability density function of the depth $D_1(t_1)$ is,

$$\boldsymbol{f_{D_i}(d(t_1)) = \left[1 - \Phi_\varepsilon\left(d_{m_i}(t_1)\right)\right]^{1-I_{A_i}} \times \left[\varphi_\varepsilon\left(d - d_{m_i}(t_1)\right)\right]^{I_{A_i} I_{B_i}} \times \left[1 - \Phi_\varepsilon\left(w_0 - d_{m_i}(t_1)\right)\right]^{1-I_{B_i}}} \tag{4}$$

Where w_0 is equal to the wall thickness and the indicators are equal to one when $\boldsymbol{0 < D_1(t_1) < w_0}$; $\boldsymbol{I_{A_i} = 0, I_{B_i} = 1}$ when $\boldsymbol{D_1(t_1) = 0}$ and $\boldsymbol{I_{A_i} = 1, I_{B_i} = 0}$ when $\boldsymbol{D_1(t_1) = w_0}$. On the other hand, if ε is defined as quotient of the real depth divided by the ILI measured depth, damaged-associated probability would be null. The random variable of depth of the ith corrosion defect at inspection time t_1 is defined by [37]:

$$\boldsymbol{D_1(t_1) = k d_{m_1}(t_1)} \tag{5}$$

Where the random variable $\boldsymbol{k}$ is lognormal. Probability density function of the ith damage depth is given by:

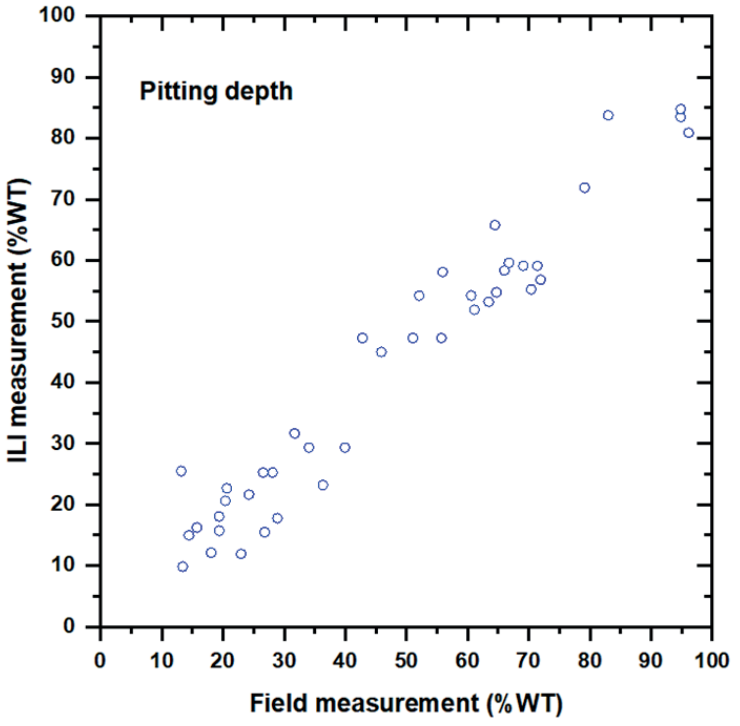

Fig. 7. Field and ILI measurement pitting depth for case 4.

