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Probabilistic Corrosion Growth Models of Buried Steel Pipelines Using Inspection and Soil Survey Data

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ABSTRACT: Buried steel pipeline corrosion management strategies need time-dependent reliability evaluation of pipelines subjected to corrosion. Therefore, developing a reliable probabilistic predictive corrosion growth model is a necessity. This paper presents a novel framework for developing corrosion depth and length growth models. More specifically, a power-law function of time model formulation is adopted herein, which considers nonconstant damage growth rate over time. Besides, the soil properties are explicitly incorporated in the model formulation and the correlation between defect depth and length growth models is also considered. Bayesian updating framework is employed to evaluate the statistics of the unknown model parameters. As the prediction response in the model is defect dimension itself at a given time not on the corrosion rate, the model can be applied when either matched or nonmatched defects data are identified in the sequent inspections. In addition, the proposed framework considers a Poisson process for the occurrence of defects, and thus it does not assume uniform corrosion initiation time for all the defects, which can also predict the number of newly generated defects since last inspection. Most importantly, the proposed framework incorporates the influential physicochemical properties of the soil without assuming homogeneous growth for defects; and therefore, the developed growth models can be used to evaluate the performance of non-piggable buried pipelines over time. In the case study, corrosion defect models are developed based on the inspection data of a 112 km pipeline, and then are used for time-dependent reliability of the studied pipeline considering two different failure modes: small leak and burst. Finally, importance analysis is conducted to determine most influential model parameters to the probability of failure.

1. INTRODUCTION

Buried steel pipelines are subjected to many possible threats during their service lives, and one of the dynamic threats to the integrity of such pipelines is external corrosion. In order to develop pipeline integrity corrosion management strategies, time-dependent performance evaluation of buried pipelines considering corrosion needs to be conducted. In this regard, the corrosion damage evolution needs to be modeled to reflect the influence of the potential factors such as the physical and mechanical properties of the pipeline and its surrounding environment (Ahammed and Melchers 1997).

To develop predictive corrosion defect growth models, field inspection data can be used. Such data are usually gathered by in-line inspection (ILI) tools (such as "pigging" technologies), which utilizes ultrasound devices to detect depth and axial length of the defects.

Generally speaking, to describe the corrosion damage growth, two different damage quantities have been used in the modeling: one is defect dimension at a time instant and the other is corrosion rate. To evaluate the corrosion rate, two damage dimensions for the same defect are needed over at least two-time instants. That is, it is required that the same defect is detected in two consecutive inspections and its dimensions are recorded. However, due to detection technology limitations/errors, matched defects from two inspections are quite rarely found in the field inspection data; thus, such data is often not suitable to model corrosion rate.

To date, different formulations of defect growth models have been proposed in the literature. One of the most commonly used ones is the linear function of time for defect dimensions (i.e., depth and length) growth models, in which the rate of evolution is considered to be constant over time (e.g., Alamilla & Sosa 2008; Li et al. 2009; Salama & Maes 2014; Zhang & Zhou 2014). However, only when the corrosion is in the stable stage this assumption is valid, and it also oversimplifies the corrosion growth process. Meanwhile, some researchers considered a power-law function of time as defect growth models, which can capture non-constant damage growth rate over time (e.g., Caleyo et al. 2009; Velazquez et al. 2009; Alamilla et al. 2009; Nahal & Khelif 2014; Miran et al. 2016).

Since a pipeline is typically very long and the soil properties along the pipeline could vary significantly along the pipe length, external corrosion evolution should be location dependent. Thus, some researchers assumed homogenous corrosion growth along multiple short-length segments of the pipeline (e.g., Miran et al. 2016; Wang et al. 2015). On the other hand, some researchers incorporated the spatial variability of the soil properties in the corrosion growth model formulation. For example, Velazquez et al. (2009) used the power-law formulation and related the model parameters to the soil and pipe characteristics through a multivariate regression analysis. Similarly, to estimate the model parameters in the power-law formulation, Alamilla et al. (2009) considered various environmental factors such as pH, resistivity, redox potential, and pipe–soil potential as the independent variables; however, they assumed a specific initiation time for all defects in each soil category. Moreover, Nahal & Khelif (2014) utilized the power-law formulation of pitting growth models with consideration of a number of variables related to space random fields to consider the corrosion distribution in a pipeline.

