# Prognosis of Time to Failure of Corroding Pipelines

## Sirous F. Yasseri[1*], Hamid Bahai[2]

[1*] Corresponding author: Brunel University London, UK; sirous.yasseri@Brunel.ac.uk
[2] Brunel University London, UK; Hamid.Bahai@Brunel.ac.uk

## ARTICLE INFO

## ABSTRACT

The oil and gas pipelines are significant assets in Iran. However, these assets are subject to degradation from corrosion. Corrosion causes gradual thinning of the pipelines' wall leading to leaks or bursts. Allowing a corroding pipeline to continue operation may lead to a finite risk of exceeding the limit state of burst. Codes of practice, such as Modified ASME B31G [1] and DNV F101 [3], among others, have developed relationships to determine the bursting pressure of corroded pipelines. The purpose of this paper is to develop, test, and illustrate a simple spreadsheet-based probabilistic procedure that can be used by practicing engineers to determine the Remaining Useful Life (RUL) of a corroding pipeline, following its first inspection. Modified ASME B31G and DNV F101 equations are used to illustrate this method. As new inspection data regarding the extent of corrosion becomes available, the results can be updated and a new probability of failure can be obtained. The calculated probability of failure is then compared with the target values to determine the remaining life. The approach is equally applicable to both onshore and offshore oil and gas pipelines.

## 1. Introduction

Iran's gas transmission network covers over 36,000 kilometres. The construction of new pipelines and the expansion of existing facilities have created an interconnected pipeline network across the country. Gas transmission pipeline investment exceeds $6.7 billion. The total length of gas distribution networks in large cities is around 264,000 kilometres with a combined asset value of almost $40 billion. Add to this the export oil pipelines and pipelines which carry crude to the refineries and of course around the refineries themselves. Moreover, 1000s of kilometres of pipelines transport crude offshore from the Persian Gulf back onshore to be made ready for sale.

Some of these pipelines have exceeded their design life and require attention, and some despite being in service for relatively short period of time are showing sign of distress. Even a small improvement in the asset management of oil and gas infrastructure can bring significant benefits. Cost savings are possible by a better maintenance planning, targeted repair and optimised renewal processes. Another benefit of proactive management of the asset is higher reliability and availability of supply in harsh winter months.

The major failure mode of pipelines is corrosion damage. Dealing with pipeline corrosion involves large uncertainties. The main uncertainties are related to imperfect measurement of metal loss, randomness of the pipeline data, and variation of operational data. DNV RP-F101 has incorporated safety factors to account for these uncertainties. However, the way this code is applied is as a deterministic approach; like other failure pressure equations such as ASME B31G. The reliability of a pipeline is also dependent on the inspection tool accuracy [4], which is dependent on the dispersion of the corrosion growth rate geometry of the damaged areas. Equations in these codes are based on large databases and are generally on the safe side but by unknown margins. Codified deterministic methods use unfavourable data; e.g. maximum corrosion depth, maximum corrosion rate, maximum design pressure and minimum wall thickness without allowing for uncertainties. Thus, such results can be somewhat conservative in terms of probability of failure, even for pipelines containing extensive corrosion defects. Monitoring the current conditions of a pipeline and predicting corrosion trends enables the necessary repair to be scheduled under favourable conditions.

For the condition based maintenance, there is a demand for forecasting of system degradation through a prognostic process. Prediction of the time to failure is known as prognosis. Prognosis is viewed as an add-on capability to the diagnosis that assesses the current health of a system, and predicts its remaining useful life based on measured data that captures the gradual

degradation during operation. Such methodologies are already used in other high reliability systems, e.g. naval ships, avionics, etc.

In the condition based monitoring literature, Prognosis is often used in relation with the remaining useful life (RUL). ISO 13381-1 defines prognosis as a "Technical process resulting in the determination of remaining useful life" – where the remaining useful life is the time left before observing a failure.

In conventional maintenance models the important uncertainties are; the uncertainty in time to failure (lifetime) and the rate of deterioration. Most mathematical models are based on describing the uncertainty in an ageing system using a lifetime distribution.

For the strength evaluation of a corroded pipe this paper has used DNV-F101 and ASME B31G [18]. A simple method is used to determine the probability of failure due to one defect for each year after the first inspection. The failure probability of each defect on a pipeline containing many defects is then calculated. By using these failure probabilities, the system reliability for each kilometre of a pipeline is determined, and compared with the target failure probabilities, which depends on the pipeline safety class. The year when the failure probability exceeds the target value gives the remaining useful life of the pipeline. However, by gathering more data this prediction can be updated. As a final resort, repair, replace or reduction of operating pressure can be used to keep a pipeline in service for longer.

The remaining useful life prediction is affected by several sources of uncertainty such as modelling errors, measurement errors, future loading uncertainty, etc. It is important to accurately account for these sources of uncertainty while estimating the RUL.

