Possible ways to achieving high-accuracy sizing of defects discovered by ILI tools

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THE MAIN GOAL of in-line inspection (ILI) is (according to the seven basic ILI quality metrics [1]) to correctly detect, locate, and identify all types of defects present in a pipeline and to size them in a fashion which allows statistical assessment of their true sizes. If achieved, the last fact opens the door widely to meaningful usage of the most sophisticated methods of structural mechanics (which were developed spending worldwide billions of $$$ but not used yet to its fullest in the pipeline industry) and obtaining most-accurate values possible of pipeline residual strength, probability of failure, and residual lifetime. This, in its turn, permits using predictive-maintenance technology in pipeline operation, introducing optimal inspections and repair logistics, and maximizing the long-term utility of the asset (in our case, the pipeline system).

The paper describes the methodology developed by the authors of a holistic innovative approach to ILI data generation and data management, which dramatically increases ILI inspection capabilities. This methodology, to a large extent, decreases the existing uncertainties and minimizes scatter of the input parameters and, thereby, makes predictions based on ILI data less conservative. As a result, this permits creation of safe solutions and avoidance of dangerous errors in predictions which include assessment of pipeline inspection frequency and safety margins.

According to the API 1163 Standard [2], the ILI measurement results are characterized by three parameters of statistical nature: tolerance, certainty, and the confidence level. Tolerance is the range with which an anomaly dimension or characteristic is sized or characterized, and certainty is the probability that a reported anomaly characteristic is within a stated tolerance. Confidence level is a statistical term used to describe the mathematical certainty with which a statement is made, and indicates the confidence with which the tolerance and certainty levels are satisfied. The paper discusses the statistical sources of these probabilities and how they should be interpreted and handled. The paper contains recommendations on how to approach different practical problems, and illustrates each case with real-life examples.

Key words: pipelines, defects, in-line inspection, measurement errors, statistical analysis.

ACCORDING TO API 1163, ILI measurement results are characterized by three parameters of statistical nature: tolerance, certainty, and confidence level. Tolerance is the range with which anomalies dimension or characteristic is sized, and certainty is the probability that a reported anomaly characteristic is within a stated tolerance. Confidence level (CL) is a statistical term used to describe the mathematical certainty with which a statement is made,

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and indicates the confidence with which the tolerance and certainty levels are satisfied. Each of the parameters will now be considered separately.

The accuracy of any ILI tool is characterized by the tolerance of the measurements for a given certainty, which are found via its measurement error (ME). It is assumed that any measurement of the defect parameter made by using an ILI tool is, with probability p, inside the limits $\pm k \cdot wt$, where k is a portion of pipe wall thickness wt. For instance, for HR ILI tools, the tolerance for defect depth is 10% wt (k = 0.1) with probability p = 0.8 (80% confidence interval). This can be expressed as:

$$P(|X-\mu| \le k \cdot wt) = 1-\alpha = p \qquad (*)$$

where X is the error of a single arbitrary measurement of the defect depth; μ is the mathematical expectation of the ME; $\alpha = 1 - p$ is the confidence level; p is the certainty according to API 1163 [2]; $k \cdot wt$ is the statistical accuracy (tolerance, according to API 1163 [2]).

Usually it is assumed that MEs are normally distributed with zero mathematical expectation. In this case the graphical interpretation of the ME distribution for different values of certainty p has the form as given in Fig.1. The random value ME is inside the symmetrical interval, as related to the origin, $[-k \cdot wt; k \cdot wt]$, with probability $p = 1 - \alpha$. For instance, p = 0.8, then 80% of all MEs will be inside the interval $[-k \cdot wt; k \cdot wt]$. Hence, the total area of the tails is equal to α. The interval is symmetric; therefore, area of each tail is equal to $\alpha/2$. According to the properties of the normal probability-density function (PDF), Equn (*) can be expressed as in Equn 1 (*below*) where $\Phi(x)$ is the standard normal cumulative distribution function (CDF).

From Equn 1 it follows that the tolerance for the ILI tool is calculated according to:

$$k \cdot wt = z_{1-\alpha/2}\sigma \qquad (2)$$

where $z_{1-\alpha/2}$ is the quantile of the standard normal distribution of level $1 - \alpha/2$.