In this study, a novel methodology is put forward to develop the corrosion damage evolution model, which has some distinguishing features compared to those models available in the past studies:

I) it employs a Poisson process for corrosion initiation, so it does not assume uniform pitting initiation time for all detected defects;

II) it uses the corrosion defect dimension directly not damage rate, therefore such methodology is applicable whether matched or nonmatched defects data are available; and

III) it incorporates the soil properties at the location of each defect in the growth model, therefore no segmentation or homogeneous assumption is needed.

As a case study, available ILI data for an in-service pipeline is used to develop the corrosion growth model using the proposed methodology and the prediction performance is then evaluated. The resulted model is then used to estimate the probability of failure of the studied pipeline over time, which is followed by sensitivity analysis of the model parameters.

2. PROBABILISTIC CORROSION DAMAGE EVOLUTION MODELING METHODOLOGY

This section describes how the soil properties are incorporated in the damage evolution, initiation time for each defect is modeled, and unknown model parameters are estimated.

2.1. General formulation

In this study, for both corrosion maximum depth and length, a power-law function of time model formulation is adopted, as it considers nonconstant damage growth rate over time. To incorporate the environmental impact, the model parameters will be considered as linear functions of the field measured physicochemical variables of the soil along the pipeline. The model formulation is expressed as:

$$z_k(t, \mathbf{\Theta}) = C_{1,k} \cdot \left(t - t_{0,k}\right)^{C_{2,k}} + \sigma_k \cdot \varepsilon_k \tag{1}$$

$$C_{1,k}(\boldsymbol{\theta}_1, \mathbf{x}) = \theta_{1,0} + \sum_{i=1}^{n} \theta_{1,i}\, x_i \tag{1a}$$

$$C_{2,k}(\boldsymbol{\theta}_2, \mathbf{y}) = \frac{\left(\theta_{2,0} + \sum_{j=1}^{m} \theta_{2,j}\, y_j\right)^2}{1 + \left(\theta_{2,0} + \sum_{j=1}^{m} \theta_{2,j}\, y_j\right)^2} \tag{1b}$$

where k = types of defect quantity (e.g., $k = D$ for the maximum defect depth and $k = L$ for the maximum defect length), $z_k(t)$ = defect dimension (e.g., maximum defect depth or defect length) at a time instant t, t_0 = corrosion initiation time, $\mathbf{\Theta}$ = unknown model parameters including $\boldsymbol{\theta} = \{\boldsymbol{\theta}_1, \boldsymbol{\theta}_2\}$, x_i and y_j influencing environmental variables, $t_{0,m}$ = initiation time of each defect, ε_k = a standard normal random variable, and σ_k = standard deviation of the model error.

Note that to ensure the growth model reflects a descending growth rate over time, the power term of the growth model, i.e. $C_{2,k}$, needs to be bounded between zero and one. Thus, a transformation as shown in Eq. (1b) is adopted to meet such requirement.

To model corrosion initiation, a Poisson process is considered for the occurrence of defects. Therefore, the proposed methodology does not assume uniform (constant) corrosion initiation time for all the defects, which can, as a result, predict the number of newly generated defects since the last inspection. To evaluate $t_{0,k}$ in Eq. (1), we assume the number of defects that occurs follows the same homogeneous Poisson process characterized by a rate parameter λ. Additionally, it is assumed that a defect with a larger detected dimensions occurs earlier than other ones with less dimensions; accordingly, the defects are sorted based on their detected dimension values and the initiation time of each defect follows a Gamma distribution, where the Gamma distribution scale parameter, β_k, is treated as an unknown model parameter to be estimated and the shape parameter, α_k, is assumed to be the ranking of each defect.