Available methods [15 and 16] and a simplified classification of prognostic approaches are presented in the next section. Broadly speaking there are three primary approaches and a combination of two of them, known as the hybrid approach, is also used. This paper uses a hybrid approach to determine the time to failure of marine pipeline [9]. The approach is a combination physics-based (or model based) approach and probability of failure method.

## 2. Available Diagnosis and Prognosis Approaches

Diagnosis focuses on detection, isolation, identification and explanation of failures when they occur; compared to prognosis, which focuses on prediction of time to failure before they occur. There is a need to describe not only the current state but also to predict the future state with some level of confidence. The main goal of the prognosis is to determine the time to failure, in other words the remaining useful life (RUL) enabling timely intervention. RUL is estimated in discrete times, which should track the eventual failure. A degrading system continues to lose its ability to function safely as time goes by. Engineering systems cannot be allowed to degrade until the probability of failure is almost 100%. Codes of practice define a minimum allowable probability of failure to ensure that the system has adequate safety margins to operate.

There are a significant number of prognostic approaches, but the approach is not clearly defined and consequently there is no generally accepted classification. The most common classification splits the prognostics approaches into three main groups: model-based prognosis, data-driven prognosis and knowledge-based prognosis [8 and 20]. It should be remembered that the variety of prognostic approaches proposed in the literature is so great, it may not be possible to classify them in a simple fashion as above [20]. However, what is described below includes major methods which show a promising contribution in this field.
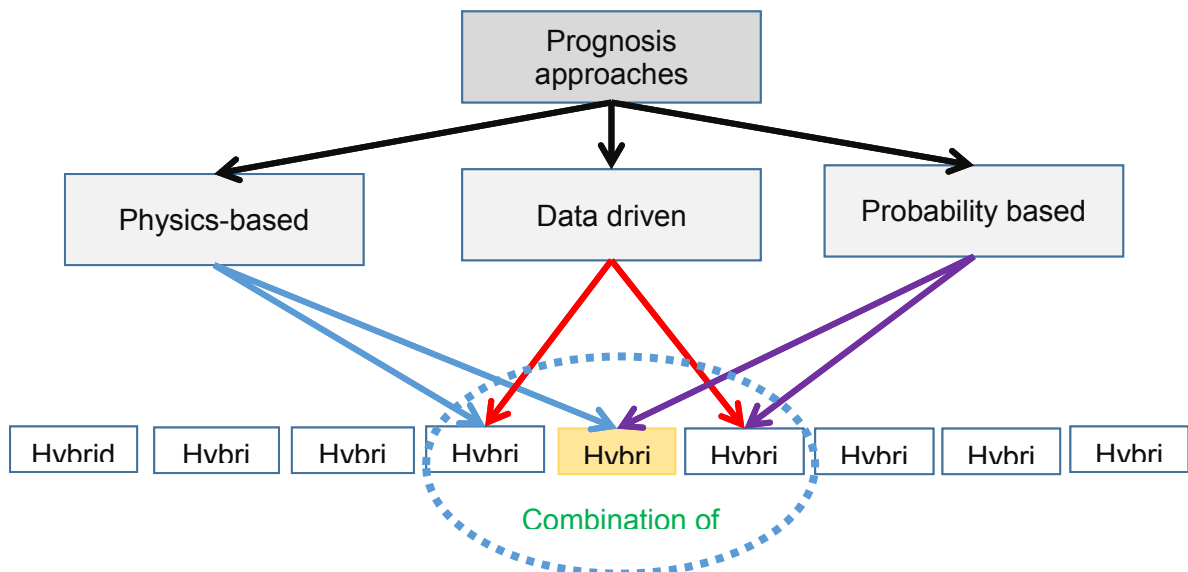


**Figure 1- Three major approaches and their combination to crate hybrid method.**

## 2.1 Data-Driven (DD)

Data-driven approaches (Figure 1) use the monitored operating data (vibration, acoustic signals, temperature, pressure, debris, defects etc.) to track, approximate and then forecast the system degradation behaviour [5 and 17]. DD approaches rely on the assumption that the statistical data are relatively stable, unless an anomaly occurs in the system. The common cause variations are entirely due to uncertainties and randomness and evolving defects causing variations, e.g. due to corrosion [6].

The data driven prognosis is based on statistical and learning techniques. These range from multivariate statistical methods (static and dynamic principle component, linear and quadratic discriminant, partial least squares, etc.) to black-box methods based on artificial neural networks (probabilistic neural networks, multi-layer perceptions, radial basis functions), graphical models (Bayesian networks, hidden Markov model [10]), self-organizing feature maps, signal analysis (filters, auto-regressive models, FFT etc.), decisions trees and fuzzy rule based systems [6, 7, 11 and 13]. Most of the work in data-driven prognostics has been applied in areas of structural health management.

The ability to transform and to reduce a large amount of noisy data into a smaller amount of valid and meaningful data set is the advantage of the data driven approaches. The disadvantage is the dependency on quality and quantity of the operating data, which is the driving key element of the prognostic accuracy and reliability. Sometimes some fault data is missing and it is not possible properly adjust/teach neural networks.