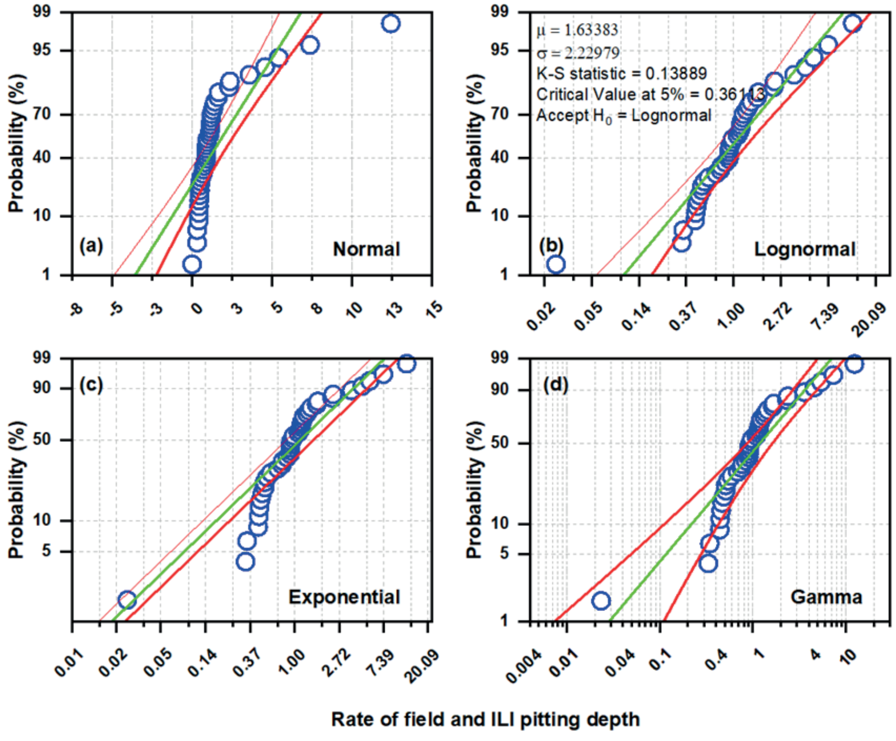

Fig. 8. Probability paper of field and ILI measurement pitting depth rate for case 4: (a) Normal, (b) Lognormal, (c) Exponential, and (d) Gamma.

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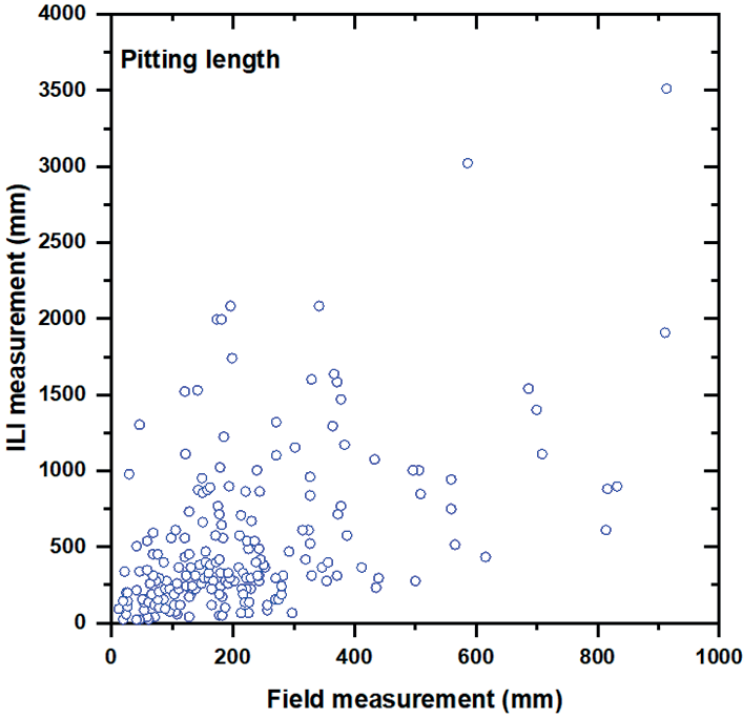

Fig. 9. Field and ILI measurement pitting length rate for case 5.