All the unknown parameters, $\mathbf{\Theta}$, including $\boldsymbol{\theta}$, β_k, and σ_k, are estimated by Bayesian Statistics through a Markov Chain Monte Carlo (MCMC) process that will be described in the next Subsection. In the MCMC sampling process, the defect initiation time, t_0, is randomly generated from the associated Gamma distribution. However, for some cases, the generated Gamma random number is greater than the time of inspection, t, meaning that the defect is initiated after the inspection time, which is unreasonable. To overcome this issue, truncated Gamma distributions were employed so that upper bound of the distributions was considered equal to the time of inspection t.

In addition, it is found that when using MCMC to search the posterior distribution of unknown parameters, the convergence is extremely slow or not achievable due to the large variability in randomly generated t_0; even for the same β, t_0 could change dramatically since it is randomly generated for each MCMC sampling. To overcome this issue, at each iteration of the MCMC process, the mean value of the corresponding truncated Gamma distribution is used as the defect initiation time, t_0 which can be calculated using the probability theory by:

$$t_0 = \int_0^t x \cdot \frac{1}{\beta^\alpha\, \Gamma(\alpha)} \cdot x^{\alpha-1} \cdot e^{-\frac{x}{\beta}}\, dx \tag{2}$$

in which $\Gamma(.)$ is the Gamma function, and t is the inspection time. Note that for non-truncated Gamma distribution, the mean value is $\alpha{\cdot}\beta$, while for truncated Gamma distribution, integration as shown in Eq. (2) is needed.

Since a unique initiation time for each defect and also soil properties at the location of each defect are considered in the proposed methodology, a unique corrosion growth model is obtained for every single defect.

2.2. Bayesian statistics

Bayesian statistics (Box and Tiao 1992) is used here to assess the joint probability density function (PDF) of the unknown model parameters, $\mathbf{\Theta}$, used in the damage evolution model. If $\mathbf{X}$ denotes the vector of data used to update the model parameters, the posterior joint PDF of $\mathbf{\Theta}$, $p''(\mathbf{\Theta})$, can be written as

$$p''(\mathbf{\Theta}) = \kappa \cdot L(\mathbf{X}|\mathbf{\Theta}) \cdot p'(\mathbf{\Theta}) \quad (3)$$

where $\kappa = [\int L(\mathbf{X}|\mathbf{\Theta}) p'(\mathbf{\Theta}) d\mathbf{\Theta}]^{-1}$, $L(\mathbf{X}|\mathbf{\Theta})$ = likelihood function, $p'(\mathbf{\Theta})$ = prior joint PDF of $\mathbf{\Theta}$. As the model error in Eq. (1) is assumed to follow a Normal distribution, the likelihood function can be written as a bi-variant Normal distribution considering the correlation between depth and length model error standard deviations (Miran et al. 2016). To effectively compute the posterior statistics, one can use a sampling-based technique like the MCMC simulations (Gilks et al. 1996). For the convergence criteria, the Geweke method (Geweke 1992) is used in this study.

2.3. Selection of soil properties in model development

To account for the spatial variability of soil property along the length of the pipeline, soil parameters will be incorporated into the growth models, as shown in Eq. (1). To determine which soil property should be employed in the model, the whole length of the pipeline can be divided into short-length segments of equal length (say, resulting in q segments). This segment length is assumed to be short enough so that one can assume the variation of the soil properties is small and the defects on the segment follows the same corrosion growth model. For each segment, one growth model is developed without using soil property in Eq. (1) with q sets of $C_{1,k}$ and $C_{2,k}$.

Next, one could examine if the values of $C_{1,k}$ and $C_{2,k}$. can be modeled by any soil properties. If a soil property is found to have a linear correlation with $C_{1,k}$ or $C_{2,k}$ (which can be checked use p-testing), this soil property will be selected and used in Eqs. (1a) or (1b).

3. MCMC RESULTS

The proposed methodology is applied to develop corrosion depth and length growth models using a set of field data. The studied onshore pipeline with a total length of 112 km has been in service since 1969 near the Gulf of Mexico and has the outside diameter of 18 in. and nominal wall thickness of 0.252 in. The pigging technology has been applied to detect the pipeline wall thickness loss (i.e., corrosion defects) at six different times where 2,583 defects were detected totally. However, the data analysis showed that no matched defects are available in the ILI database for this pipeline. Soil properties including soil moisture, pH, SO_4, resistivity, redox potential, CO_3, etc are also available at the location of each detected defect.