## 2.2 Model-based (MB)

Model-based (or physics-based [2]) approaches, are very useful, when relatively accurate mathematical based models can be developed. Models can be classified as qualitative or quantitative descriptors of the system. Quantitative models represent mathematical and functional relationships between the inputs and outputs of a system; while qualitative models represent these relationships in terms of qualitative functions centred on different units in the system [14]. There are a limited number of applications of MB to real-world problems, even though MB can be considered as the most accurate approach.

Model-based prognostic approaches are also limited by the ability to develop high-fidelity models, of complex systems and processes. In many situations, where models based on the first principles, are not available, it is possible to assume a certain form for a dynamic model which describes the evolution of a degradation process. Then, using observed inputs and outputs, the model parameters can be identified in a process known as model identification [3]. Prognostic approaches using such models are sometimes described as hybrid approaches, crossing the boundary between model-based and data-based prognostics. With the availability of sufficiently descriptive models of a degradation process, either physics of failure models, or models derived to describe the behaviour of historical failure examples, the development of prognostic algorithms based upon the application of recursive Bayesian estimation techniques are possible [10].

The major advantage of the model-based approach is the possibility to accounting the physical knowledge of the system into the monitoring process, in other words it means that we can reduce the level of sensed parameters, or we could determine some parameters directly from a model. Model adaptation to a system degradation is another advantage of these methods, because it helps to keep the prognostics accuracy at the demanded level.

## 2.3 Knowledge/Probability Based Methods

This group of methods have the longest history when compared to other previously mentioned approaches, and does not require too much detailed data, as they utilize different kinds of probability distribution functions. (PDF) The most commonly used distribution functions are normal, Weibull and exponential distribution. This group of prognostics methods also provides a confidence level. This is important for determining the probability and accuracy of our estimate. PDF is used in reliability analysis.

This paper focuses on the estimation of the remaining useful life (RUL) for prognosis application, combining physics based models of evolving corrosion and reliability method. Model based methods require understanding the physics of degradation, while data driven approaches establish trends or relationships for the failure data, without too much attention to the physics of the problem.

The first step is to survey the current state of the system. The second step is to predict how the degradation could progress as a function of time, using a degradation model which may either be physics-based or data-driven. The third step is to define a threshold function which defines the end-of-life; this threshold function is a binary function and can be used to calculate the remaining useful life. The remaining useful life prediction is affected by several sources of uncertainty such as modelling errors, measurement errors, future loading uncertainty, etc., and it is important to accurately account for these sources of uncertainty while estimating the RUL. Remaining useful life is defined as the time when equipment performance degrades to the failure threshold for the first time.

## 3. Failure Pressure of a Corroded Pipe

Failure Pressure (FP) models are used for the assessment of corroded pipelines. Examples of FP models are the DNV-RP-F101 [3] and Modified ASME B31G. Each FP model is governed by input parameters of the pipe outer diameter (D), wall thickness (t), minimum yield strength (SMYS) or ultimate tensile strength (UTS), longitudinal extent of corrosion (l) and corrosion defect depth (d). These models have helped to avoid unnecessary repairs and replacement.

These models use single simple corrosion geometry and the corrosion circumferential width (w) is not considered [17]. Generally, it is agreed that the longitudinal extent of corrosion is always more important than the circumferential width. Defects in the longitudinal direction have been reported to be the most severe since they alter the hoop stress distribution and promote bulging. Hoop stress is the dominant stress for internal pressure and hence the parameter d and l have become the important inputs for the FP models. The influence of corrosion's circumferential width (w) to failures is not that significant [17]. The parameter w becomes important when qualitatively assessing the interaction of a group of defects under the Fitness-for-Service approach.

There are numerous corrosion models, ([12 and 8]), both stochastic and deterministic. Some authors assume corrosion starts after a certain number of years, while others assume the corrosion process starts immediately. In this paper, we study a pipeline after the first inspection, when defects have been detected.

The most popular model for the pipeline defect growth is linear described by the power law model.

$$d(T) = d_0 + V_d(T - T_0) \tag{1a}$$

$$L(T) = L_0 + V_L(T - T_0) \tag{1b}$$

Where $V_d = d_0/\Delta T_e$ is the rate of corrosion depth, and $V_L = L_0/\Delta T_e$ is the rate of corrosion length. Generally assigned a single value (say 0.4mm/year), or the average of total loss for a given number of years (say $\Delta T_e = 15$years), i.e. *thickness/number of years* [4]. $d_0$ and $L_0$ are defect depth and length at the zero time.

## 4. Reliability Index

The conditional probability of bursting failure of a corroded pipeline can be written as:

$$P_f = P(failure|IP) = P(IP, X_1, X_2, \cdots, X_n) \tag{2}$$

In the second term, the symbol "|" is read *given* and the variable *IP* is the *Internal pressure*. In the third term, the random variables $X_1$ through $X_n$ denote relevant parameters such as material strength, pipe diameter, thickness, defect dimensions, etc. [17].

