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RELIABILITY BASED FITNESS-FOR-SERVICE ASSESSMENT OF CORROSION DEFECTS USING DIFFERENT BURST PRESSURE PREDICTORS AND DIFFERENT INSPECTION TECHNIQUES

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ABSTRACT

A comprehensive reliability based formulation is proposed for the assessment of the integrity of corroded pipelines. In this formulation, the inspection technique, the pipeline geometric and material characteristics, operational parameters, and Limit State model for burst are combined in a general approach. This approach is illustrated with application to evaluation of an in-service gas pipeline.

INTRODUCTION

Reliability analyses can provide pipeline engineers with important insights to help better assess and manage the risks associated with pipelines. This paper presents and illustrates a simplified and realistic approach to allow pipeline engineers to analyze the reliability of corroded pipelines based on results from inline instrumentation. A reliability based approach is also developed for corroded pipelines that can not be instrumented.

NOMENCLATURE

D - Demand
C - Capacity
D_o - Diameter (nominal)
d - defect depth
FS - Factor-of-Safety
POD - Probability of Detection
POF - Probability of Failure
PND - Probability of Non-Detection
Pfi - Probability of failure of pipeline segment i.
Pfd - Probability of failure of detected defects
Pfnd - Probability of failure of non-detected defects
Pb - Pipeline burst pressure
P_O - Operating pressure
Ro - Pipe mean radius (D_o - t_o / 2)
t_o - Wall thickness (nominal)
SMYS - Specified Minimum Yield Strength
SMTS - Specified Minimum Tensile Strength
V_X - Coefficient of Variation of variable X (standard deviation of X / mean of X)
X_{50} - median value of the parameter X
Φ - Standard Cumulative Normal Distribution Function
β - Safety Index
$\sigma_{\ln X}$ - Standard Deviation of the Logarithms of variable X
ρ_{ij} - Correlation coefficient for paired variables ij

PROPOSED FRAMEWORK

Figure 1 shows the components of the proposed reliability based approach. Two probability density functions are shown; one for the pipeline demand (D) and the other for the pipeline capacity (C). Five components form the input to the analyses:

1. Operational parameters - internal pressure, temperature, in-place profile, and other elements that determine the pipeline demand (stresses, strains) and their probabilistic distributions form this input. Pressure relief systems and their reliability can be important elements in this characterization.
2. Pipeline characteristics - geometric descriptions (e.g. diameter, wall thickness), material properties (e.g. SMYS, SMTS), coating.
3. Inspection information - based on analyses of results from in-line inspection tools, defect characterizations (type, depth, width, length), sizing accuracy, probabilities of detection (POD).

4. Environmental information - observed external and internal corrosion, burial depths, water depths, coating failures, etc.
5. Limit State Model - used to predict the burst pressure characteristics. There are several models that are in use by the industry; this approach will allow the user to use any of the models provided that the accuracy of the models are incorporated into the analyses.

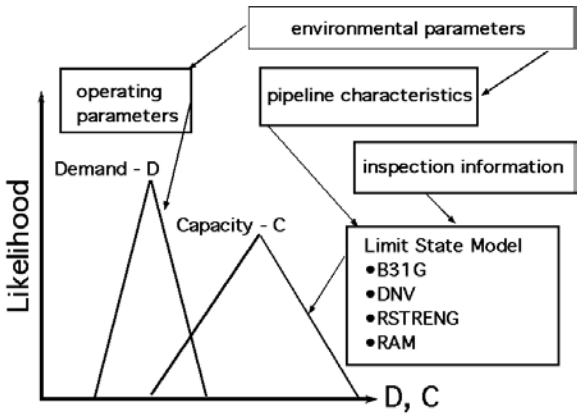

Fig. 1: Reliability framework for corroded pipeline integrity assessment

RELIABILITY

Reliability (Ps) is defined as the likelihood that a segment of a pipeline will not lose containment. The probability of failure (Pf, POF) is the compliment of the reliability (Pf = 1 - Ps). The probability of failure can be expressed as the likelihood (P) that the pipeline 'demand' (D, e.g. internal pressure) exceeds the pipeline 'capacity' (C, e.g. burst pressure)

$$Pf = P[D \geq C] \tag{1}$$

The probability of failure can be evaluated from the Safety Index (β):

$$Pf = 1 - \Phi(\beta) \tag{2}$$

Φ is the Standard Cumulative Normal Variable. For independent and Lognormally distributed D and C, the Safety Index can be determined from:

$$\beta = \frac{\ln\left[\frac{C_{50}}{D_{50}}\right]}{\sqrt{\sigma_{\ln D}^2 + \sigma_{\ln C}^2}} \tag{3}$$

C_{50} is the median (50th percentile) pipeline segment capacity. D_{50} is the median pipeline segment demand. $\sigma_{\ln D}$ is the standard deviation of the logarithms of the pipeline segment demands. $\sigma_{\ln C}$ is the standard deviation of the logarithms of the pipeline segment capacities.