First, following the procedure described in Section 2.3, the 112 km pipeline is divided into 56 segments with 2 km length for each segment. Then, 56 sets of $C_{1,k}$ and $C_{2,k}$ values are obtained by considering them to be constants in Eq. (1).

Then linear regression is conducted by treating the resulted $C_{1,k}$ or $C_{2,k}$ as the response and the mean values of the soil parameters for each segment as the predictors. The results indicate that the soil moisture, M, and soil sulfate level, SO_4, have the least p-value in the developed linear models for $C_{1,k}$ and $C_{2,k}$, respectively. Thus, Eqs. (1a) and (1b) become as follows:

$$C_{1,k}(\boldsymbol{\theta}_1, M) = \theta_{1,0} + \theta_{1,1} \cdot M \quad (4a)$$

$$C_{2,k}(\boldsymbol{\theta}_2, SO_4) = \frac{\left(\theta_{2,0} + \theta_{2,1} \cdot SO_4\right)^2}{1 + \left(\theta_{2,0} + \theta_{2,1} \cdot SO_4\right)^2} \quad (4b)$$

With incorporating the soil properties at the location of each defect, the unknown model parameters are assessed based on all the defect data of the whole pipeline using MCMC. Table 1 summarizes the obtained statistics of the model parameters' posterior distribution in Eqs. (1), (4a), and (4b) with assuming no prior for the unknown model parameters. Also, the correlation between depth and length model errors is computed to be around 5%.

The predicted corrosion depth and length and the associated actual measured quantities obtained through ILI are compared in Figure 1. For a perfect prediction model, the predicted data should line up along the 1:1 line. For both defect depth and length, Figure 1 shows that most of the predicted data are located around the 1:1 line within the ± 1 standard deviation band (i.e., dashed lines). This indicates that the proposed defect growth models provide unbiased prediction

Table 1: Posterior distribution statistics of model parameters

	Model parameter	Mean	Standard deviation	Median	geweke
depth	$\theta_{1,0}$	-0.531	0.005	-0.531	0.975
	$\theta_{1,1}$	3.366	0.139	3.348	0.922
	$\theta_{2,0}$	0.942	0.059	0.944	0.904
	$\theta_{2,1}$	-0.551	0.004	-0.552	0.986
	β_D	0.816	0.014	0.817	0.981
	σ_D	0.283	0.004	0.283	0.999
length	$\theta_{1,0}$	0.497	0.092	0.497	0.613
	$\theta_{1,1}$	-0.813	0.386	-0.823	0.218
	$\theta_{2,0}$	5.674	1.156	5.711	0.491
	$\theta_{2,1}$	0.344	0.027	0.342	0.933
	β_L	0.148	0.001	0.148	0.993
	σ_L	2.961	0.044	2.960	0.994

with sufficient accuracy despite only one single growth model formulation is used for the whole length of the pipeline, while the localized soil properties and unique corrosion initiation time are able to differentiate each defect growth. The accuracy of the model, however, decreases for larger values of depth and length for which less data is available compared to the smaller defects. Figure 2 also shows the predicted corrosion damage evolution over time compared with the inspected defects. As shown in Figure 2, the initiation time and growth trend for each defect is unique for itself, as the proposed method does not assume constant initiation time and incorporates local effect by using soil properties in the model. In addition, the corrosion rate tends to decrease over time, as expected: while the evolution of maximum depth of defects follows a nonlinear behavior, the maximum defect length develops in a rather linear manner.