Assuming the capacity, C, and demand, D, are lognormal random variables, then $\ln(C)$ and $\ln(D)$ are normally distributed. Defining the safety factor $FS = C/D$, then $lnFS = (lnC) - \ln(D)$ and $lnFS$ is normally distributed. Defining the reliability index as the amount that $lnFS$ exceeds zero, then:

$$\beta = \frac{E(lnC - lnD)}{\sigma_{(lnC-lnD)}} = \frac{E\big(ln(C/D)\big)}{\sigma_{ln(C/D)}} = \frac{E(lnFS)}{\sigma_{lnFS}} \tag{3}$$

Code equations can be put in the form of the safety factor, where capacity and demand are not explicitly separated. The reliability index must be determined using $E(FS)$ and $\sigma_{FS}$ which is calculated using multiple runs.

Thus, the reliability index is determined as follows:

**Table 1- Failure pressure equation of three codes**

| Failure Pressure | Failure Pressure Expression | Folias Factor |
|---|---|---|
| **Modified ASME B31G** | $F = \dfrac{2(\sigma_Y + 68.95)t}{D}[1 - (d/t)/M]$ <br> $for\ G = 0.893\dfrac{L(T)}{\sqrt{Dt}} < 4$ | $M$ $= \sqrt{1 + 0.6275\left(\dfrac{l^2}{Dt} - 0.003375\ \dfrac{l^4}{D^2 l^2}\right)}$ <br> $If, \sqrt{l^2/Dt} \le 50$ <br><br> $M = 3.3 + 0.032\left(\dfrac{l^2}{DT}\right)$ <br> $If, \sqrt{l^2/Dt} > 50$ |
| **FITNET** | $PF = \dfrac{2\sigma_U t}{(D-t)2^{(65/\sigma_Y)}} \dfrac{1 - (d/t)}{1 - (d/t)/M}$ | $M = \sqrt{1 + 0.8\left(\dfrac{l^2}{Dt}\right)}$ |
| **DNV RP F101** | $PF = \dfrac{2\sigma_U t}{D - t} \dfrac{1 - (d/t)}{1 - (d/t)/M}$ | $M = \sqrt{1 + 0.31\left(\dfrac{l^2}{Dt}\right)}$ |

**Table 2- Design data for the case study**

| Symbol | Variable | Unit | Mean | Standard Deviation |
|--------|----------|------|------|--------------------|
| $d_0$ | Corrosion Depth | mm | 8.24 | 0.1 |
| $l$ | Corrosion Longitudinal length | mm | 200 | 0.1 |
| $w$ | Corrosion Circumferential width | mm | 40 | 0.1 |
| $D$ | Pipe Diameter | mm | 914.4 | 0.02 |
| $t$ | Pipe wall thickness | mm | 20.6 | 0.05 |
| $SMTS$ | Specified minimum Tensile strength | MPa | 455 | 0.07 |
| $SMYS$ | Specified minimum Yield strength | MPa | 358 | 0.07 |
| $P_o$ | Operating Pressure | MPa | 7.8 | 0.2 |
| *Model uncertainty* | | | 1.0 | 0.175 |

$$V_{FS} = \frac{\sigma_{FS}}{E(FS)} \tag{4}$$

$$\sigma_{lnFS} = \sqrt{ln(1 + V_{FS}^2)} \tag{5}$$

$$E(lnFS) = lnE(FS) - \frac{1}{2}ln(1 + V_{FS}^2) \tag{6}$$

The reliability index, $\beta$, is defined as:

$$\beta = \frac{E(lnFS)}{\sigma_{lnFS}} = \frac{ln\left(E(FS)/\sqrt{1 + V_{FS}^2}\right)}{\sqrt{ln(1 + V_{FS}^2)}} \tag{7}$$

In this study, the model uncertainty is added as another random variable in determining the reliability index. For the DNV method the critical value of the safety factor is taken to be 1/0.9=1.111 and for the modified B31G is $FS = 1$.

## 5. Case Study

Table 2 shows the values of the six variables chosen for this example. Definition of defect parameters is shown in Figure 2. Additionally, model uncertainty is assumed to be another random variable.
All variables are listed on the top row. Three values for each variable is assumed (mean, mean plus and minus one standard deviation). This creates three realisations of all variables. The middle columns of the Table 2 are calculations of the PF. For the first analysis (Case 1), the seven random variables are taken at their expected values (Table 3).
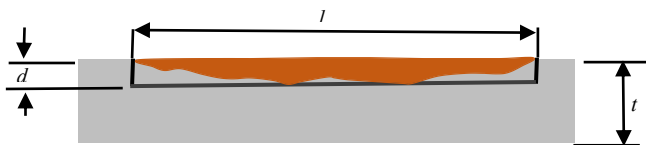