Hence, with known ILI tool tolerance (from Equn 2) it is possible to define the standard deviation (SD) of tool MEs.

The meaning of the confidence level is in that when, for instance CL = 95%, the certainty = 80%, and the tolerance = 10% wt, then in 95% of the time conducting ILIs, 80% of the MEs will be within the boundaries ±10% wt. Visualization of this fact is given in Fig.2, which reflects results of 15 computer-simulated ILIs. In each of the virtual ILIs, 30 MEs were made. In Fig. 2 the rectangle represents a sample of MEs. The red vertical lines are sample medians (50% level quantile), and the boundaries of the rectangles are the 10% and the 90% sample quantile. The length of the rectangle embodies 80% of all the MEs. The horizontal lines represent the scatter of the MEs. From Fig.2 it can be seen than in one of the 15 sets of virtual ILIs the left boundary of the rectangle is out of the 10% wt limit.

Types of defect size adjustments

Over the years, the world pipeline industry has developed several engineering schools of thought (ESTs) regarding defect sizing (see, for instance, Refs 3, 10, 11). One of the ESTs is presented in the API 1163 Standard [2], and utilizes the unit curve concept (which is equivalent to accepting no bias in both ILI and verification instrument (VI) readings, no MEs in the VI readings and normal distribution of the ILI MEs). The other, most commonly used types of adjustment can be formalized as follows:

$$\textit{Unit curve (no bias admitted)} \qquad (3)$$

$$d_V = d_{tr} \left(\sigma_V \equiv 0\right) \qquad (4)$$

$$d_{adj} = d_I \cdot k \qquad (5)$$

$$P(-k \cdot wt < X < k \cdot wt) = 1-\alpha = 2\Phi\left(\frac{k \cdot wt}{\sigma}\right) - 1 \qquad (1)$$

$$d_{adj} = d_I + k\sigma_{\varepsilon I} \quad (6)$$

$$\sigma_{adj} = k\sigma_{\varepsilon I} \quad (7)$$

$$\sigma_{adj} = \sigma_{\varepsilon I} + \Delta_{adj} \quad (8)$$

$$d_{adj} = \varphi(d_I, d_V, \sigma_{\varepsilon I}, \sigma_{\varepsilon V}) \quad (9)$$

$$d_{adj} = d_I + \sqrt{tol_I^2 + tol_V^2} \quad (10)$$

Probability of exceedance method (11)

Here d_I, d_V are correspondingly the ILI tool and the VI measurements; $\sigma_{\varepsilon I}$, σ_{eV} are correspondingly the SDs of the ILI tool and the VI measurement errors; tol_I, tol_V are correspondingly the tolerances for the ILI tool and the VI measurements; d_{adj}, σ_{adj}, Δ_{adj} are correspondingly the adjusted ILI tool reading, adjusted SD, and the adjusting safety margin; k ($k > 1$) is a multiplicative safety coefficient.

We will now proceed to a description of each approach defined above.

The statement in Equn 3 surmises that both measurement instruments (ILI tool and VI) are free of any MEs.

Equation 4 means that the VI measurements do not contain MEs, i.e. VI is 'ideal', and this can never happen. The assumption that VI is ideal may lead to assigning *de facto* its MEs to the ILI tool, which will lead to an unjustified low assessment of its quality. This is especially important to account for when assessing possibilities of an ILI tool or of a candidate diagnostician. Hence, it is necessary to assess the MEs of each instrument separately.