4. RELIABILITY ANALYSIS

4.1. Failure modes

In this section, the developed growth model is used to assess the performance of an aged pipeline system by assessing probability of failure over time. A pressurized pipeline with different corrosion defect may fail by two distinctive failure modes, namely small leak and burst. The

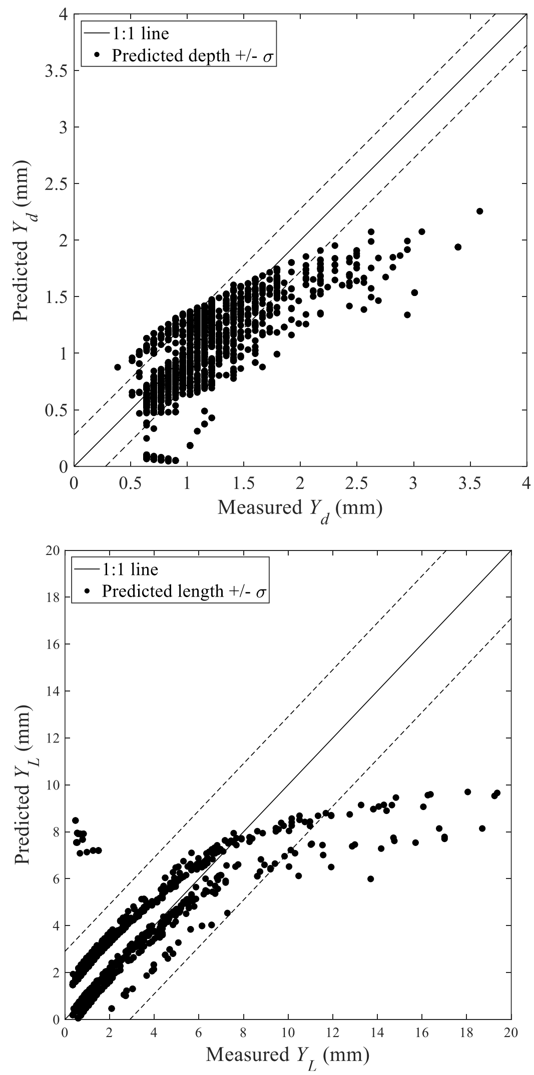

Figure 1: Comparison between predicted v. measured defect dimension: (top) depth and (bottom) length.

small leak failure mode refers to when a corrosion defect reaches 0.8 times the pipe wall thickness, and the probability of which is

$$P_{f,\text{leak}}(t) = P(0.8 \cdot d_\text{w} - d(t) \leq 0) \quad (5)$$

where d_w = pipeline wall thickness and $d(t)$ = maximum depth of a corrosion defect at time t, which can be predicted from Eq. (1).

The burst failure mode refers to a plastic collapse under the internal pressure, which happens when the working pressure exceeds the pressure capacity of the pipeline that decays with the presence of corrosion defects. The probability of burst failure mode can be calculated as:

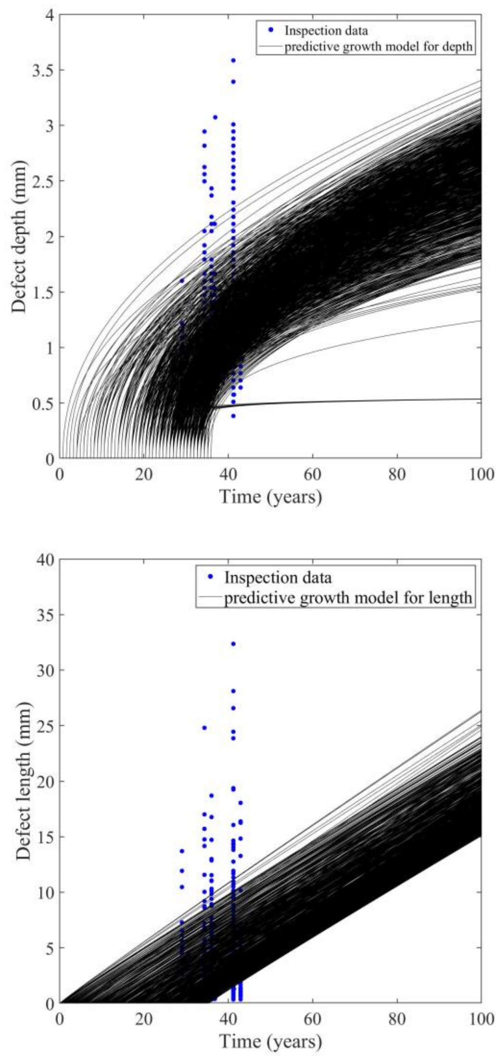

Figure 2: Predictive corrosion evolution over time: (top) depth, and (bottom) length.