This expression for the Safety Index is based on the premise that the distribution of the likelihood of the pipeline segment demands and capacities are Lognormal or that the logarithms of the demands and capacities are Normally distributed. This premise can be justified based on the nature of the random variables that determine the pipeline segment demands and capacities (multiplicative random variables), fitting the Lognormal distribution to the important parts of experimental data on pipeline demands and capacities (fitting to higher demands and lower capacities), and the utility of an analytical expression that can be used by pipeline engineers as part of their daily work.

The standard deviations of the logarithms of the pipeline segment demands and capacities can be related to the Coefficients of Variation (Vx = standard deviation of X / mean or average of X) of the demands and capacities as:

$$Vx = \left[\exp(\sigma_{\ln x}^2) - 1\right]^{0.5} \tag{4}$$

For small values of Vx (less than about 40%) $\sigma_{\ln X}$ is approximately equal to Vx. Vx is a normalized measure of the variability or uncertainty associated with the variable x.

Equation 3 can be simplified:

$$\beta = \frac{\ln\left[FS_{50}\right]}{\sigma_{\ln DC}} \tag{5}$$

This indicates that the Safety Index is fundamentally a function of two key variables: the median factor of safety (FS_{50}) and the measure of total uncertainty ($\sigma_{\ln DC}$).

UNCERTAINTIES

The uncertainties of importance in this formulation can be organized into three categories:

- Type 1 - natural, inherent, information insensitive (aleatory)
- Type 2 - professional, modeling, parametric, state, information sensitive (epistemic)
- Type 3 - human and organizational

Type 3 uncertainties should be addressed using proactive, reactive, and interactive approaches that will address reductions in the likelihood of their occurrences, reductions in their effects, and their detection and correction.

Accurate measured prototype data are the key to characterizing Type 2 uncertainties. Type 2 uncertainties can be evaluated as a 'Bias' where the Bias is defined as the ratio of the 'true' (measured) value of the variable to the nominal or predicted value of the variable. In the characterization of Type 2 uncertainties, it is important to try to use measured values of all of the variables that are input to the analytical model that are used to produce the predicted results. In this way, the uncertainty contributed by the analytical model is not combined or mixed with nominal values used as input to the model. Because of the normal 'conservatisms' injected into nominal or engineering predictive analytical models, it is very important to identify and characterize these conservatisms and their associated uncertainties. Realistic reliabilities can not be developed without such efforts.

Often, it proves to be difficult to clearly separate Type 1 and Type 2 uncertainties. But, given that one is interested in determining how professional or modeling uncertainties impact reliability (e.g. to determine how research and development work or improved measurements could impact reliability), it becomes necessary to try to develop clear characterizations of Type 2 uncertainties. Also, sometimes depending on how the desirable or acceptable reliabilities have been determined, it may be necessary to eliminate the variability part of the Type 2 uncertainties (retaining the central tendency 'corrections' to the predicted or nominal values).

The next step in developing characterizations of uncertainties concerns how they can be assessed based on the various parameters or variables that can be involved in determining the pipeline segment demands and capacities. Here, an example will prove to be a useful way to illustrate how this might be done. Assume that the pipeline internal burst pressure capacity (Pb) can be determined from a hoop stress formulation:

$$Pb = (t / R)\ UTS \quad (6)$$

where t is the pipeline wall thickness, R is the mean radius, and UTS is the ultimate tensile strength of the pipeline steel. the pipeline burst pressure is a function of three random variables (t, R, UTS). Using a First-Order Second-Moment (FOSM) approach, and presuming Lognormally distributed variables, the median value of the burst pressure (Pb_{50}) could be determined from the median values of the other variable as:

$$Pb_{50} = (t_{50} / R_{50})\ UTS_{50} \quad (7)$$

Let t_{50} = 0.5 inches (12.7 mm), R_{50} = 12 inches (304.8 mm), and UTS_{50} = 60,000 psi (414 Mpa); thus Pb_{50} = 2,500 psi (17.3 Mpa).

Let V_t = 2%, V_R = 1%, and V_{UTS} = 8%. The resultant uncertainty can be determined from the square root of the sums of the squares of these coefficients of variation or V_{Pb} = 8.3%. Note that the variability is dominated by the variability in the UTS.

