Probabilistic Model for Internal Uniform/Pitting Corrosion of Gas pipelines

Keo Yuan Wu and Ali Mosleh
The B. John Garrick Institute for the Risk Sciences
Department of Materials Science & Engineering
University of California, Los Angeles, USA

Abstract: CO_2/H_2S corrosion is a major threat to gas pipelines because it often leads to loss of life and property when explosions happen as a result of corrosion. Corrosion inspection is one of the best ways to mitigate the potential risk, however, it is often costly in money and time if inline inspection is not done efficiently. This paper presents a probabilistic corrosion model that is able to predict the internal corrosion rate of gas pipelines in an aqueous CO_2/H_2S environment. Firstly, the corrosion type between uniform and pitting corrosion is determined for each pipeline by the extreme value analysis. Then, the proposed model for uniform corrosion and the Papavinasam model for pitting corrosion, respectively, are applied to predict the corrosion rate. Monte Carlo simulation is used for the calculation to include uncertainties of operating and basic design variables of gas pipelines. The results show good agreement between the observational corrosion rates and the predicted corrosion rates on eight wet gas gathering pipelines in Sichuan province, China. In addition, it is found that gas gathering pipelines tend to suffer uniform and pitting corrosion depending on ages when they are under similar operating conditions with the presence of chloride ions.

Keywords: Gas Pipeline, Uniform/Pitting Corrosion, Extreme Value Analysis, Corrosion Rate

1. INTRODUCTION

Much of the world relies on gas pipelines, which transport gas from where they are extracted to where they are needed. Regarding gas composition, corrosive matters such as CO_2 and H_2S are often unavoidable, which introduce the risk of corrosion to steel pipeline segments and potentially result in severe health and environmental hazards due to pipeline failure such as pipeline explosion. Therefore, it is important to develop predictive models of pipeline corrosion for different types of corrosion, and thus actions such as maintenance and replacement could be implemented proactively.

To date, numerous models have been developed to quantitatively predict the corrosion rate. These corrosion rate models are categorized into mechanistic, semi-empirical, and empirical models [1]. Most of the time, linear-growth model or power-function model based on corrosion depth data can't accurately predict the corrosion rate for the future; therefore, corrosion rate models based on operating parameters are of special interest. De Waard and Milliams firstly proposed a mechanistic corrosion rate equation as a function of the temperature and the partial pressure of CO_2 for sweet corrosion [2]. A few years later, their model was further modified into a semi-empirical model to account for other environmental factors such as protective layers, pH value, and flow velocity [3]. Southwest Research Institute (SWRI) derived an empirical corrosion rate equation as a function of the concentration of O_2, partial pressure of CO_2 and H_2S, and pH for CO_2/H_2S corrosion based on experimental data, which is able to be implemented in the regime of sour corrosion [4, 5]. Nešic's group have demonstrated several mechanistic models based on electrochemical concepts, which are able to be applied to the regime of both sweet and sour corrosion [6-9]. Among three kinds of corrosion rate models, most corrosion rate models used by industries are empirical as they are more adjustable with respect to operating parameters, however, mechanistic models are suggested to be more reliable because of their reliability of extrapolation to wider domains of application.

*Corresponding author's email address: keoyuan0703@g.ucla.edu.

These models are often carried out using the deterministic approach in which mean or average values for environmental and operating parameters are considered. However, the deterministic approach has limited application as these parameters change all the time, introducing substantial uncertainty in the model outcomes. On the other hand, the probabilistic approach uses probability distributions to account for the uncertainties of these parameters, meaning they are more reliable in regard to pipeline corrosion modelling [10-14]. Besides, the statistical model such as extreme value analysis has been used to analyze localized corrosion (e.g. pitting) because of its applicability on maximum value (e.g. pit depth) and its ability of extrapolation for un-inspected data [15].

Many research has been done to develop predictive models for corroded gas pipelines, however, none of them combines the statistical model (e.g. extreme value analysis) with corrosion rate models as an integrated modelling tool. The main goal of this paper is to develop a probabilistic model to study the internal corrosion of gas pipelines subject to an aqueous CO_2/H_2S environment and predict reasonably accurate corrosion rate. This model applied extreme value analysis to identify the corrosion type between uniform and pitting corrosion. Then, a proposed model for uniform corrosion and the Papavinasam model for pitting corrosion, respectively, were used to calculate the predicted corrosion rate. To verify the validity of this model on operating gas pipelines, eight wet gas gathering pipelines in Sichuan province, China were studied and the results of the observational corrosion rates and the predicted corrosion rates were compared.

2. MODEL DESCRIPTION

2.1. Uniform corrosion

Uniform corrosion is a common type of corrosion inside a gas pipeline subject to the aqueous CO_2/H_2S environment, which uniformly proceeds and thins the entire metal surface. The proposed model is a modified model based on the Sun and Nešic model for uniform corrosion [16]. This model is a mechanistic model, which assumes that the corrosion process is under mass transfer control in the presence of corrosion product layers (i.e. mackinawite layers). The diffusion processes of corrosive species e.g. H_2S, CO_2, and H^+ control the severity of corrosion inside a gas pipeline. Take H_2S for example, the steady state H_2S flux ($Flux_{H_2S}$) in mol/(m^{2}s) and its contribution to the corrosion rate (CR_{H_2S}) in mm/y are represented as Eq. (1) and Eq. (2), respectively.