$$P_{f,\mathrm{burst}}(t) = P\big(C_\mathrm{p}(t) - D_\mathrm{p} \leq 0\big) \tag{6}$$

where C_p = burst pressure capacity that is a function of the defect quantity and can be evaluated based on ASME B31G modified (Kiefner and Vieth 1989) as

$$C_\mathrm{p}(t) = \frac{2\big(\sigma_{\mathrm{min,\,y}} + 68.95\big)d_\mathrm{w}}{d_\mathrm{O}}\left[\frac{1 - 0.85\,\dfrac{d(t)}{d_\mathrm{w}}}{1 - 0.85\,\dfrac{d(t)}{d_\mathrm{w}}F^{-1}}\right] \tag{7}$$

where $\sigma_{\mathrm{min,y}}$ = specified minimum yielding stress (MPa) and d_O = outer diameter of the pipeline, F = Folias factor, which can be determined by:

$$F = \begin{cases} \sqrt{1 + 0.6275\,\dfrac{l^2(t)}{d_\mathrm{O}d_\mathrm{w}} - 0.003375\,\dfrac{l^4(t)}{d_\mathrm{O}^2 d_w^2}} & \dfrac{l^2(t)}{d_\mathrm{O}d_\mathrm{w}} \leq 50 \\ 3.3 + 0.032\,\dfrac{l^2(t)}{d_\mathrm{O}d_\mathrm{w}} & \dfrac{l^2(t)}{d_\mathrm{O}d_\mathrm{w}} > 50 \end{cases} \tag{8}$$

4.2. System reliability

To consider the reliability of the pipeline system, each kilometer is treated as a sub-system and the probability of failure per kilometer is assessed. Each sub-system is considered as a series system where the failure of any defect within that sub-system indicates the failure of the whole sub-system. Thus, the probability of failure of a sub-system can be computed using:

$$P_f(t) = 1 - \prod_{j=1}^{N_\mathrm{d}}\big[1 - P_{\mathrm{f},j}(t)\big] \tag{9}$$

where $P_{\mathrm{f},j}$ = failure probability of the jth detected defect, and N_d = number of detected defects in the sub-system.

4.3. Probability of failure of a pipeline

Based on the damage quantities calculated from the proposed prediction model, the probability of failure of the first kilometer of the pipeline is computed for the two failure modes using FORM (first-order reliability method) within FERUM application (Bourinet 2010) in MATLAB. Generally, the computed probability of failure should be less than a target value. When it exceeds, it indicates that at that point of time an appropriate action (such as repair or replacement) is needed for that part of the pipeline.

In this study, the uncertainties considered in the reliability analysis include the model errors in the prediction models, statistical uncertainties in the model parameters, mechanical and geometrical properties of the pipeline and working pressure of the pipeline.

Figure 3 shows the probabilities of failure of the small leak and burst failure modes for this pipeline segment based on Eq. (9). As expected, the calculated probability of failure shown is monotonically increasing due to the corrosion evolution. To understand if such probability of failure is acceptable, one can compare them with specific target values. For example, Det Norske

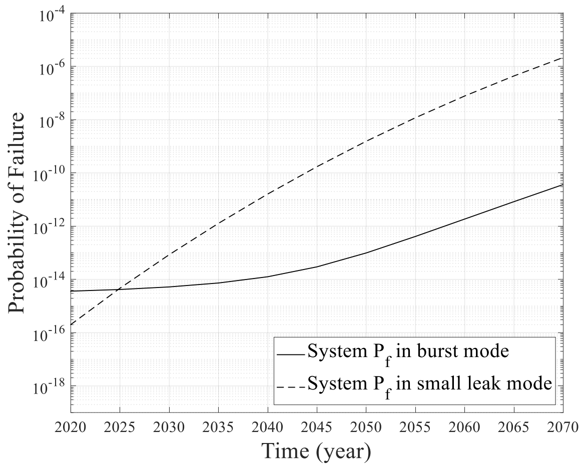

Figure 3: Time-dependent failure probability of studied subsystem for two failure modes.