The next step in this example is to use a nominal or design guideline based formulation for the burst pressure:

$$Pbn = (2\ t / D)\ SMYS \quad (8)$$

where t is the nominal wall thickness, D is the nominal diameter, and SMYS is the specified minimum yield strength. Comparisons of this design formulation with high quality laboratory test results indicates that the median Bias is 1.25 and the coefficient of variation of the Bias is 16%. In developing these comparisons of laboratory and nominal burst pressures, the actual pipe wall thickness and diameter were used. In this case, the resultant Type 1 and Type 2 uncertainty would be the square root of the sums of the squares of 8.3% and 16% or V_{PB} = 18% ≈ $\sigma_{\ln Pb}$.

PIPELINE SEGMENTS & SYSTEM

A pipeline system can be characterized as a series system comprised of a number of pipeline segments; e.g. riser segment 1, expansion loop segment 1, segment 1, segment 2, … expansion loop segment 2, riser segment 2. This is a 'series system' comprised of a chain of segments. The question of the probability of failure of the pipeline system is not the same as the question of the probability of failure of the pipeline segments. The term 'segments' is used here to delineate portions or lengths of the pipeline in which the magnitude of the demand and capacity characteristics are very similar or highly correlated. The operating and environmental conditions frequently determine what defines these segments.

For a pipeline system comprised of n 'independent' - non correlated segments, the probability of failure of the system can be evaluated as:

$$Pfs = 1 - \Pi_{i=1}^{i=n} (1 - Pfi) \quad (9)$$

For small Pfi this can be approximated as

$$Pfs \approx \sum Pfi \quad (10)$$

For highly correlated ($\rho_{ij} \geq 0.8$)pipeline segments

$$Pfs \approx Pfmax \quad (11)$$

or the Pf is well approximated as the probability of failure of the most likely to fail segment: a chain is most likely to fail in its weakest link. This development suggest that a reasonable way to evaluate the probability of failure of a pipeline system is to determine the probability of failure of its highly correlated segments and then to use Eq. 9 to evaluate the probability of failure of the pipeline system.

Given such an assessment, it will obviously be important to carefully correlate the definition of the target or desirable probabilities of failure with those that are determined from a reliability analysis for the pipeline segments and system.

PIPELINE DEFECTS AND DAMAGE

One of the primary reasons to use reliability based methods is to assist pipeline engineers in evaluating the effects of damage and defects on the pipeline fitness for purpose. The primary contribution of the reliability approach is to allow explicit assessment of the effects of uncertainties. The appropriate degree of 'conservatism' is subjected to a direct evaluation.

During their service life, pipelines can experience a wide variety of types of damage and defects. For offshore pipelines, internal corrosion, external corrosion and wear (risers), dents - gouges (dropped objects, anchor collisions), and weld cracking (often exacerbated or initiated by corrosion) are primary means of damage in defects.

At this time, there are two major categories of pipelines: newer (1990s and later) and older (pre 1990s). The steels and welding and inspection process used to construct the older pipelines have resulted in a distinctive category of pipelines that must be maintained. The newer pipelines have utilized superior steels, welding and inspection processes. Reliability analyses for older and newer pipelines must recognize these differences. Due to the very large infrastructure of offshore pipelines installed around the world principally before the 1990s, there is a major concern for the fitness for purpose of this category of pipelines.

There are also two additional major categories of pipelines: in-line instrumented and non-in-line instrumented. Many of the older pipelines can not or have not been in-line instrumented. However, most of the newer pipelines can be or have been in-line instrumented. Maintenance of the pipelines that can not or have not been in-line instrumented presents major challenges for the pipeline engineer that would like to use reliability based methods to assist in the evaluation of fitness for purpose.

Offshore the U.S. today, there is approximately 30,000 miles (48,300 km) of pipelines [1]. Approximately 90% of these pipelines were installed before the 1990s and approximately 90% of these pipelines can not be in-line instrumented. There are major challenges associated with maintaining this existing pipeline infrastructure. This category of pipelines pose a major challenge for application of reliability based methods.

In this paper, the category of older pipelines that can be or have been in-line instrumented and that have been subjected to significant internal corrosion will be addressed. An example will be used to illustrate how a reliability based analysis can be used to evaluate the pipeline's fitness for purpose.

Figure 2 shows results from recent in-line high resolution Magnetic Flux Leakage (MFL) instrumentation of a 20-inch (508 mm) diameter (Do), 0.5-inch (12.7 mm) wall thickness (to) gas offshore pipeline fabricated with X52 steel and located in a water depth of 98 feet (30 m). The measured data are shown as the depth of the detected corrosion features (d) (percentage of nominal wall thickness, general corrosion defects) as a function of the position along the length of the pipeline from the deck of the processing platform outlet (zero distance) to the inlet at the deck of the production platform (14,000 m).