$$Flux_{H_2S} = A_{H_2S} \ln\left[\frac{c_{b,H_2S} - Flux_{H_2S}\left(\frac{\delta_{OS}}{D_{H_2S}\varepsilon\varphi} + \frac{1}{k_{m,H_2S}}\right)}{c_{s,H_2S}}\right] \tag{1}$$

$$CR_{H_2S} = \frac{Flux_{H_2S} M_{Fe}}{\rho_{Fe}} \tag{2}$$

$Flux_{H_2S}$ is the flux of H_2S k_{m,H_2S} is the mass transfer coefficient (= 1×10^{-4} m/s); c_{b,H_2S} is the bulk concentration of H_2S in the liquid phase in mol/m^3; D_{H_2S} is the diffusion coefficient for dissolved H_2S in water (= 2×10^{-9} m^2/s); ε is the outer mackinawite layer porosity (= 0.9); ψ is the outer mackinawite layer tortuosity factor (= 0.003); δ_{OS} is the thickness of mackinawite layers in m; A_{H_2S} is the solid state diffusion kinetic constant for H_2S (= 2×10^{-5} mol/(m^{2}s)); c_{s,H_2S} is the near zero concentration of H_2S on the steel surface (= 1×10^{-7} mol/m^3); M_{Fe} is the molar mass of iron (= 55.84 g/mol); ρ_{Fe} is the density of iron (= 7.874 g/cm^3). It should be noted that further correction is needed for corrosion rate unit mm/y. As corrosion process proceeds, mackinawite layers grow in thickness as a diffusion barrier and the thickness of it is determined by the sulfide layer retention rate (SRR) in mol/(m^{2}s), which is a tradeoff between the sulfide layer formation rate (SFR) and the sulfide layer damage rate (SDR) given by Eq. (3).

$$SRR = CR - SDR_M - SDR_D \tag{3}$$

SFR is the corrosion rate (CR) in mol/(m^2s) because the supplier of Fe^{2+} for mackinawite layers is the steel itself. On the other hand, SDR includes the sulfide layer mechanical damage rate (SDR_M) and the sulfide layer dissolution rate (SDR_D). SDR_M, representing the effect of intrinsic growth stresses and extrinsic hydrodynamic forces, is defined as Eq. (4).

$$SDR_M = \alpha \times CR \tag{4}$$

α is the sulfide layer mechanical damage coefficient, which is a function of temperature, pH, flow velocity, and partial pressure, ranging from 0 to 1. SDR_D is a function of pH, temperature, which has a first-order dependence on H^+ concentration in acid solutions and a H^+ concentration independent term in neutral to alkaline solutions given by Eq. (5) [17].

$$SDR_D = k_1[H^+] + R(k_2) \tag{5}$$

$[H^+]$ is the hydrogen ion concentration in mol/cm^2; $R(k_2)$ is the H^+ concentration independent dissolution rate of iron sulfides in mol/(cm^2 min) given by Eq. (6); k_1 is the rate constant that dominates in acid solutions (= 0.18 ± 0.06 cm/min at 25°C) and k_2 is the rate constants that dominates in neutral to alkaline solutions (= $1.9 \pm 0.9 \times 10^{-9}$ mol/(cm^2 min) at 25°C).

$$R(k_2) = \left(1 - \frac{c}{c_s}\right) k_2 \tag{6}$$

c is the concentration of dissolved iron sulfides in mol/cm^3; c_s is the saturation concentration (= 2×10^{-9} mol/cm^3) for the medium at the natural water pH. R is the gas constant (= 8.314 J/(mol K)); T is the temperature in K. The unknown parameter c is simplified into a one-dimensional problem for simplicity and is expressed as Eq. (7).

$$c = c_s\left(1 - \exp\left[-\left(\frac{2k_2}{Dc_s r}\right)^{0.5} \delta_{os}\right]\right) \tag{7}$$

Mackinawite layers are assumed to be composed of many mackinawite particles with the radius (r) in m; δ_{os} is the thickness of mackinawite layers in m; D is the diffusion coefficient of dissolved iron sulfides (= 3×10^{-3} cm^2/min). After CR, SDR_M, and SDR_D are obtained, SRR can be obtained by Eq. (3) and then used to calculate the thickness growth of mackinawite layer thickness ($\Delta\delta_{os}$) in a time interval (Δt) in seconds given by Eq. (8).

$$\Delta\delta_{os} = \frac{\Delta m_{OS}}{\rho_{FeS} A} = \frac{SRR \times M_{FeS} \times \Delta t}{\rho_{FeS}} \tag{8}$$

Δm_{OS} is the change in mass of mackinawite layers in kg; A is the surface area of mackinawite layers in m^2; ρ_{FeS} is the density of mackinawite in kg/m^3; M_{FeS} is the molecular mass of mackinawite in kg/mol. These steps are repeated and δ_{OS} is then updated for the CR_{H_2S} calculation of the mission time.

2.2. Pitting corrosion

Pitting corrosion is a typical kind of localized corrosion, which appears in the form of small pits. As it is hard to be detected inside gas pipelines, it often results in destructive consequences. There are three stages of pitting: passive film breakdown, metastable pitting, and pit growth [18]. Over the past thirty years, many models have been developed to study and simulate these three stages, however, most of them require complicated experiments to determine critical parameters for modelling, limiting their practicability on operating gas pipelines [19-22]. In recent years, Papavinasam et al. proposed a model to predict pit growth rates in which they introduced three kinds of parameters (i.e. construction, operating, and computable parameter) as inputs based on laboratory experiments to simulate real operating conditions [23]. In this paper, this model is used to predict pitting corrosion rates given by Eq. (9).

$$PCR_{mean} = \{(-0.33\theta_c + 55) + (0.51W\% + 12.13) + (0.19W_{ss} + 64) + (50 + 25R_{solid}) + (-0.081P + 88) + (-0.54P_{H2S} + 67) + (-0.63P_{CO2} + 74) + (-0.013[SO_4^{2-}] + 57) + (0.57T + 20) + (-0.014[HCO_3^-] + 81) + (0.0007[Cl^-] + 9.2) + PCR_{addition}\}/12 \quad (9)$$

PCR_{mean} is the mean pitting corrosion rate in mpy; θ_c is the contact angle of oil in a water environment in degree; W is the water production rate/(water + oil production rates) × 100; Wss is the wall shear stress in Pa; R_{solid} is 1 if solids exist; otherwise it is 0; T is the temperature in °C; P is the total pressure in psi; P_{H2S} is the partial pressure of H_2S in psi; P_{CO2} is partial pressure of CO_2 in psi; $[SO_4^{2-}]$ is sulfate concentration in ppm; $[HCO_3^-]$ is bicarbonate concentration in ppm; $[Cl^-]$ is chloride concentration in ppm; $PCR_{addition}$ is the mean value of these 11 pitting corrosion rates. θ_c and W are not considered in this case. In general, pitting corrosion rate diminishes parabolically with time, and therefore the average pitting corrosion rate for mission time ($PCR_{average}$) in mpy can be expressed as Eq. (10) [24].

$$PCR_{average} = \left(\frac{PCR_{mean}}{1} + \frac{PCR_{mean}}{2} + \ldots + \frac{PCR_{mean}}{t}\right)\Big/ t \quad (10)$$

t is the mission time in year.