The simplest types of adjustments are presented by Equns 5 and 6. They amount to multiplying the ILI readings ('raw' ILI data) by a coefficient, which is more than unity. Sometimes, this type adjustment is applied to the SD of ILI readings; see Equns 7 and 8. In Equn 8 the term is a safety margin added to the SD. In general, the adjusted ILI reading is a function of the readings of both ILI and VI instruments, and of the SDs of

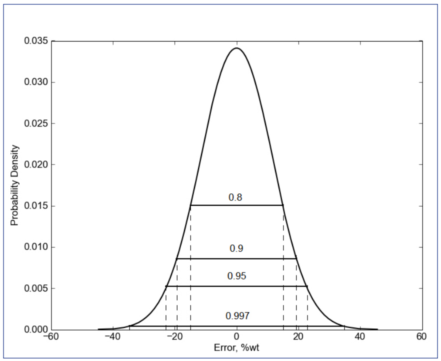

Fig.1. Error bands for different certainties for the case when the PDF of ME is normal.

the MEs of both tools (Equn 9). The explicit expression which accounts for this is given by Equn 10, and Figs 1 and 3. According to them, the tolerance for the ILI readings is taken at the certainty (in API 1163 wording) of 80% (recently, some companies started to prefer 90%). Under the 80% certainty the tolerance for the ILI tool would be ± 1.28 $\sigma_{\varepsilon I}$ (see Equn 2). For the 90% certainty the tolerance is ± 1.65 $\sigma_{\varepsilon I}$.

The probability of exceedance approach *per se* (Equn 11) is a staple model in structural reliability theory, where it is widely used in conjunction with the random-function theory. When applied to the problem being discussed in this paper, the main problem is how to construct the PDF for the ME of the ILI tool, and whether to select the level of exceedance as a deterministic or a random value.

Full statistical analysis method of ILI results

This section describes a methodology for full statistical analysis of ILI results considering a more-general practical case, when the ILI tool measurements contain not only random ME, but also systemic ones (constant and multiplicative bias). The methodology consists of the actual ILI tool accuracy-assessment technique used in the process of a specific pipeline inspection, and the calibration technique of all (verified and unverified) ILI tool measurements for the purpose of

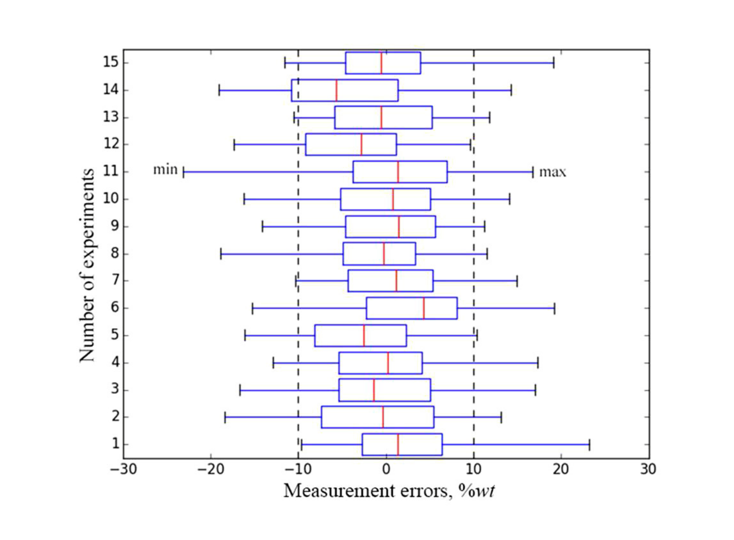

Fig.2. Graphical interpretation of the confidence level.

obtaining more-accurate values of the measured defect parameters.

Consider the most-common practical case when the ILI tool possesses both random and systemic MEs, and the verification tool only random ME. The mathematical model of measurements in this case will have the form:

$$p_i = \alpha + \beta p_{tr} + \varepsilon_I \quad (12)$$
$$p_v = p_{tr} + \varepsilon_V$$

where p_{tr} is the true (unmeasurable) value of the parameter to be measured; p_i is the ILI tool reading; p_v is the VI reading; α and β are, respectively, the intercept and the slope of the regression line (RL) of the ILI tool, related to constant systemic measurement errors: α is the average bias, β is the multiplicative bias; ε_I is the random measurement error of ILI tool; e_V is the random measurement error of the VI.

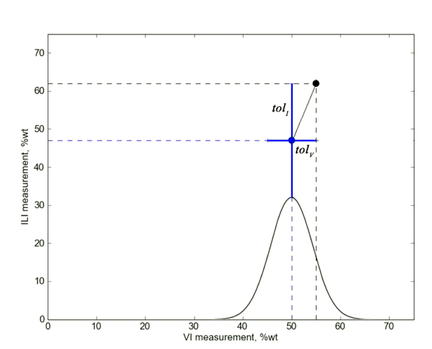

Fig.3. Design (adjusted) point taking into account the tolerances of both tools.