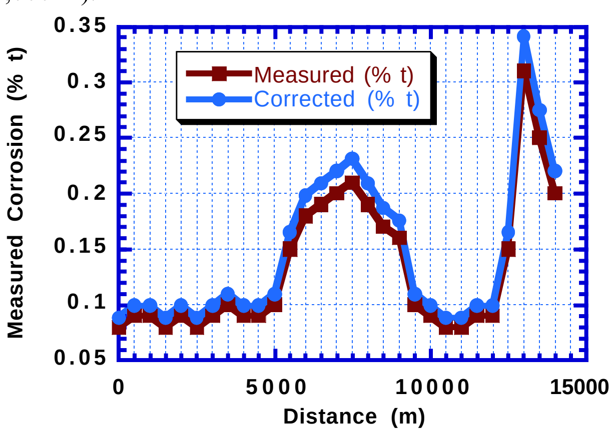

Fig. 2: Raw and corrected results from MFL in-line instrumentation

Based on results provided by the in-line instrumentation contractor, the 'raw' in-line instrumentation results were evaluated to have a Bias (true d / measured d) that indicated an average tendency to under-call the detected features (magnetization effects) by 5% (small depths of general corrosion features ≈ 10% to) to 10% (large depths ≈ 30% to). Based on results provided by the in-line instrumentation contractor from test loop runs using the MFL tool, the uncertainty attributed to the measured corrosion features reported was Vd = 15%. Figure 2 shows the depths of the detected corrosion features corrected for the mean depth detection Bias.

The next step in the reliability based formulation is to address the likelihood of failure due to detected and non-detected features in the example pipeline. The pipeline segment probability of failure (Pfi) is evaluated from the union of the two exclusive and exhaustive probabilities of failure due to detected features (Pfd) and non-detected features (Pfnd):

$$Pfi = Pfd + Pfnd \qquad (12)$$

Evaluation of Pfd requires an assessment of the Probabilities of Detection (POD) associated with various sizes of features. Based on results from test loop in-line runs with the MFL instrument, the in-line instrumentation contractor indicated a 90% POD for features that were ≥20% t_o, 50% POD for features that were ≥ 10 % t_o, and 100% POD for features that were ≥ 40% t_o.

For each of the corrected defect depths shown in Figure 2, the POD must be evaluated. The probability of non-detection (PND) is then:

$$PND = 1 - POD \qquad (13)$$

The probability of failure of the detected feature is computed based on the corrected depth of the feature and the uncertainty associated with the depth assessment added to the assessments using the FOSM formulation. These steps will be illustrated later in this paper.

The probability of detection of the non-detected features can be developed in a variety of ways:

- use results from previous in-line instrumentation on comparable pipelines to indicate the likelihood of different sizes of defects.
- use results from the current in-line instrumentation on the pipeline to estimate the likelihood of different sizes of defects.
- use 'off-line' analytical models to predict the likelihood of different sizes of defects.

In this example, in-line results from other comparable (product, age, location) gas pipelines were used to determine the likelihood of different sizes of potential non-detected defects [2]. The results indicated that for comparable gas pipelines, the mean corrosion rate in both the pipeline and the riser sections were 0.01 inches (0.25 mm) per year for pipelines that had been in service for 10 to 12 years. The Coefficient of Variation of this rate was determined to be 40%.

Beyond the issues concerning POD, PND, and the accuracy of the instrumentation 'calls', there are issues concerned with the probabilities of 'false calls' - the likelihood that features are detected that are not really there (false positives) and the likelihood that features are not detected that are really there. Treatment of these additional issues is beyond the scope of this paper and perhaps is beyond the current technology of current in-line instrumentation.

In a recent field experiment that involved hydro-testing to failure a 22-year old pipeline that had been removed from service, high resolution MFL in-line instrumentation was performed and the results analyzed by highly trained interpreters to evaluate the defect characteristics [3]. Then analyses were performed using a variety of burst pressure predictive models to determine the pressure and location at which the pipeline would loose containment. The pipeline lost containment at a location in a manufacturing defect. Even though there was very significant corrosion defects (40% to 50% of t_o) in other parts of the pipeline, the pipeline ruptured at a small lamination in the pipe wall at a pressure close to the intact pipe burst pressure. The initiation of the rupture was exacerbated by the older grade of steel used in the pipeline manufacture as indicated by definite signs of brittle fracture in the retrieved section of the burst pipeline. Highly ductile, crack propagation resistant modern steels very likely would have prevented such a condition. But, this type of challenge can be expected in some older pipelines.