2.3. Extreme value analysis

As localized corrosion is stochastic in nature, statistical approaches have been used to study localized corrosion inside gas pipelines [10, 25, 26]. Kowaka suggested that pit depth and pit growth rate can be well described by extreme value distribution [27]. Specifically, Gumbel distribution is found to be suitable for maximum value analysis such as maximum pitting corrosion rate and maximum wall loss. In this paper, extreme value analysis is applied to observational data as a tool to identify the corrosion type between uniform and pitting corrosion. In addition, estimation of corrosion rate for un-inspected regions along a pipeline is also available. The sequence of steps of extreme value analysis is as follows:

Step 1: Collect corrosion rate data and arrange data in ascending order.
Step 2: Compute the cumulative probability distribution of the observational data using the average rank method given by Eq. (11).

$$F(y) = \frac{i}{N+1} \quad (11)$$

i is the rank of the observational corrosion rate; N is the total number of data points.

Step 3: Fit the observational data to the Gumbel distribution by Eq. (12). In this model, the distribution is recognized as a good fit to the observational data only when R^2 is equal to or larger than 0.95.

$$z = -\alpha[\ln(-\ln F(y))] + \lambda \quad (12)$$

z is the observational corrosion rate in mm/y; α is the Scale parameter; λ is the Location parameter.

Step 4: Estimate corrosion rate across the range of interest inside a pipeline.

Once the parameters of Gumbel distribution are obtained, an updated cumulative distribution function was then calculated using Eq. (13), which is capable of estimating corrosion rate across the range of interest inside a pipeline.

$$F(y) = \exp[-\exp(-y)] \quad (13)$$

y is denoted as $(x-\lambda)/\alpha$; x is the corrosion rate in mm/y.

3. RESULTS AND DISCUSSION

In this paper, the field data of eight wet gas gathering pipelines in Sichuan Province, China, was used to validate the proposed model [28]. The gas composition of these pipelines is CH_4 (≥ 94%) with a small amount of CO_2 (0.5 ~ 2.0%) and H_2S (1.7 ~ 2.3%). As pCO_2/pH_2S ratios are in the range of 0.3 ~ 0.9, the corrosive environments of these pipelines are categorized as the sour regime ($pCO_2/pH_2S < 20$) [29]. The pipe material is 20 Gauge steel. The basic design variables relevant to these pipelines are given in Table 1 and the operating variables are given in Table 2. They are length (L), diameter (D), thickness (d) of the pipe, temperature (T), operating pressure (P), percentage of H_2S in the gas composition ($\%H_2S$), the percentage of CO_2 in the gas composition ($\%CO_2$), flow velocity (V), pH level (pH), concentration of chloride ions (Cl^-), and presence of solids (R_{solid}). As the paper [28] only provides a value for each parameter, these values were viewed as the means values of the assigned distribution types. The coefficient of variation (COV) was determined depending on the degree of uncertainty of each variable, in which the operating variables often have higher COV than the basic design variables. These assumptions were made based on the suggestions of some literature [25, 30].

Table 1: Basic design variables of eight gas pipelines

Variables	Data									
	Type	COV	Mean							
			No.1	No.2	No.3	No.4	No.5	No.6	No.7	No.8
L (km)	Normal	0.05	12.26	2.69	2.82	2.47	2.16	3.52	8.41	7.84
D (mm)	Normal	0.05	159	108	108	108	108	108	219	273
d (mm)	Normal	0.05	8	6	6	6	6	6	8	8
t (y)	Normal	0.05	17	7	6	7	6	8	20	20

Table 2: Operating variables of eight gas pipelines (partly [28])

Variables	Data									
	Type	COV	Mean							
			No.1	No.2	No.3	No.4	No.5	No.6	No.7	No.8
T (K)	Lognormal	0.10	299.5	299.5	299.5	299.5	299.5	299.5	299.5	300
P (MPa)	Lognormal	0.15	4.15	1.95	2.65	5.15	1.95	1.95	4.35	4.45
pH_2S (Pa)	Lognormal	0.15	72625	33540	46640	89095	41535	40950	93525	101905
pCO_2 (Pa)	Lognormal	0.15	33200	11505	27825	41715	28080	35880	39585	56960
V (m/s)	Lognormal	0.10	2	2	2	2	2	2	2	2
pH	Lognormal	0.05	6.58	6.58	6.58	6.58	6.58	6.58	6.58	6.58
O_2+Ar (Pa)	Lognormal	0.15	8300	390	N.A.	N.A.	N.A.	390	870	2225
Cl^- (ppm)	Lognormal	0.15	92000	92000	92000	92000	92000	92000	92000	92000
Inhibitor Availability(%)	Uniform	**Lower limit**				85	**Upper limit**			95
Inhibitor Efficiency(%)	Uniform					60/25				95/50
R_{solid}	Uniform					0				1

*pH_2S and pCO_2 are calculated by P×mol% H_2S/100 and P×mol% CO_2/100, respectively.
*N.A. means the data is unknown.

Firstly, extreme value analysis was carried out for the observational corrosion rate data of each pipeline to classify eight gas pipelines into uniform and pitting corrosion. Here, pipeline No.1 is taken as an example for the demonstration. Fig. 1(a) depicts the Gumbel distribution fit of the observational data of pipeline No.1 with 50% confidence. The result shows a good fit with R^2 = 0.9527, and therefore the corrosion type in pipeline No.1 is categorized as pitting corrosion. According to Eq. (12), the estimated scale parameter (α) is the slope and the estimated location parameter (λ) is the intercept of the fitted line. It should be noted that a fitted line with 90% confidence is recommended and used for the following analysis. Once these parameters are obtained, the cumulative density function can be calculated as shown in Fig. 1(b).