**Figure 2- Dimensions of a corrosion defect.**

For the subsequent analyses, one variable is taken at a time and its value is assumed to be the expected value, plus or minus one standard deviation, while the other three variables are kept at their expected values. Results obtained from these analyses are used to calculate the total variance related to the Safety Factor, *FS*. For instance:

$$Var[FS] \approx \left(\frac{FS[X_{i+}] - FS[X_{i-}]}{2}\right)^2$$

$$= \left(\frac{1.6517 - 2.807}{2}\right)^2 = 0.0008$$

When the variance components are summed, the total variance will be: 0.1285. Taking the square root of the variance gives the standard deviation of 0.3566.
The Safety Factor, *FS*, is assumed to be log-normally distributed random variable with the expected value (first moment) $E(FS) = 1.6628$ and $\sigma_{FS} = 0.3584$. Using the properties of the lognormal distribution, the equivalent normally distributed random variable has the following parameters:

$$E(lnFS) = lnE[FS] - \frac{1}{2}\sigma_{lnFS}^2 = 0.4788$$

And

$$\sigma_{lnFS} = \sqrt{ln(1 + V_{FS}^2)} = 0.2145$$

The probability of failure is given by:

$$P_f = P(lnFS > lnFS_{crit}) \tag{8}$$

The probability is determined assuming the normal distribution by calculating the standard normalised variable z (analogous to $\beta$):

$$\beta = \frac{lnFS_{crit} - E(lnFS)}{\sigma_{lnFS}} = \frac{0.0 - 0.4788}{0.2145} = -2.2320$$

For this value, the cumulative distribution will be $F(Z) = 0.010944$, which represent the probability that the safety factor is below the critical value. The probability that the safety factor is above the critical value is:

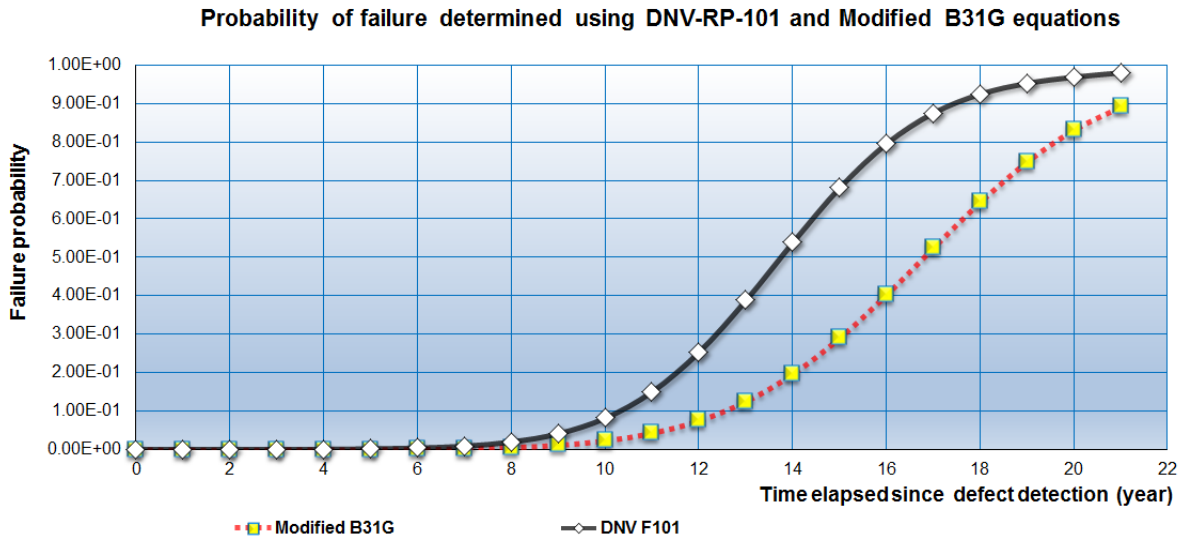$$P_f = 1 - F(z) = 1 - 0.0128 = 0.9872$$

**Probability of failure determined using DNV-RP-101 and Modified B31G equations**



**Figure 3- Probability of failure for the example problem since inspection using Modified B31G and DNV F101**

**Conditional probability of failure determined using DNV-RP-101 and Modified B31G equations**
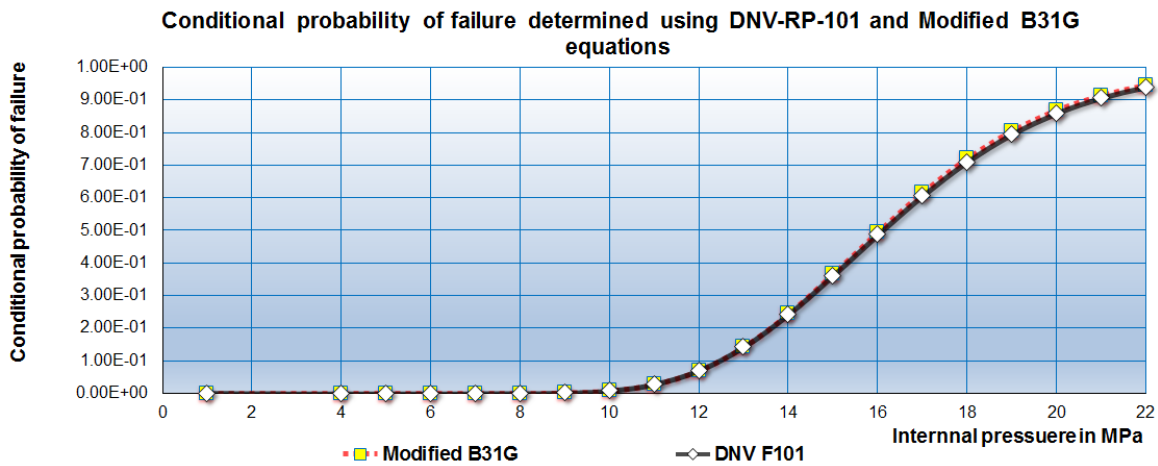