BURST PRESSURE MODEL BIAS

The next step in the reliability analysis is to assess the Bias in the predicted burst pressure characteristics of the corroded pipeline. The burst pressure prediction model used in this example is a simplified model that was developed to evaluate the burst pressure characteristics of corroded pipelines based solely on the depth of the corrosion features [2-4]; the width and length of the features are assumed to be large relative to the diameter of the pipeline and the depth of the features are assumed to be less than 90% of the wall thickness:

$$Pbd = \frac{1.6t_o(SMYS)}{R_o \cdot SCF} \tag{14}$$

Pbd is the predicted burst pressure for a corroded pipeline with a defect depth d. t_o is the nominal wall thickness of the pipeline, SMYS is the specified minimum yield strength of the pipeline steel, R_o is the mean radius of the pipeline ($(D_o\text{-}t_o)/2$), and SCF is the Stress Concentration Factor associated with the corrosion feature of depth d:

$$SCF = 1 + 2\sqrt{\frac{d}{R_o}} \tag{15}$$

This analytical model to evaluate burst pressures of corroded pipelines was compared with measured data from 151 physical laboratory tests on corroded pipelines. This comparison utilized nominal values for the pipeline wall thickness and radius and SMYS; thus, mixing Type 1 and Type 2 uncertainties. The comparisons were based on directly measured maximum depths of corrosion. Thus, the comparison does not include the uncertainty associated with the maximum depth of the corrosion feature.

This formulation developed a median Bias of B_{PB50} = 1.03 and Coefficient of Variation of the Bias of V_{BPB} = 22% for all of the test data (d/t_0 = 0 to 0.9). Because of concerns that the laboratory test data primarily contained data from specimens in which corrosion features had been machined and etched, the data were reanalyzed and included only the naturally corroded features. The formulation developed a median Bias of B_{PB50} = 1.1 and Coefficient of Variation of the Bias of V_{BPB} = 26% [4].

Since this study of Pbd bias was completed, attention has been focused on re-examination of the data that was incorporated into the burst pressure database [5]. It has been found that the test database has become 'polluted' with data gathered from different sources at different times. The pollution has developed in a variety of ways that involve errors in recordings, 'inferred' input data (e.g. ultimate tensile strength deduced from SMYS), and missing data (found in original laboratory test reports, but not included in the database). Currently efforts are being directed at developing a 'clean' database in which all of the reported data can be tracked back to an 'original' source. But, differences have been found in some of the original source data for some tests! The determination of the Bias associated with analytical models has to be very carefully developed to be sure that the data included in the database are accurate and that the data apply to the problem that is being addressed.

Another point needs to be made regarding the particular burst pressure prediction analytical model that is used in the analyses. There are a large number of these models. Most of these models are intended primarily for use in traditional engineering design and reassessment of pipelines and have conservatism embedded in their formulations and parameters that are intended to produce useable and acceptable results for deterministic-type analyses. Many of these models can be adapted for use in reliability analyses with modifications that are intended to reduce the Bias produced by the model. The primary objective for reliability based analyses should be to identify a model that will produce the median Bias that is closest to unity and that (most importantly) has the smallest Coefficient of Variation of the Bias. Even though the central tendency measure of the Bias can be entered directly into the reliability analysis, there will be a penalty for analytical models that have high uncertainties; these will be reflected in computed high probabilities of failure.

INTERNAL MAXIMUM PRESSURES

Maximum internal pressures were recorded and analyzed for the example pipeline during the period of a year. The results are summarized in Figure 3. The maximum allowable operating pressure for this pipeline was set at 1,100 psi (7.6 MPa). The recorded data indicated an annual maximum median operating pressure of P_{o50} = 912 psi (6.3 Mpa) with a Coefficient of Variation of V_{po} = 8%. This indicates that the ratio of the mean maximum operating pressure to the maximum allowable design pressure is 80%. This is typical of other gas pipelines in this offshore location.

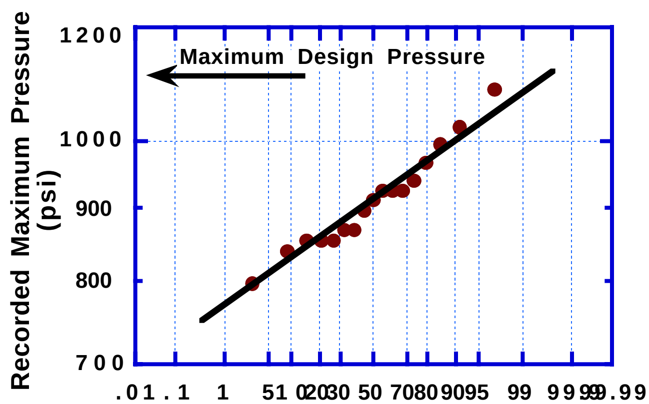

Fig. 3: Recorded maximum operating pressures on example gas pipeline during one-year period

It is important to note that pressure relief equipment located in the gas pipeline system would not allow the internal pressures in the pipeline exceed 1,100 psi (7.6 Mpa). However, the analytical model that is used to characterize the internal pressures has a 'right tail' that includes pressures beyond this limit. To recognize the potential effects of such pressure 'truncations' requires more sophisticated analyses. Studies currently are being conducted to develop engineering approximations that will allow pressure truncations to be used with the simplified reliability analysis methods. The work to this point indicates that potential pressure truncations such as are indicated in Figure 3 have a relatively small effect on the computed probabilities of failure; this is due to the relatively small or low uncertainties associated with the maximum pressures [6].