Estimated maximum pitting corrosion rate for inspection area of interest was calculated by Eq. (13). Considering that only 10% of total area was inspected, $F(y) = 1\text{-}1/N = 0.9$ where $N = 10$, the estimated corrosion rate will be less than or equal to 0.15 mm/y for pipeline No.1 with 90% confidence. The same analysis was done for the rest pipelines, and the observational data can be described by Gumbel distribution only when R^2 is equal or larger than 0.95. Otherwise, the inspected pipeline is said to mainly suffer uniform corrosion with its observational corrosion rate described by Generalized Extreme Value distribution, which is the best-fit distribution estimated by EasyFit 5.6 [31].

The detailed results of the extreme value analysis on the observational corrosion rates for eight gas pipelines are shown in Table 3. It is found that pipelines No.1, No.3, No.7, and No.8 tend to mainly suffer pitting corrosion, whereas pipelines No.2, No.4, No.5, No.6 tend to mainly suffer uniform corrosion. In addition, the probability distributions of pitting corrosion rates spread wider than uniform corrosion, indicating that extreme corrosion rates are more likely to happen. In addition, pipelines suffer pitting corrosion have higher mean values of the corrosion rates. According to the film-breaking mechanism for pit initiation, the first step of pitting corrosion [21, 32], a local breakdown of passive films is not only related to the presence of chloride ions but also mechanical stresses (e.g. surface tension effect) at flaws on the passive film surface in contact with the electrolyte. It is suggested that pipelines that have been operated for a long time (i.e., No.1, No.7, and No.8) are likely to have more flaws and point defects on the passive film surface, which expose them to a higher possibility of passive film breakdown and make them vulnerable to pitting corrosion. This phenomenon is further facilitated in the presence of chloride ions which can be seen in these pipelines.

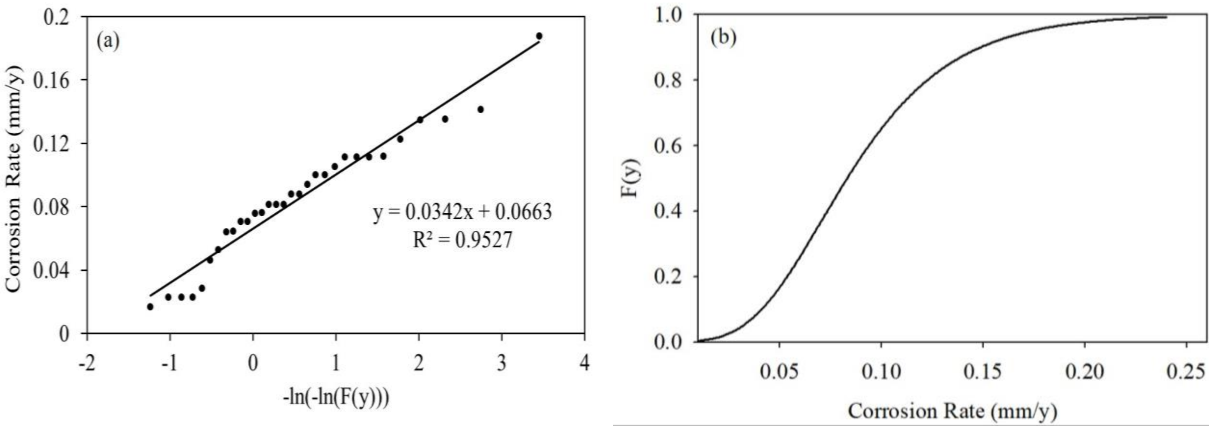

Fig. 1. (a) Gumbel distribution fit; (b) Cumulative density function of the observed data of pipeline No.1.

Secondly, corrosion rate models (i.e., the Papavinasam model for pitting corrosion and the proposed model for uniform corrosion) were used to calculate the estimated corrosion rate for mission time based on basic design variables and operating variables listed in Table 1 and Table 2 by Monte Carlo method to consider the uncertainties of these variables. As the pipelines have different ages, the simulation time was extended to the specific operating time for different pipelines in which this process is repeated for thousands of time. It should be noted that the proposed model predicts instantaneous uniform corrosion rates at a specific time interval (i.e., daily in this case) and the Papavinasam model predicts average pitting corrosion rates on a yearly basis, however, the observational corrosion rates are the average corrosion rates for how long these pipelines have been operated; therefore, further conversions were conducted before the comparison was made in terms of corrosion rate. Considering the factor of inhibitors, the inhibited corrosion rate was calculated based on the inhibition efficiency (E%) as follows:

$$E\% = \left(\frac{CR_{un} - CR_{inh}}{CR_{un}}\right) \times 100 \tag{14}$$

CR_{un} is the uninhibited corrosion rate; CR_{inh} is the inhibited corrosion rate. As Swidzinski et al. and Bouklah et al. indicate that E% is largely dependent on the concentration of the inhibitor, due to lack of data, E% is conservatively set in the range of 60% to 95% [33, 34]. Also, E% is assumed to drop to a range between 25% to 50% when the corrosion rate is lower than 0.1 mm/y because it is more difficult to further reduce the corrosion rate when it is lower given the same concentration of corrosion inhibitors. Due to many factors such as failures of injection pumps or human errors the availability of inhibitors is hard to maintain at 100% over the entire life of a pipeline. Studies show that it is often found to be between 85% and 95% in practice. The overall corrosion rate for an inhibited system should be calculated on the basis of the inhibitor availability principle as follows [30]:

$$CR_{tot} = f \times CR_{inh} + (1 - f) \times CR_{un} \tag{15}$$

f is the fraction of time the inhibitor is available (i.e. availability).