According to measurement model (Equn 12), the accuracy will be determined by statistical characteristics of measurement errors ε_I, e_V, in particular, only by their variances; the mathematical expectation of ME equals zero.

The methodology consists of subsequently solving the following sub-problems:

- assessment of the measurements model parameters (Equn 12) (constant ILI tool measurement bias);
- assessment of the ILI tool and VI MEs variance;
- assessment of the true sizes of verified defects;
- assessment of the calibration line parameters, using which it is possible to obtain more accurate values of the unverified ILI tool measurements.

This technique is based on variance and regression analysis, and consists in comparing of the diagnostics results with the verification data, limited in scope. Its final goal is calibration of the diagnostic results for obtaining a more-accurate assessment of the true values of the defects parameters. The technique provides capability for:

Assessment of the actual accuracy of the implemented ILI tool in real-life conditions of its operation.

Improving the accuracy of all (verified and unverified) measurements of defects sizes based on joint analysis of the diagnostics results and the limited in scope verification. This leads to a significant savings of funds and labour.

Assessment of the constant bias of the ILI tool measurements

Method of moments

For assessing the average and the multiplicative bias of the ILI tool measurements, which are included in the measurement model (Equn 12), it is necessary to build a scatter diagram of the verified measurements and determine the RL parameters of the ILI tool and the VI measurements. The VI measurements are assumed to be the independent variable (regressor). In this case the problem of assessing the regression line parameters is non-trivial, since the independent variables of the measurements regression model (Equn 12) contain 'inherent' errors (stochastic regressors). Therefore, the use of the classic least-squares method (LSM) becomes impossible because the assessment by LSM will be, in general, biased and inconsistent [8].

Provided that the VI ME is known in advance, the consistent assessments of parameters α and β of the measurement model (Equn 12) has the form [4]:

$$\hat{\beta} = \frac{s_{IV}}{s_V^2 - \sigma_{\varepsilon V}^2}, \quad s_V^2 > \sigma_{\varepsilon V}^2$$
$$\hat{\alpha} = \bar{p}_I - \hat{\beta} \cdot \bar{p}_V \qquad (13)$$

where $\bar{p}_I, \bar{p}_V$ are the sample averages of the ILI tool and VI measurements respectively; s_I^2 is the unbiased sample variance of the ILI tool measurements; $s_V^2$is the unbiased sample variance of the VI measurements; $s_{VI}^2$is the ILI tool and the VI measurements covariance.

Assessment of the ILI instrument accuracy

The case when the ILI tool measurements do not contain a multiplicative bias

For this case, when in the measurements model (Equn 12) β = 1, the method of assessing the error variances ε_I, e_V was proposed by Grubbs [6]. According to his approach, the variance of the measurements, obtained using an arbitrary MI, consists of two parts:

- variance of the true values of the measured parameter (i.e. defect depths);
- variance of the ME of the measurement instrument used.

The sample assessment of the covariation between two MIs is a non-biased assessment of the true sizes of defects. Then, the assessment of the ME variance of each MI can be evaluated as the difference between the sample variance of measurements of the MI being assessed, and the sample assessment of the covariation of the measurements:

$$\hat{\sigma}_{tr}^2 = s_{IV}$$
$$\hat{\sigma}_{\varepsilon V}^2 = s_V^2 - s_{IV} \qquad (14)$$

$$\hat{\sigma}_{\varepsilon I}^2 = s_I^2 - s_{IV} \qquad (15)$$

In the case when one of the assessments in Equns 14 or 15 turns out to be negative, Thompson [9] suggested using the following assessments (on the premise, that $\hat{\sigma}_{\varepsilon I}^2$ is negative):

$$\hat{\sigma}_{tr}^2 = s_I^2$$
$$\hat{\sigma}_{\varepsilon V}^2 = s_I^2 + s_V^2 - 2s_{IV}$$
$$\hat{\sigma}_{\varepsilon I}^2 = 0$$

In other words, if the variance assessment is negative, it is assumed to be equal to zero. For the case when $\hat{\sigma}_{\varepsilon V}^2$ is negative, the same lines of argument are used.