At this juncture, it is important to also recognize that there can be truncations in the 'left tail' of the pipeline capacity distribution. Such truncations can be developed from such things as hydro-testing. These potential effects are being studied in conjunction with the assessment of the demand truncations. The potential effect of the capacity truncations is highly dependent on the level of the pressure testing relative to the pipeline burst pressure capacity. If the pressure test is performed at relatively high pressures relative to the burst pressure capacity, then the effect can be important to the computed burst pressure probability of failure; but, the study indicates that for most pressure testing levels, the test is not very effective in decreasing the computed probabilities of failure. The testing of course can be effective at discovering 'gross defects' that are not recognized and there are some indications that such testing can be harmful in that cracks are developed and / or propagated in the pipeline as a result of the test induced stresses.

COMPUTED PROBABILITIES OF FAILURE

Based on these developments, it is possible to compute the annual probabilities of failure at various points along the length of the example gas pipeline. The computed probabilities of failure can be expected to be high at two locations: at a distance between 5,000 m and 10,000 m and at the inlet riser - expansion loop section between 12,000 m and 13,000 m (Fig. 2).

The maximum annual probability of failure for the central segment of the pipeline could be computed based on the following information: Do = 20 inches, to = 0.5 inches, Ro = 9.75 inches; SMYS = 52 ksi, d = 0.12 inches (0.24 t_o), POD = 90%, PND = 10%, P_{o50} = 912 psi, V_{po} = 8%, B_{Pb50} = 1.1, V_{Pb} = 26%, V_d = 15%.

For the maximum detected defect in this segment of the pipeline (d = 0.24 t_o), the median burst pressure capacity could be computed as follows:

$$Pbd_{50} = \frac{1.1 \cdot 1.6 \cdot 0.5in \cdot 52{,}000 psi}{9.75in \cdot (1 + 2\sqrt{\frac{0.12in}{9.75in}})} = 3841 psi \quad (16)$$

The central factor-of-safety would be FS_{50} = 3841 psi / 912 psi = 4.21.

The coefficient of variation of the burst pressure is a function of the coefficient of variation of the burst pressure model given the direct measurement of the maximum corrosion depth (26%) and the coefficient of variation associated with the measured defect depth (15%). Because the defect depth in this formulation affects the burst pressure in proportion to the square root of the defect depth (Eq. 15), the coefficient of variation of the burst pressure can be computed from the square root of the sums of the square of the burst pressure model coefficient of variation and square of one half of the coefficient of variation of the defect depth. This gives the coefficient of variation in the burst pressure of V_{Pbd} = 27%. Note that the uncertainty is dominated by the uncertainty associated with the burst pressure Limit State model.

The standard deviation of the logarithms of the pipeline maximum internal pressures (demands) and pipeline burst pressures (capacities) could be computed from the square root of the sums of the squares of the coefficients of variation to be σ_{lnDC} = 0.28.

Given the results, the annual Safety Index and probability of failure associated with the detected feature would be computed from Eq. 5 to be β = 5.14 and Pf = 1.7 E-7 per year, respectively. The resultant probability of failure associated with the detected feature times the POD would be Pf_D = 1.5 E-7 per year.

Next, the probability of failure associated with the non-detected features must be evaluated. In this case, the information on the comparable pipelines indicates a median corrosion rate of 0.01 inches (0.25 mm) per year [2]. For the 12 year life of the pipeline, this indicates a feature depth of 0.12 inches. It is interesting to note that this is the same depth as the detected feature. The burst pressure capacity of the pipeline segment would be identical to that computed in Eq. 16. However, there would be a much larger uncertainty that is associated with the variability attributed to the corrosion rates (Vd = 40%). This much larger uncertainty results in a standard deviation of the logarithms of the pipeline demands and capacities of σ_{lnDC} = 0.34. An annual Safety Index and probability of failure of β = 4.25 and Pf = 1.1 E-5 would be computed. When this probability of failure is multiplied times the probability of non-detection, a Pf_{ND} = 1.1 E-6 would result. The total computed probability of failure would be 1.3 E-6. In this particular example, the total probability of failure is dominated by the probability of failure contributed by the non-detected features. This is not always the case, particularly when the depth of the detected features becomes large compared with the wall thickness and the POD approaches unity.