**Figure 4- Comparison of conditional probability of failure for the case study after the inspection**

These analyses were repeated up to 20 years. The resulting probabilities of failure are shown in Figure 3. The same procedure was repeated for the DNV equation and these results are superimposed on Figure 4. In the above analyses the internal pressure was kept at 7.2 bar for all cases, only the size of the defect changed as a function of time. Taking data after the inspection (year zero), but changing the internal pressure gives the conditional probability of failure of the defective pipe for the internal pressure, as shown in Figure 3. DNVF101 gives somewhat higher probability of failure compared with Modified 31G.

## 6. System Reliability of Corroding Pipeline

Codes of practice generally define three safety classes, namely 'low', 'normal' and 'high' for pipelines (Table 4). For example, water injection lines may be classified as being a 'low' safety class while oil transportation lines may be considered as a 'high' safety class.

The target failure probabilities in Table 4 is for all hazards, but approximately half of all failures are due to corrosion. Thus, for a normal safety class, the target for corrosion only, is taken to be $5 \times 10^{-5}$

**Table 4: Target failure probabilities per km per year**

| Code | Safety class | | |
|---|---|---|---|
| | Low | Normal | High |
| RP-F101 (DNV 1999) | $10^{-3}$ | $10^{-4}$ | $10^{-5}$ |
| OS-F101 (DNV 2000) | $10^{-3}$ | $10^{-4}$ | $10^{-5}$ |
| (SUPERB project) (1997) | $10^{-2} - 10^{-3}$ | $10^{-3} - 10^{-4}$ | $10^{-4} - 10^{-5}$ |

**Remaining wall thickness along 1000 m of the pipeline after the first inspection**
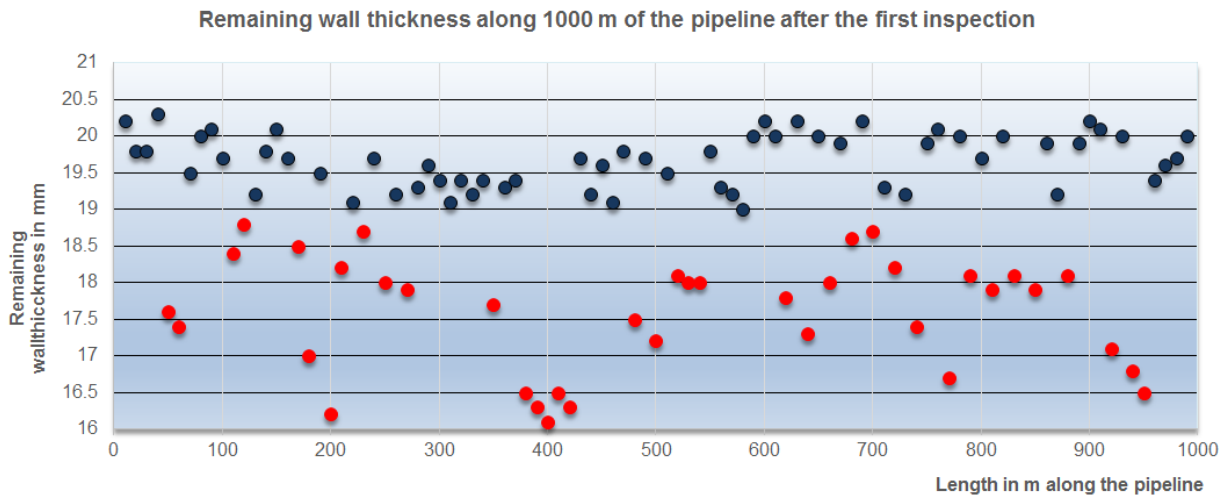


**Figure 5: Detected defects along the one kilometre of the pipeline. There are 38 large defects shown in red.**

The failure probability calculations, as outlined in the previous section, are for just one defect. Each kilometre of the pipeline may contain many defects of varying sizes.

Consider a pipeline with the same geometry and material as given in Table 1, and operating at 7.2 MPa internal pressure, and with the measured defects detailed below (Figure 5).

The maximum measured defect was 4.5 mm deep and 46 mm long. To simplify calculations and for illustration purposes, only defects between 1.6 mm deep and 4.5 mm deep are considered (38 of them).