Table 3: Detailed results of extreme value analysis on the observational corrosion rate

	No.1	No.3	No.7	No.8
Corrosion type	Pitting			
Distribution type	Gumbel			
Scale parameter, α	0.035	0.024	0.020	0.038
Location parameter, λ	0.070	0.033	0.039	0.047
Mean (mm/y)	0.090	0.043	0.050	0.069
Std dev (mm/y)	0.045	0.031	0.025	0.048
Median (mm/y)	0.083	0.042	0.046	0.060
Mode (mm/y)	0.070	0.033	0.039	0.047
F(y) = 0.9 (mm/y)	0.150	0.087	0.085	0.135
	No.2	**No.4**	**No.5**	**No.6**
Corrosion type	Uniform			
Distribution type	Generalized Extreme Value			
Scale parameter, σ	0.019	0.007	0.014	0.013
Location parameter, μ	0.016	0.004	0.008	0.007
Shape parameter, κ	0.480	0.054	-0.092	0.018
Mean (mm/y)	0.037	0.008	0.015	0.015
Std dev (mm/y)	0.062	0.010	0.016	0.017
Median (mm/y)	0.023	0.007	0.014	0.012
Mode (mm/y)	0.010	0.004	0.011	0.007
F(y) = 0.9 (mm/y)	0.081	0.020	0.031	0.037

To test the validity of the proposed probabilistic model, the predicted corrosion rates were compared to the observational corrosion rates. Fig. 2 compares the predicted corrosion rates with the observational corrosion rates for pitting corrosion (i.e., pipeline No.1, No. 3, No.7, and No.8). The predicted corrosion rates follow generalized extreme value (GEV) distributions and most of the model predictions show good agreement with the observational corrosion rates except pipeline No. 3. Direct comparison in terms of distribution parameters e.g. median and mean values as shown in Fig. 3 presents that the predicted corrosion rates deviate within or around a factor of 2. Fig. 4 compares the predicted corrosion rates with the observational corrosion rates for uniform corrosion (i.e., pipeline No.2, No.4, No.5, and No.6). All the average B values (i.e., sulfide layer mechanical damage coefficients) for these pipelines are found to be around 0.22 because of the similar operating conditions (i.e., temperature, pH, and flow velocity). The predicted corrosion rates also follow generalized extreme value (GEV) distributions and these findings are in agreement with a study by Modiri et al. [26] although a different corrosion rate model is used in their study. The figures show that the predicted uniform corrosion rates have smaller spreads of values as well as smaller maximum values (F(y) = 0.9) compared to the predicted pitting corrosion rates. Most model predictions have reasonable agreement with the observational corrosion rates. Comparison between the predicted and observational corrosion rates in terms of median and mean values (see Fig. 5) shows that most predicted corrosion rates deviate within or around a factor of 2 except pipeline No. 4. Due to limited historical information on maintenance or repair and replacement records, it is difficult to explain why the model prediction for pipeline No.3 and No. 4 have higher deviations.

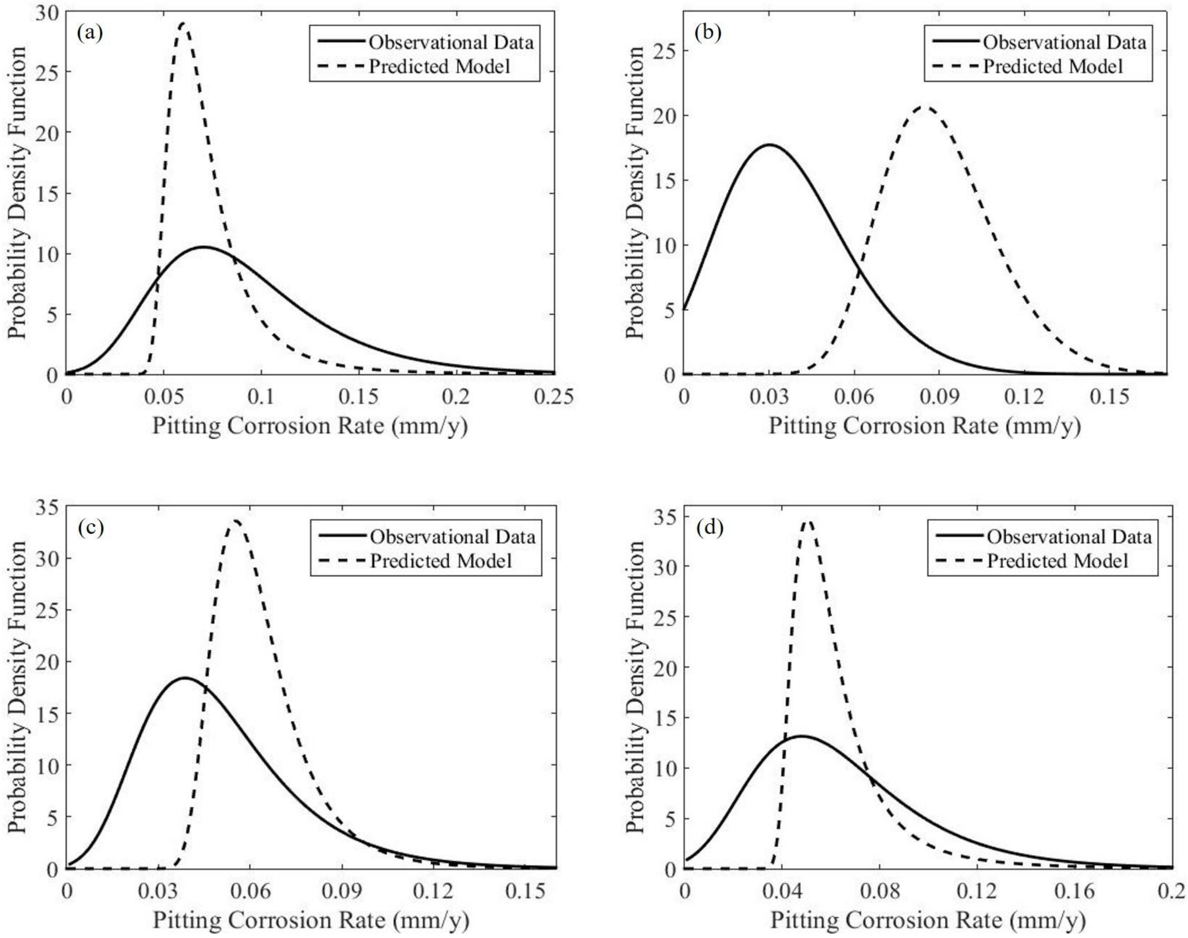

Fig. 2. Comparison between predicted corrosion rate and observational corrosion rate for pitting corrosion (a) No.1, (b) No.3, (c) No.7, and (d) No.8.