For the maximum defect depth found in the inlet riser section (d = 0.35 t_o), the POD was determined to be 0.99 and the PND = 0.01. The burst pressure capacity for this segment of the riser could be computed in the same manner shown in Eq. 16. The computed median burst pressure is P_{bd50} = 3701 psi. In the same way detailed for the central section, the annual Safety Index and probability of failure for the detected feature could be found as β_D= 4.96 and Pf_D = 3.5 E-7 per year. The probability of failure for the non-detected features in the riser section would be the same as for the central section except that there would be a probability of non-detection of P_{ND} = 0.01.

This would result in a probability of failure associated with the non-detected features in the riser section of 1.1 E-7 per year. The total probability of failure for the detected and non-detected features would be 4.6 E-7 per year.

INFLUENCE OF THE UNCERTAINTY OF DEPTH ESTIMATION

The evaluation of data gathered by in-line inspection tools provides information about the depth and the extent of corrosion within the pipe wall. Therefore, the defect depth (d) is one of the important parameters, which is input to the Limit State algorithm used to calculate the POF. The uncertainty of the depth estimation resulting from the intelligent inspection devices is typically given within the tool-performance specification document provided by the vendor of these services.

Several years ago a specification format was issued by the Pipeline Operator Forum, which outlines the required information for a statistically based description of the performance of inline inspection tools [7]. This standard has been widely used by the pigging industry and in particular for MFL-inspection systems. Beside values like probability of detection or probability of identification, according to this standard, the depth accuracy as a fraction of the intact wall thickness must be specified at a confidence level of 80% for different types of pipe anomalies. In the following the influence of the uncertainty of the depth estimation on the probability of failure will be discussed. For the presented algorithm the input of the standard uncertainty of the depth is required, which is the accuracy at 80% confidence divided by 1.28 (normal distribution presumed). Within this paper different values were chosen for the depth uncertainty representing the typical range between high- and low-resolution inspection tools (σ_d =0.04 - 0.24 of t_o).The assumed corrosion depth was varied between 0% and 80% of t_o. For the example shown in Fig. 4 the following parameters for the 20 inch offshore pipeline were used: D=20 inches, SMYS=52ksi, t_o=0.5", V_{OD}=5%, V_{SMYS}=10%, V_t=5%. The operating pressure was set to 0.72 times hoop stress pressure: P_D=1872psi, V_{PD}=8%. The results shown are the POF for detected features.

First it can be observed that an increasing uncertainty does have a bigger effect on the probability of failure for shallow defects, than for deep defects. Second the general reduction of the POF due to an improved (reduced) uncertainty, is not linear proportional. Thus the benefit of reducing the uncertainty is getting smaller as the uncertainty decreases (refer to Fig. 5).

Another impact on the POF is caused by the bias of the depth calculation (B_d). The bias is defined here as the median of the quotient of actual depth value and the estimated depth value. The bias of depth should not be confused with the bias of burst pressure calculation. Under-sizing of defects in a pipeline will result in a bias greater than 1, while over-sizing will cause a Bias smaller than 1. The impact of this is shown in Fig. 6.