Each kilometre of the pipeline consists of a chain of pipe segments in series [19]. Assuming N components at time t then the overall reliability of the system can be mathematically expressed as:

$$R_{system}(t) = \prod_{i=1}^{N} R_i(t) \tag{9}$$

Failures at individual defects are likely to be correlated, because the defects are subjected to the same internal pressure and pipe properties (e.g. wall thickness, yield strength and tensile strength). The geometry and growth characteristics of individual defects will also be correlated if the defects' locations are exposed to similar environments. Because the pipeline segment is a series system, it is conservative to ignore the correlation between multiple defects for the evaluation of the system reliability. As correlations are ignored and all defects are assumed to be the same size as the largest measured defect, this analysis is somewhat conservative, but will serve for the purpose of illustration.

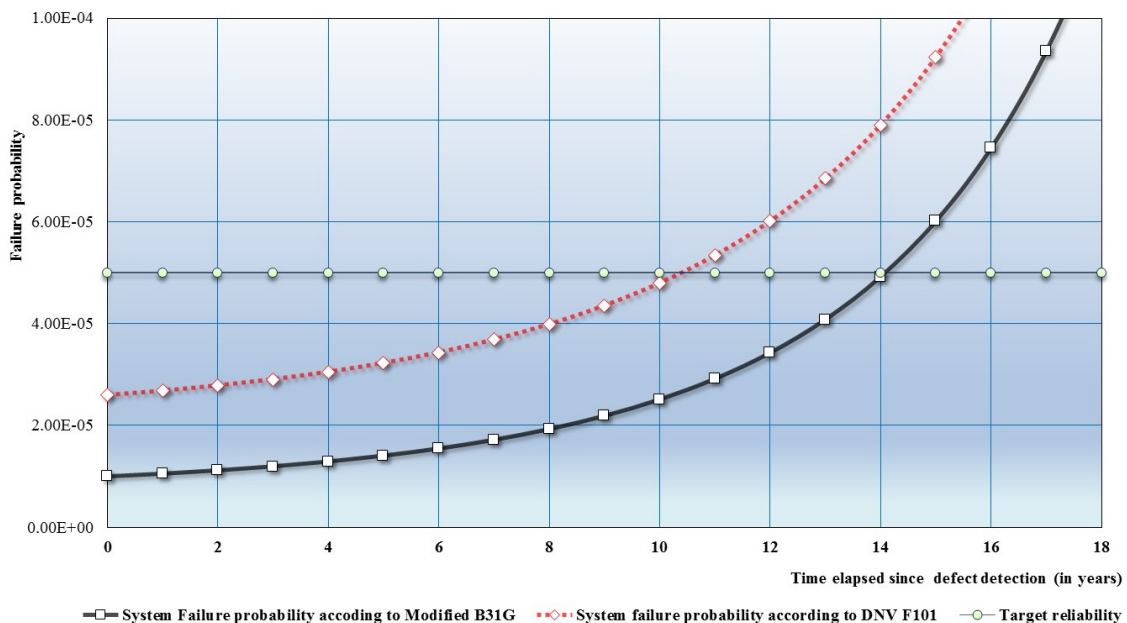**Probability of failure determined using DNV-RP-101 and Modified B31G equations**



**Figure 6- Failure probability for system and the target level using two codes**

The reliability of one kilometre of pipeline containing 38 defects is determined, using DNV F101and B31G equations. Results are shown in Figure 5. The horizontal line on this figure shows the target reliability. According to DNV equations this pipeline must be inspected 11 years after its initial inspection, when the probability of failure exceeds the target value.

## 7. Conclusions

A simple spreadsheet method to determine the failure probability of corroded pipelines has been outlined. The model allows for uncertainty in the variables to be accounted for. A linear corrosion model has been used for illustration purposes, but one can equally use another model.

A target probability of failure is used to decide the end of useful life. As such the remaining useful life is dependent on the tolerable failure probability. The method described provides a basis for determining pipeline inspection priority and ultimately for developing a renewal strategy.

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## Appendix A-TAYLOR'S SERIES METHOD

In order to estimate the variability of design results in terms of their mean and standard deviations, the First Order Second Moment (FOSM) method that involves approximation based on Taylor expansion are employed in this paper. $E(FS)$ can be expressed as:

$$E[FS] = FS(E[X_1], E[X_2], \cdots, E[X_n]) \qquad (A1)$$

where $X_i (i = 1,2,3, \cdots)$ represents the random variables such as material yield strength, wall thickness, outside diameter, defect size and so on.