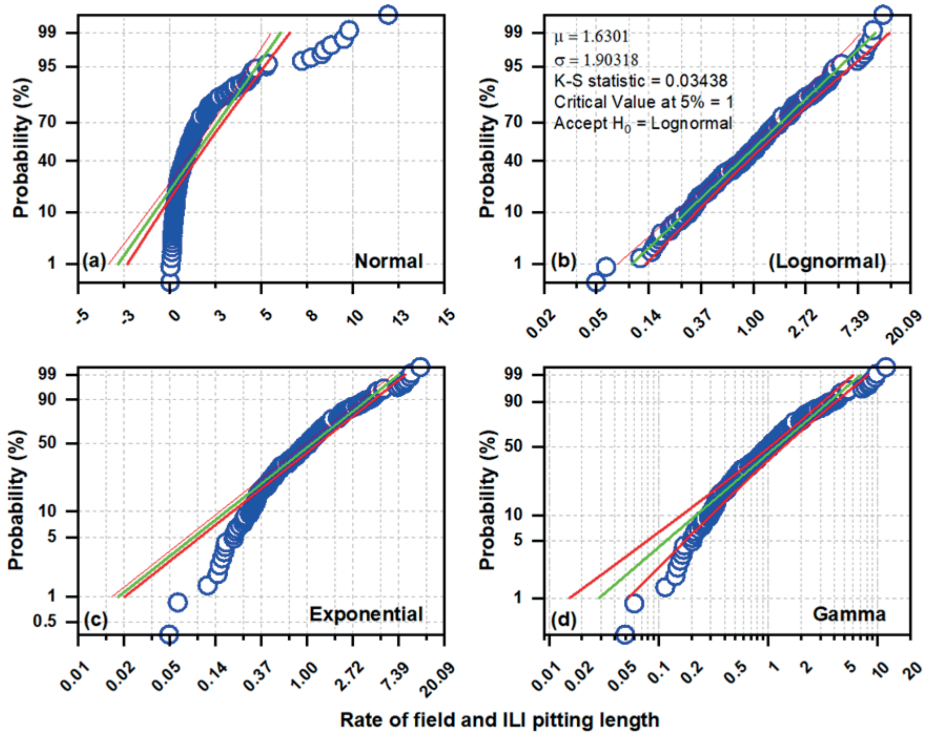

Fig. 10. Probability paper of field and ILI measurement pitting length rate for case 5: (a)Normal, (b) Lognormal, (c) Exponential, and (d) Gamma.

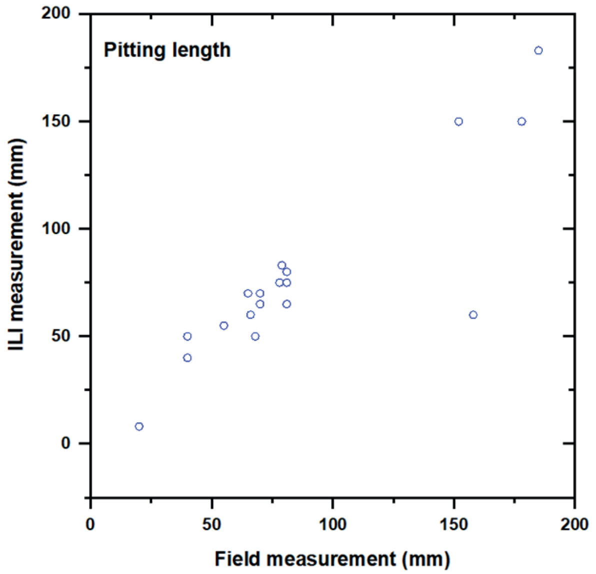

Fig. 11. Field and ILI measurement pitting length rate for case 6.