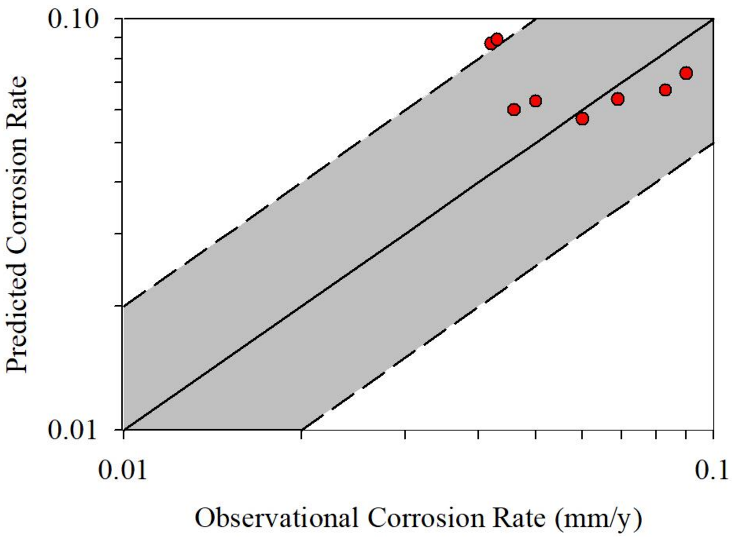

Fig. 3. Predicted vs. Observational corrosion rates in terms of median and mean values for pipelines No.1, No.3, No.7, and No.8 that suffer mainly pitting corrosion. The solid line outlines the perfect fit while the dashed lines depict an area that is within a factor of 2.

The proposed model for uniform corrosion has been shown to be capable of predicting reasonably accurate corrosion rates in terms of median and mean values, however, it could not capture either extremely large or small values of observational corrosion rates. Most of the time the places where maximum corrosion rates happen are the places where pipeline failures such as leakage and burst will occur if they are not detected and treated properly; therefore, this issue should be taken care carefully.

Undoubtedly, the possibility that some segments of these pipelines may suffer small extent of pitting corrosion more or less can't be ruled out although more data is required to verify this statement. Another viewpoint which is also worth mentioning is that the uncertainties of the observational corrosion rates are far beyond than what are considered in this study. For example, this study considers the uncertainties of operating parameters and how they affect the corrosion rate as time proceeds, however, the modelling scope is limited in a segment of the pipeline. As the observational corrosion rates are randomly generated from the whole pipes which are several kilometers long, the operating parameters are believed to vary on different positions, each of which should be considered as an independent corrosion process. The issue of positional variability of operating parameters and its effect on the corrosion rate will be addressed in the future work.

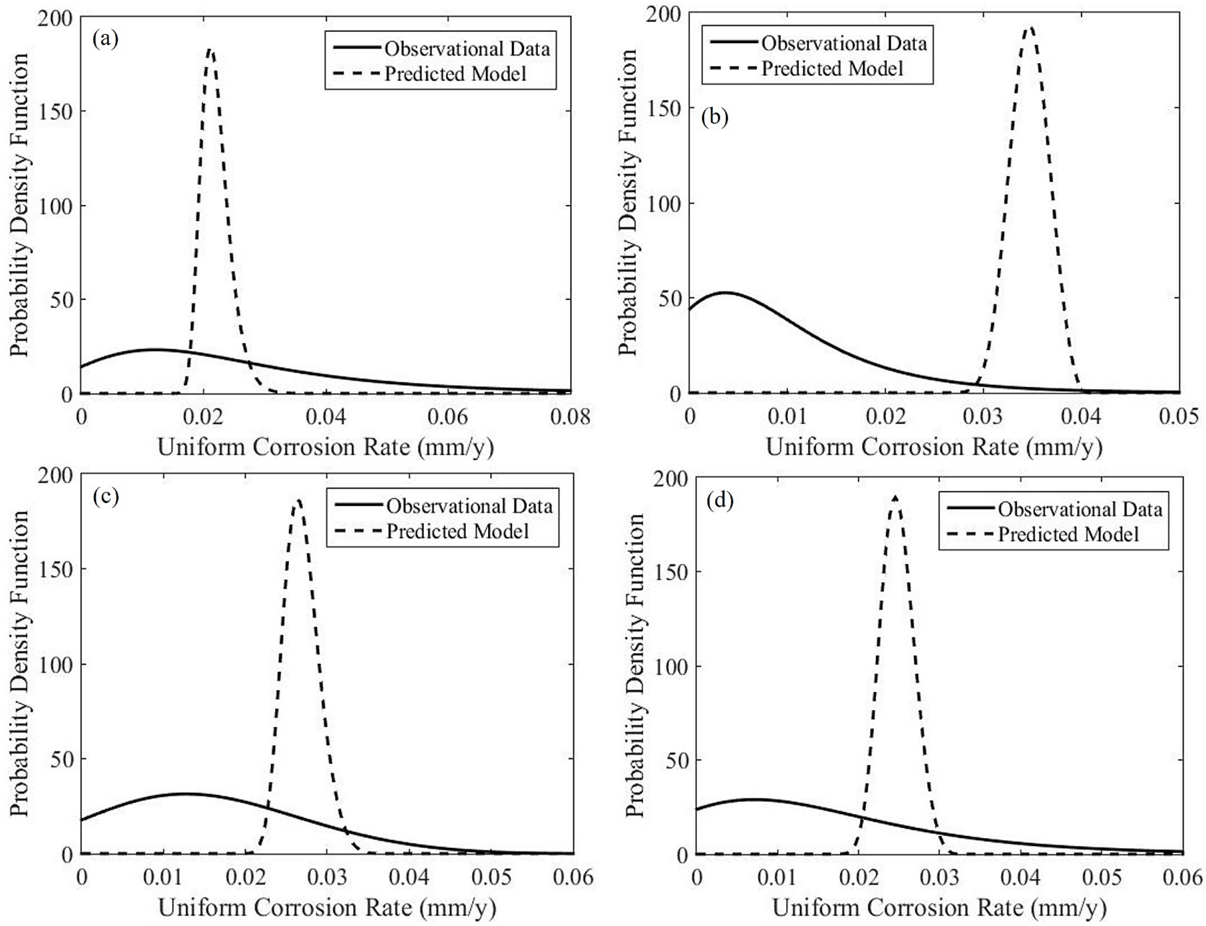

Fig. 4. Comparison between predicted corrosion rates and observational corrosion rates for uniform corrosion (a) No.2, (b) No.4, (c) No.5, and (d) No.6.