If the Taylor series expansion for a performance function of several random variables, $E(FS)$, is performed about the mean values of the random variables, and only first order terms are retained, approximate variance of the function can be expressed as:

$$Var[FS] = \sum \left[ \left( \frac{\partial FS}{\partial X_i} \right)^2 \sigma_{X_i}^2 \right.$$
$$+ 2 \sum \frac{\partial FS}{\partial X_i} \qquad (A2)$$
$$\left. \times \frac{\partial FS}{\partial X_j} \rho_{X_{i,} X_j} \sigma_{X_i} \sigma_{X_j} \right.$$

When the random variables in function $FS$ are assumed uncorrelated, Equation (A2) can be presented in a simpler form as follows:

$$Var[FS] = \sum \left[ \left( \frac{\partial FS}{\partial X_i} \right)^2 \sigma_{X_i}^2 \right] \qquad (A3)$$

It is quite common in engineering to encounter non-closed form of the performance functions. When $FS$ is a non-closed form function, the partial derivatives of $FS$ can be estimated numerically using the finite difference method, i.e.:

$$\frac{\partial FS}{\partial X_i} \approx \frac{FS[X_{i+}] - FS[X_{i-}]}{X_{i+} - X_{i-}} \qquad (A4)$$

where; $X_{i-}$ and $X_{i+}$ represents the random variable $X_i$ taken at some increment above and below its expected values (e.g. $\pm 1\sigma$ or $\pm 2\sigma$). Theoretically, an extremely small increment gives the most accurate value of the derivative at the expected value. This FOSM method allows the engineer to see the contribution of each random variable to the total uncertainty in the $FS$ function.

$$Var[FS] \approx \sum_{i=1}^{n} \frac{FS[X_{i+}] - FS[X_{i-}]}{2} \qquad (A5)$$

# Apendix B: Table 3: Inputs for the reliability calculation and results (based on DNV-RP-F101)

| Based on Modified B31G | | | | | Operating Pressure 7.2 MPa | | | | | 10 | | Years after inspection | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Case | Variable's level | *l (mm)* | d (mm) | w (m) | D (mm) | t (mm) | SMTS | STD | M | PF (MPa) | | FS | |
| 1 | | 320 | 13.18 | 40 | 914.40 | 20.60 | 427 | 1 | 2.0741 | 11.8923 | 1.6517 | 1.6517 | |
| 2 | Low | 300 | 13.18 | 40 | 914.40 | 20.60 | 427 | 1 | 1.9780 | 12.1013 | 1.6807 | 1.6807 | |
| 3 | High | 340 | 13.18 | 40 | 914.40 | 20.60 | 427 | 1 | 2.1709 | 11.7067 | 1.6259 | 1.6259 | 0.0008 |
| 4 | Low | 320 | 12.36 | 40 | 914.40 | 20.60 | 427 | 1 | 2.0741 | 12.5012 | 1.7363 | 1.7363 | |
| 5 | High | 320 | 14.01 | 40 | 914.40 | 20.60 | 427 | 1 | 2.0741 | 11.2557 | 1.5633 | 1.5633 | 0.0075 |
| 6 | Low | 320 | 13.18 | 36 | 914.40 | 20.60 | 427 | 1 | 2.0741 | 11.8923 | 1.6517 | 1.6517 | |
| 7 | High | 320 | 13.18 | 44 | 914.40 | 20.60 | 427 | 1 | 2.0741 | 11.8923 | 1.6517 | 1.6517 | 0.0000 |
| 8 | Low | 320 | 13.18 | 40 | 896.11 | 20.60 | 427 | 1 | 2.0897 | 12.1027 | 1.6809 | 1.6809 | |
| 9 | High | 320 | 13.18 | 40 | 932.69 | 20.60 | 427 | 1 | 2.0589 | 11.6898 | 1.6236 | 1.6236 | 0.0008 |
| 10 | Low | 320 | 13.18 | 40 | 914.40 | 19.57 | 427 | 1 | 2.1142 | 10.7126 | 1.4879 | 1.4879 | |
| 11 | High | 320 | 13.18 | 40 | 914.40 | 21.63 | 427 | 1 | 2.0369 | 13.0559 | 1.8133 | 1.8133 | 0.0265 |
| 12 | Low | 320 | 13.18 | 40 | 914.40 | 20.60 | 401.94 | 1 | 2.0741 | 11.1944 | 1.5548 | 1.5548 | |
| 13 | High | 320 | 13.18 | 40 | 914.40 | 20.60 | 452.06 | 1 | 2.0741 | 12.5903 | 1.7486 | 1.7486 | 0.0094 |
| 14 | Low | 320 | 13.18 | 40 | 914.40 | 20.60 | 427 | 0.825 | 2.0741 | 11.8923 | 1.3627 | 1.3627 | |
| 15 | High | 320 | 13.18 | 40 | 914.40 | 20.60 | 427 | 1.175 | 2.0741 | 11.8923 | 1.9408 | 1.9408 | 0.0835 |
| | | | | | | | | | | | | | 0.1285 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| E(i)= | 1.6517 | | E(ln)= | 0.4788 | | z= | -2.2320 |
| Var(i)= | 0.1285 | | | | | | |
| Sigma(i)= | 0.3584 | | Sigm(ln i) | 0.2145 | | Pr(f)= F(z) | 0.0128 |
| V(i)= | 0.2170 | | | | | | |
| I(crit) | 1.0000 | | Ln(I crit)= | 0.0000 | | Pf=1-F(z) | 0.9872 |