Generalized case

The Grubbs method may be modified and summarized for the case when the ILI tool measurements contain both average and multiplicative biases. According to the measurement model (Equn 12), because of independence of p_{tr} and ε_I, e_V, the RVs p_V and p_I will have variances:

$$\sigma_I^2 = \beta^2 \sigma_{tr}^2 + \sigma_{\varepsilon I}^2$$
$$\sigma_V^2 = \sigma_{tr}^2 + \sigma_{\varepsilon V}^2 \qquad (16)$$

where σ_{tr}^2 is the true value of the defect parameter p_{tr} variance.

Considering that the unbiased sample variances of ILI tool and VI measurements s_I^2, s_V^2 are the unbiased assessments of theoretical variances σ_I^2, σ_V^2 respectively, the assessment of ILI tool ME and the assessment of the defect parameters true values variances may be found from Equn 16 by equations:

$$\hat{\sigma}^2_{\varepsilon V} = s^2_V - \frac{s_{IV}}{\hat{\beta}}$$
$$\hat{\sigma}^2_{\varepsilon I} = s^2_I - \hat{\beta} s_{IV} \qquad (17)$$

where $\hat{\beta}$ is the assessment of the RL slope.

In a number of real-life cases the assessments obtained with the use of Equn 17 were negative. This occurs when, and only when [5]:

$$s^2_I \left(s^2_V - \sigma^2_{\varepsilon V} \right) - s^2_{IV} \leq 0 \qquad (18)$$

When assessments of the ME variance (Equn 17) ae negative, it is possible to use the method developed by Jaech [7], according to which:

$$S = \hat{\sigma}^2_{\varepsilon V} + \hat{\sigma}^2_{\varepsilon I} = s^2_V - \frac{s_{IV}}{\hat{\beta}} + s^2_I - \hat{\beta} s_{IV} =$$
$$s^2_V + s^2_I - s_{IV} \left(\frac{1}{\beta} + \beta \right) =$$
$$s^2_V + s^2_I - s_{IV} \left(\frac{1+\beta^2}{\beta} \right)$$

(19)

The formulas in Equn 19 are used when the ILI tool measurements do not contain a multiplicative bias. If $\beta \neq 1$, the Jaech method has to be modified in the following way. Zero-in on the expression for covariation, for which purpose modify formulas for S and *f(x)*.

Now consider the sum of MEs variations, using Equn 17:

$$\sigma^{\bar{}}_{\varepsilon V} = \frac{\breve{}}{I}$$
$$\hat{\sigma}^2_{\varepsilon I} = S - \hat{\sigma}^2_{\varepsilon V}$$
$$S = \frac{n-1}{n} (s^2_I + s^2_V - 2 s_{IV})$$
$$I_0 = \int_0^1 x \cdot f(x) dx$$
$$I_1 = \int_0^1 f(x) dx;$$
$$f(x) \left[s^2_I (1-x)^2 + x^2 s^2_V + 2x(1-x) s_{IV} \right]^{-}$$

(20)

The sum of S and function *f(x)* are interconnected; hence, expression for *f(x)* can be written as follows:

$$f(x) = \left[\frac{n}{n-1} S x^2 + 2x (s_{IV} - s^2_V) + s^2_V \right]^{-n/2}$$

(21)

Then, taking into consideration Equn 20, Equn 21 takes the form of Equn 22 (*below*).

Therefore, when $\beta \neq 1$ in Equn 19, S is calculated using Equn 20 instead of Equn 19 and Equn 22 instead of *f(x)*. Other equations of the Jaech method remain unchanged.

It should be noted, that in reality the sample covariation S_{IV} may also be negative. This happens only in the case when small values of one tool's measurements are related to the large values of the other measurement tool. This is a sign to reject one of the tools as unsuitable for use.