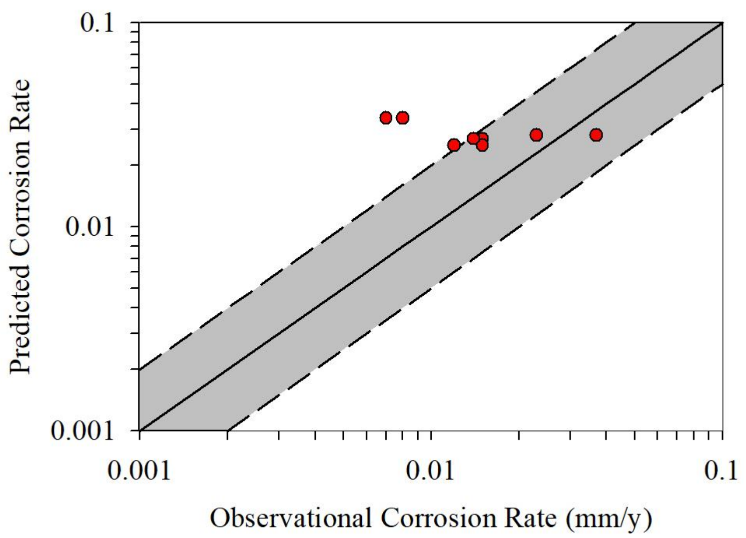

Fig. 5. Predicted vs. Observational corrosion rates in terms of median and mean values for pipelines No.2, No.4, No.5, and No.6 that suffer mainly uniform corrosion. The solid line outlines the perfect fit while the dashed lines depict an area that is within a factor of 2.

In view of the findings in this study, it can be inferred that gas gathering pipelines are likely to mainly suffer uniform corrosion after a few years of operation (i.e., less than 10 years) while the dominating corrosion mechanism may change into pitting corrosion after a longer time of operation (i.e., more than

15 years) in an environment with corrosive electrolytes especially chloride ions. However, the exact transition periods among uniform corrosion and pitting corrosion are still unclear, which requires more studies on available field data before it can be determined.

The proposed probabilistic model is proven to be able to predict reasonably accurate corrosion rate for the operating gas pipelines subject to the aqueous CO_2/H_2S environment, and it could also be used to predict the corrosion rate of other gas pipelines with similar operating conditions. However, this model should be applied with cautions because both corrosion rate models mentioned in this model have their own domains of application in which they will be less reliable when operating parameters of a pipeline deviate too much from the domains. The recommended domains of application for the proposed uniform corrosion model are: pH should be larger than 4 and smaller than 7; pH_2S and pCO_2 should be smaller than 10 bar because the precipitation effect of protective layers, which becomes prominent at high pressure, is not accounted for in this model, whereas those for the Papavinasam model are referred to the paper [23].

4. CONCLUSION

In this research, a probabilistic model consisting of an extreme value analysis and two corrosion rate models for uniform corrosion and pitting corrosion has been demonstrated to study internal corrosion of gas pipelines subject to the aqueous CO_2/H_2S environment. This model is able to predict the corrosion rate based on specific corrosion types among uniform and pitting corrosion.

Eight wet gas gathering pipelines in Sichuan province, China were studied to validate the proposed model. Probability distribution functions of operating and basic design variables were applied as input parameters for the proposed corrosion rate model for uniform corrosion and the Papavinasam model for pitting corrosion. Model predictions in terms of corrosion rate calculations were done by Monte Carlo simulation to consider the uncertainties of operating parameters. Most results show reasonable agreement between the observational corrosion rates and the model predictions in terms of median and mean values.

Older pipelines were found to be more vulnerable to pitting corrosion, whereas younger pipelines tend to suffer mainly uniform corrosion. It is suggested that older pipelines have a higher possibility of passive film breakdown due to the presence of chloride ions as well as surface tension effect at more accumulated flaws that make them vulnerable to pitting corrosion.

Acknowledgements

The research leading to the development of this paper was supported by Pipeline System Integrity Management research project sponsored by the Petroleum Institute, Abu Dhabi, UAE through a subaward from the University of Maryland Department of Mechanical Engineering.

References

[1] S. Nešić, "Key issues related to modelling of internal corrosion of oil and gas pipelines–A review," *Corrosion science*, vol. 49, pp. 4308-4338, 2007.
[2] C. De Waard and D. Milliams, "Carbonic acid corrosion of steel," *Corrosion*, vol. 31, pp. 177-181, 1975.
[3] C. De Waard, U. Lotz, and D. Milliams, "Predictive model for CO2 corrosion engineering in wet natural gas pipelines," *Corrosion*, vol. 47, pp. 976-985, 1991.
[4] H. U. Schutt and F. F. Lyle, "CO2/H2S Corrosion Under Wet Gas Pipeline Conditions in the Presence if Bicarbonate, Chloride, and Oxygen," in *CORROSION 98*, 1998.
[5] N. Sridhar, D. Dunn, A. Anderko, M. Lencka, and H. Schutt, "Effects of water and gas compositions on the internal corrosion of gas pipelines—modeling and experimental studies," *Corrosion*, vol. 57, pp. 221-235, 2001.