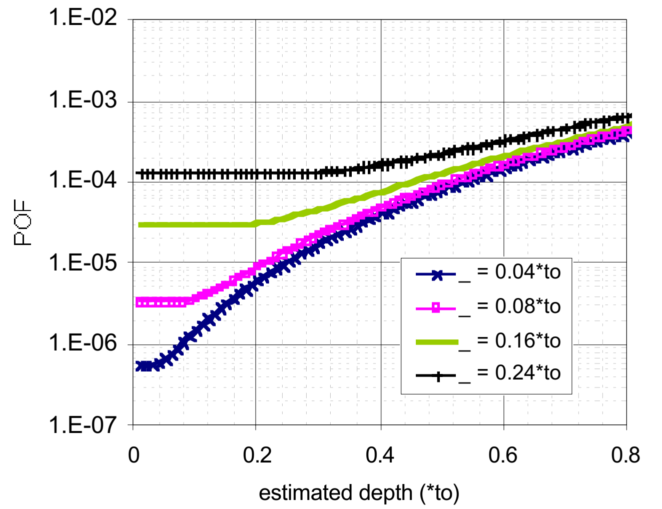

Fig. 4 Impact of depth uncertainty on the probability of failure

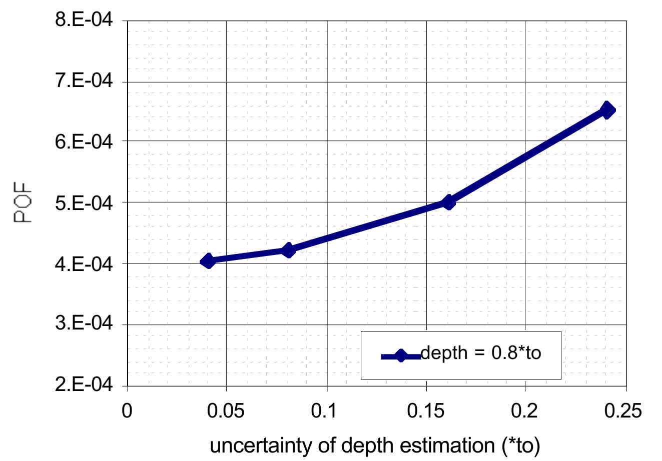

Fig. 5. Influence of under-sizing (Bd=1.3) and over-sizing (Bd=0.7) on probability of failure

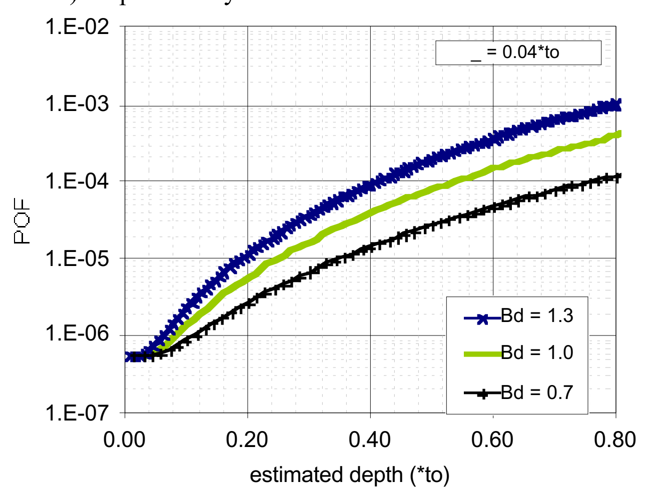

Fig. 6. Influence of under-sizing (Bd=1.3) and over-sizing (Bd=0.7) on probability of failure

The POF for deep defects is more sensitive to changes in bias than for shallow defects. In this example the bias was assumed to be constant as a function of depth. An increase of the Bias with depth can also be observed [4].

Uncertainty and Bias are affecting the calculation of the POF of a pipeline segment. While the uncertainty is an inherent property of the inspection physics and data interpretation processes, the Bias can be corrected close to unity by appropriate validation measures after an inspection.

ACCEPTABLE PROBABILITIES OF FAILURE

The operator - owner of the example pipeline had developed general guidelines to help guide decisions regarding acceptable and unacceptable probabilities of failure [8]. In this case, the owner - operator defined acceptable probabilities of failure that were based on historic precedents and consideration of the potential economic cost -benefit characteristics of different types and locations of pipelines. These guidelines indicated that for existing gas pipelines, the target annual Safety Indices should be 3.4 or larger (maximum Pf = 3.4 E-4 per year in segment). For the gas pipeline risers adjacent to the platforms, the target annual Safety Indices were indicated to be 3.8 or larger (maximum Pf = 7.2E-5 per year in segment).

These target reliabilities indicated that the central section of the pipeline and the inlet riser segments were fit for purpose.

Field studies performed following the analyses of the in-line instrumentation results indicated that the high probabilities of failure associated with the section of the pipeline near the middle of its length were most likely associated with a low-section that had allowed the accumulation of water inside the pipeline. The same field studies indicated that the higher probabilities of failure at the inlet riser - expansion loop section of the pipeline were due to the much higher temperatures of the gas at this location and on accumulation of water entrapped in the expansion loop section.

CONCLUSIONS

Reliability based analytical methods as applied to assessment of existing pipelines to determine their fitness for purpose can provide some important additional insights to assist pipeline engineers in reaching rational conclusions about maintenance of these pipelines. The reliability methods do not need to be very complicated. However, these methods need to be carefully applied to be sure that realistic input characterizations are developed.

Additional work is continuing on the developments summarized in this paper. Work is being focused on development of 'clean' laboratory test databases to help characterize the Biases associated with alternative methods to evaluate the burst pressure capacities of pipelines constructed from newer and older steels and for different types of defects and damage. Assessment methods are being developed to allow evaluation of the benefits provided by in-line instrumentation tools that can develop improved POD and defect geometry accuracy. Additional work also is being devoted to improving characterizations of internal pressure demands in different types of pipelines and to developing analytical methods to assess the effects of internal pressure controls and hydro-testing pipelines.

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