Veritas standard (DNV 2012) states the three ultimate limit state target failure probabilities corresponding to three safety classes are 10^{-3}, 10^{-4}, and 10^{-5}, respectively. As shown in Figure 3, by 2070, the estimated probability of failure in neither of the failure mode exceeds the target levels; thus, this 1-km pipeline segment does not require further actions.

Last, importance analysis is performed for the studied subsystem to determine to which parameter(s) the reliability of pipeline is most sensitive. Figure 4 shows the time-dependent importance measures of model parameters incorporated in the two failure modes considered. A negative value of importance measure indicates that increasing in a model parameter, will decrease the probability of failure; and the opposite can be concluded for the positive values. As shown in Figure 4, for both failure modes, d_w is the most important parameter. Moreover, while model error, ε, is the second most important factor for small leak failure mode, P_d and D_O are the second most important parameters for burst failure mode.

5. CONCLUSIONS

Time-variant reliability analysis of pipelines is necessary for developing cost-effective management strategies for pipeline inspection, maintenance, and rehabilitation. In this process, developing a reliable corrosion defects evolution

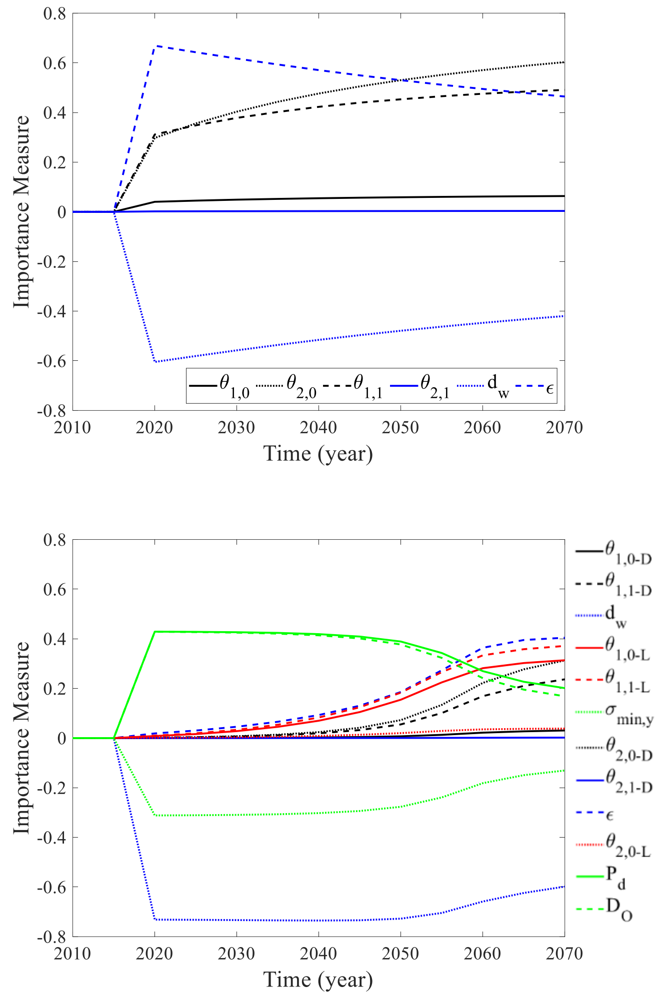

Figure 4: Time-dependent importance measures for (top) small leak mode and (bottom) burst failure mode.

is of crucial importance. In this study, a new methodology is proposed to model steel pipelines external corrosion defect evolution of maximum depth and length. The main merits of this methodology are: the methodology is suitable for matched or nonmatch defects detected in a sequential inspections, and the prediction model is defect-specific without using homogenous assumption. This is achieved by modeling the corrosion defect size at instantaneous time instead of modeling corrosion rate, by considering the corrosion occurrence to follow a Poisson process, and by explicitly incorporating soil properties in the model formulation. Thus, the growth model is believed to be more reliable.