Example 1

Initial data for simulating measurements of defects depth was obtained using Equn

$$f(x) = \left[s^2_V (1-x)^2 + s^2_I x^2 + s_{IV} x \left(2x \frac{1+\beta^2}{\beta} \right) \right]^{-n/2} \qquad (22)$$

12 which has α = 0, β = 1, and the Monte Carlo simulation method. Conduct an experiment which consists in modelling N = 10000 sets of pairs of measurements of defect depths. Applying the Grubbs method (or the modified Grubbs method) to each set of measurements, we find that in most cases the assessments of the MEs variances are negative (see Fig.4). Application in this case of the Jaech method or its modification allows obtaining only positive values of the MEs variance (see Fig.5).

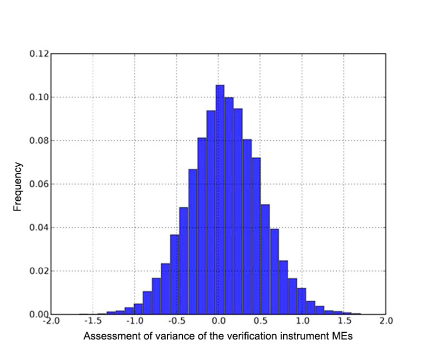

Fig.4. Assessments of the VI ME variances obtained using the Grubbs method.

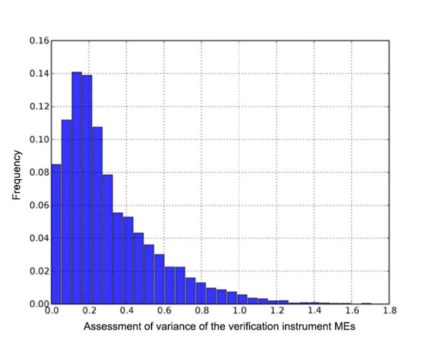

Fig.5. Assessments of the VI ME variances obtained using the Jaech method.

Method of increasing the measurement accuracy (calibration) of defects parameters

Consider the method of assessing the true sizes of defects, and rewrite the measurements model (Equn 12) in matrix form:

$$\begin{pmatrix} p_I - \alpha \\ p_V \end{pmatrix} = \begin{pmatrix} \beta \\ 1 \end{pmatrix} p_{tr} + \begin{pmatrix} \varepsilon_I \\ \varepsilon_V \end{pmatrix}$$

Denote:

$$Y = \begin{pmatrix} p_I - \alpha \\ p_V \end{pmatrix}, \quad X = \begin{pmatrix} \beta \\ 1 \end{pmatrix}, \quad E = \begin{pmatrix} \varepsilon_I \\ \varepsilon_V \end{pmatrix}$$

Then, the measurements model can be rewritten as:

$$Y = p_{tr} X + E \qquad (23)$$

Expression 23 is a generalized linear regression model, where p_{tr} is the unknown parameter (the true value of the verified defect parameter).

According to the Aitken theorem [8], the best (effective) unbiased assessment of the unknown parameter p_{tr} of Equn 23 is the assessment obtained using the generalized least-squares method (GLSM).

Assessment of the true size of the verified defect parameter shall assume the: form:

$$\hat{p}_{tr} = p_V + c_2 r \qquad (24)$$

where $c_2 = f\left(\hat{\beta}, \hat{\sigma}_{\varepsilon I}^2, \hat{\sigma}_{\varepsilon V}^2\right)$. This function is determined from the assessment of the unknown parameter p_{tr} with GLSM.

The final goal of this method is calibration of the raw ILI tool measurements, i.e. defining the calibration line parameters, with the help of which it is possible to adjust the defect parameters values of all other, unverified ILI tool measurements. If the calibrating experiment is performed on a sample of size n, then the adjusted defect parameter value for the (n + 1)-th unverified measurement p_I^{n+1} is determined from equation:

$$\hat{p}_{tr}^{n+i} = \hat{\xi} + \hat{\gamma} p_I^{n+i} \qquad (25)$$

where $\hat{\xi}, \hat{\gamma}$ are the calibration line parameters.