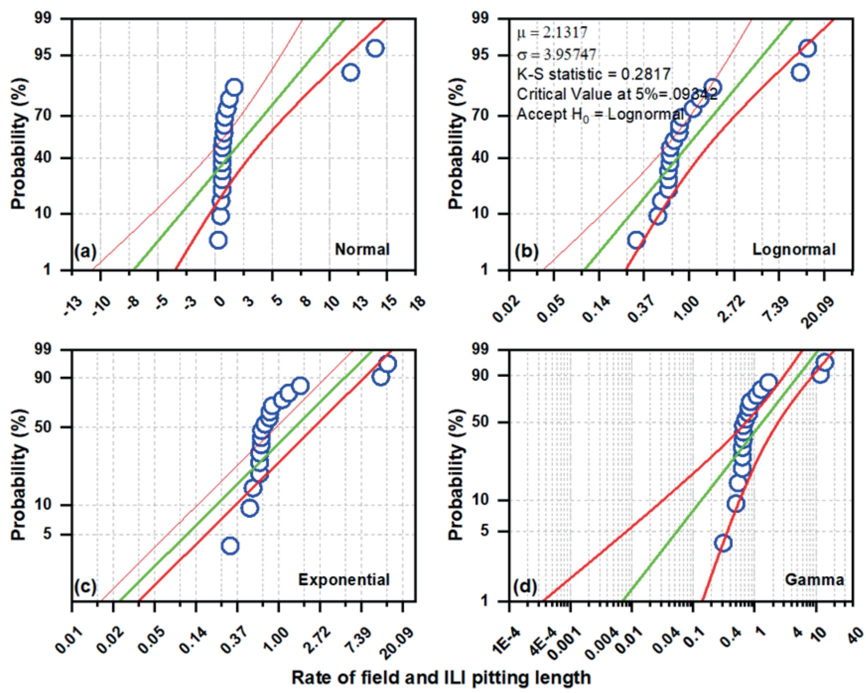

Fig. 12. Probability paper of field and ILI measurement pitting length rate for case 6: (a)Normal, (b) Lognormal, (c) Exponential, and (d) Gamma.

Case	Minimum value	Maximum value	Mean value	Standard Deviation	p-Value	Distribution
1	0.1058	30.1576	1.7093	2.5323	0.4622	lognormal
2	0.1457	10.2758	1.7539	2.3660	0.7194	lognormal
3	0.3832	39.2162	3.0001	9.0442	0.0825	lognormal
4	0.0235	12.4420	1.6338	2.2297	0.3610	lognormal
5	0.0495	11.9370	1.6301	1.9031	1.0000	lognormal
6	0.3113	13.9991	2.1317	3.9574	0.9342	lognormal

Table. 1. Statistical information of the cases under study

$$f_{D_i}(d(t_1)) = \left[1 - \Phi_K\left(ln\left(\frac{w_0}{d_{m_i}(t_1)}\right)\right)\right]^{1-I_{A_i}} \left[\frac{1}{d_{m_i}(t_1)}\varphi_K\left(ln\left[\frac{d}{d_{m_i}(t_1)}\right]\right)\right]^{I_{A_i}} \quad (6)$$

The probability density function of the equation (6) avoids the artificial truncating issue of normal distribution function for pitting depth of less than 0 and greater than wall thickness, which allows for the corrosion prediction probabilistic model based on it to be more reliable and accurate.

CONCLUSIONS

In this work, six sets of in-line inspection data and direct non-destructive test data in excavation sites were gathered and an analysis were performed by The Kolmogorov-Smirnov test to establish an adequate distribution on the in-line inspection data error, which were expressed as the rate of non-destructive direct measurement in excavation sites for some selected verified pitting locations on right of way and the in-line inspection pitting dimensions. Some candidate distributions such as Normal, Lognormal, Gamma, and Exponential were used to verify the adequate distribution. It aims to finally develop a probabilistic model for prediction of corrosion rate. It can be concluded that the assumption that lognormal distribution is more adequate for all the data set under study when the field and ILI rate is employed for the error distribution analysis. Certainly, it cannot be regarded that the Lognormal is always adequate for all data set. It is suggested that a good practice for establish an adequate distribution of in-line inspection error is to test it for each ILI equipment and to find out if the data collected from the ILI's have a Lognormal or some other distribution. This way the subsequent developed prediction model of damage growth is specifically for the ILI data and hence it may be more accurate for the prediction of corrosion pitting growth and the assessment of the pipeline integrity and corresponding fitness for purpose procedure. An own corrosion prediction model for each pipeline based on the own distribution of in-line inspection data error is a tendency for modern pipeline maintenance, a general use prediction model cannot provide the same reliability and accuracy.

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