A dataset of field ILI of an existing pipeline was used to develop growth models which later were used to evaluate the time-dependent system failure probabilities. The comparison between predicted and measured defect dimensions signified the acceptable accuracy of the developed growth models based on the methodology proposed. This accuracy leads to a more reliable estimation of the system probability failure, which can provide useful information for pipeline corrosion management actions.

In future work, this methodology is applied to develop growth models based on different datasets of detected defects of steel pipelines to assess its suitability for other datasets.

6. REFERENCES

Ahammed M, Melchers RE. Reliability estimation of pressurized pipelines subject to localized corrosion defects. International Journal of Pressure Vessels and Piping; 1996, 69: p. 267-272.

Ahammed, M., and Melchers, R. E. (1997). “Probabilistic analysis of underground pipelines subject to combined stresses and corrosion.” Eng. Struct., 19(12), 988–994.

Alamilla, J. L., and Sosa, E. (2008). “Stochastic modelling of corrosion damage propagation in active sites from field inspection data.” Corros. Sci., 50(7), 1811-1819.

Alamilla, J. L., Espinosa-Medina, M. A., and Sosa, E. (2009). “Modelling steel corrosion damage in soil environment.” Corros. Sci., 51(11), 2628-2638.

Box GEP, Tiao GC. Bayesian inference in statistical analysis. New York:Wiley; 1992.

Bourinet, J. M. (2010). “Ferum 4.1 user’s guide.” Institute Français de Mécanique Avancée (IFMA), Clermont-Ferrand, France.

Caleyo, F., Velázquez, J. C., Valor, A., and Hallen, J. M. (2009). “Probability distribution of pitting corrosion depth and rate in underground pipelines: A Monte Carlo study.” Corros. Sci., 51(9), 1925-1934.

Det Norske Veritas (DNV). (2012). “Submarine Pipeline Systems: Offshore standard DNV-OS-F101.” <https://exchange.dnv.com/publishing/Codes/download.asp?url=2012-08/os-f101.pdf>, (Sep. 09, 2015).

Gilks WR, Richardson S, Spiegelhalter DJ. Markov chain monte carlo in practice. London: Chapman & Hall; 1996.

Geweke J. Evaluating the accuracy of sampling-based approaches to the calculation of posterior moments. In: Bernardo JM, Berger J, Dawid AP, Smith AFM, editors. Bayesian Statistics 4, Oxford: Oxford University Press; 1992, p. 169-93.

Kiefner, J. F., and Vieth, P. H. (1989). “A modified criterion for evaluating the remaining strength of corroded pipe.” Final Report on Project PR 3-805, Battelle Memorial Institute, Columbus, OH (USA).

Li, S. X., Yu, S. R., Zeng, H. L., Li, J. H., and Liang, R. (2009). “Predicting corrosion remaining life of underground pipelines with a mechanically-based probabilistic model.” J. Petrol. Sci. Eng., 65(3), 162-166.

Miran, S. A., Huang, Q., & Castaneda, H. (2016). Time-Dependent Reliability Analysis of Corroded Buried Pipelines Considering External Defects. Journal of Infrastructure Systems, 22(3), 04016019.

Nahal, M., and Khelif, R. (2014). “Failure Probability Assessment for Pipelines under the Corrosion Effect.” Am. J. of Mech. Eng., 2(1), 15-20.

Salama, M. M., and Maes, M. A. (2014). “Assessment of pipeline integrity based on successive inspection data.” Proc., ASME 2014 33rd Int. Conf. on Ocean, Offshore and Arctic Eng., American Society of Mechanical Engineers, San Francisco, CA, USA.

Velázquez, J. C., Caleyo, F., Valor, A., and Hallen, J. M. (2009). “Predictive model for pitting corrosion in buried oil and gas pipelines.” Corrosion, 65(5), 332-342.

Wang, H., Yajima, A., Liang, R. Y., & Castaneda, H. (2015). A clustering approach for assessing external corrosion in a buried pipeline based on hidden Markov random field model. Structural Safety, 56, 18-29.

Zhang, S., and Zhou, W. (2014). “Bayesian dynamic linear model for growth of corrosion defects on energy pipelines.” Reliab. Eng. Syst. Safe., 128, 24-31.