Some analysis results from real cases

Case 1: oil pipeline

Measurements of defect depths conducted by the ILI tool and the VI were used. Information about the accuracy of both the ILI tool and the VI are absent. This circumstance (here and everywhere

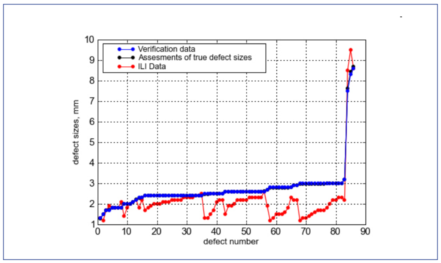

Fig.6. Verification data, assessments of true sizes of defects, and the ILI readings.

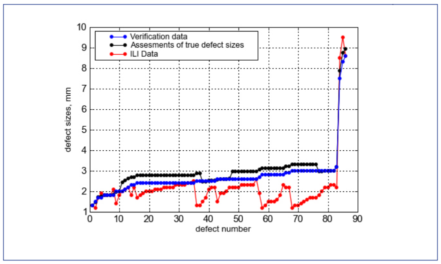

Fig.7. Verification data, assessments of true sizes of defects, and the ILI readings.

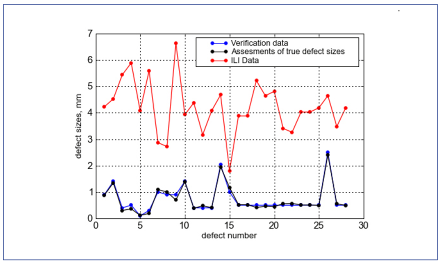

Fig.8. True sizes of defects, their assessments, and the ILI readings.

below) is not an obstacle for assessing the accuracy of both tools. In the calculations 86 pairs of independent measurements (ILI + VI) of 86 defects were used. Calculations were conducted for cases, when:

- all measurements were verified (Fig.6);
- only 30 measurements were verified (Fig.7).

Comparing these cases, it can be seen that just 30 verification measurements yield results which are very close to the results obtained when total verification is performed.

Case 2: gas pipeline

Analysis of the ILI results was performed as requested by the pipeline operator. It shows (see Fig.8), that for some reason the ILI data are over-reporting: they have a considerable (though conservative) bias and a large variance. This could be the result of a 'safe' adjustment of the raw ILI data.

The difference between the variances of the ILI tool and the verification instrument was larger than 10%. According to the EPRI (USA) criteria, in such cases the ILI tool has to be recalibrated or the results rejected. Using the above algorithm allows the operator to independently assess the actual accuracy of the ILI tool as demonstrated on the specific inspected pipeline. The operator should provide for both measurements to be conducted independently.

Conclusions

The general methodology of statistical analysis of ILI data outlined here permits:

- Assessing the components of the total variance of the ILI technology, including attribution of measurement-error variance to the ILI tool and the verification tool.

- Constructing consistent assessments (with minimal bias) of true sizes of defect parameters and their variances for cases when information about the ILI tool and VI is available , by filtering the measurement results from statistical debris, outliers, and noise.

- Implementation of the approach described above, as it opens the door for a consistent solution of problems of residual strength, lifetime, reliability, and risk assessment of pipelines.

Usage of this methodology necessitates relatively insignificant expenditures, but yields substantial savings in pipeline operation and risk.

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Listing of forthcoming industry events (*continued from p 184*)

Australasian Oil & Gas Exhibition & Conference (AOG)
14-16 March 2018
Perth, Australia
http://www.aogexpo.com.au
The annual Australasian Oil & Gas Exhibition & Conference (AOG) is the platform event for the Australian oil and gas industry featuring over 200 exhibiting brands. This event is a showcase of the latest products and attracts over 8,000 global visitors providing opportunities to network and learn about the latest technological and innovative breakthroughs which will drive the industry into the future.

5th East Africa Oil & Gas Summit and Exhibition
14-16 March 2018
Nairobi, Kenya
http://www.eaogs.com
The oil and gas show for the East Africa region with more than 2,500 participants, 380 companies and 30 countries. Hosted by the Ministry of Petroleum.

49th Annual Conference
15-18 March 2018
Stein Eriksen Lodge, Deer Valley, Utah, USA
https://psig.org
Advancing the state of the art of modelling, simulation, optimization, steady-state and transient flows, single and multiphase flows, and related subjects as applied to fluid pipeline systems.

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