[6] S. Nešic, M. Nordsveen, R. Nyborg, and A. Stangeland, "A mechanistic model for carbon dioxide corrosion of mild steel in the presence of protective iron carbonate films—part 2: a numerical experiment," *Corrosion,* vol. 59, pp. 489-497, 2003.
[7] S. Nesic, J. Postlethwaite, and S. Olsen, "An electrochemical model for prediction of corrosion of mild steel in aqueous carbon dioxide solutions," *Corrosion,* vol. 52, pp. 280-294, 1996.
[8] Y. Zheng, J. Ning, B. Brown, and S. Nešić, "Electrochemical model of mild steel corrosion in a mixed H2S/CO2 aqueous environment in the absence of protective corrosion product layers," *Corrosion,* vol. 71, pp. 316-325, 2014.
[9] Y. Zheng, J. Ning, B. Brown, and S. Nešić, "Advancement in Predictive Modeling of Mild Steel Corrosion in CO2-and H2S-Containing Environments," *Corrosion,* vol. 72, pp. 679-691, 2016.
[10] K. Lawson, "Pipeline corrosion risk analysis–an assessment of deterministic and probabilistic methods," *Anti-Corrosion Methods and Materials,* vol. 52, pp. 3-10, 2005.
[11] Y.-S. Chang and A. Mosleh, "Physics-based model of the degradation of cable insulation subject to radiation and heat," in *Electrical Insulation and Dielectric Phenomenon (CEIDP), 2017 IEEE Conference on*, 2017, pp. 145-148.
[12] Y.-S. Chang, "Predictive Model of the Degradation of Cable Insulation Subject to Heat and Radiation," Ph.D., Materials Science and Engineering, University of California, Los Angeles (UCLA), Los Angeles, CA, 90095, USA, 2017.
[13] Y.-S. Chang and A. Mosleh, "Probabilistic Degradation Models for Cable Insulation in Nuclear Power Plants," presented at the ANS Winter Meeting and Nuclear Technology Expo, Washington, D.C., 2017.
[14] Y.-S. Chang and A. Mosleh, "Predictive model of the degradation of cable insulation subject to radiation and temperature," presented at the International Topical Meeting on Probabilistic Safety Assessment and Analysis (PSA), Pittsburgh, PA, 2017.
[15] F. Khan and R. Howard, "Statistical approach to inspection planning and integrity assessment," *Insight-Non-Destructive Testing and Condition Monitoring,* vol. 49, pp. 26-36, 2007.
[16] W. Sun and S. Nešic, "A mechanistic model of uniform hydrogen sulfide/carbon dioxide corrosion of mild steel," *Corrosion,* vol. 65, pp. 291-307, 2009.
[17] J. F. Pankow and J. J. Morgan, "Dissolution of tetragonal ferrous sulfide (mackinawite) in anoxic aqueous systems. 2. Implications for the cycling of iron, sulfur, and trace metals," *Environmental Science & Technology,* vol. 14, pp. 183-186, 1980.
[18] G. Frankel, "Pitting corrosion of metals a review of the critical factors," *Journal of the Electrochemical Society,* vol. 145, pp. 2186-2198, 1998.
[19] G. Frankel, L. Stockert, F. Hunkeler, and H. Boehni, "Metastable pitting of stainless steel," *Corrosion,* vol. 43, pp. 429-436, 1987.
[20] F. Hunkeler and H. Bohni, "Determination of pit growth rates on aluminum using a metal foil technique," *Corrosion,* vol. 37, pp. 645-650, 1981.
[21] N. Sato, "A theory for breakdown of anodic oxide films on metals," *Electrochimica Acta,* vol. 16, pp. 1683-1692, 1971.
[22] T. Shibata, "Stochastic studies of passivity breakdown," *Corrosion science,* vol. 31, pp. 413-423, 1990.
[23] S. Papavinasam, A. Doiron, and R. W. Revie, "Model to predict internal pitting corrosion of oil and gas pipelines," *Corrosion,* vol. 66, pp. 035006-035006-11, 2010.
[24] S. Papavinasam, *Corrosion control in the oil and gas industry*: Elsevier, 2013.
[25] A. Kale, B. H. Thacker, N. Sridhar, and C. J. Waldhart, "A probabilistic model for internal corrosion of gas pipelines," in *Proceedings of IPC 2004 international pipeline conference, Calgary, Alberta, October*, 2004, pp. 4-8.
[26] B. Modiri, M. P. Mohammad, M. Yazdani, F. Nasirpouri, and F. Salehpour, "Piping Anti–Corrosion Coating Life Assessment," in *ASME 2014 International Mechanical Engineering Congress and Exposition*, 2014, pp. V014T08A013-V014T08A013.
[27] M. Kowaka and H. Tsuge, *Introduction to life prediction of industrial plant materials: Application of the extreme value statistical method for corrosion analysis*: Allerton Pr, 1994.
[28] K. Liao, Q. Yao, X. Wu, and W. Jia, "A numerical corrosion rate prediction method for direct assessment of wet gas gathering pipelines internal corrosion," *Energies,* vol. 5, pp. 3892-3907, 2012.

[29] B. F. Pots, S. D. Kapusta, R. C. John, M. Thomas, I. J. Rippon, T. Whitham, *et al.*, "Improvements on de Waard-Milliams corrosion prediction and applications to corrosion management," in *CORROSION 2002*, 2002.
[30] J. Hobbs, "Reliable corrosion inhibition in the oil and gas industry," *Health and Safety Laboratory for the Health and Safety Executive,* p. 28, 2014.
[31] EasyFit, "Distribution Fitting Software " in *MathWave Technologies* vol. Version 5.6, ed, (assessed from 2016).
[32] J. Richardson and G. Wood, "A study of the pitting corrosion of Al byscanning electron microscopy," *Corrosion Science,* vol. 10, pp. 313-323, 1970.
[33] M. Bouklah, B. Hammouti, M. Lagrenee, and F. Bentiss, "Thermodynamic properties of 2, 5-bis (4-methoxyphenyl)-1, 3, 4-oxadiazole as a corrosion inhibitor for mild steel in normal sulfuric acid medium," *Corrosion science,* vol. 48, pp. 2831-2842, 2006.
[34] M. Swidzinski, B. Fu, A. Taggart, and W. Jepson, "Corrosion inhibition of wet gas pipelines under high gas and liquid velocities," in *CORROSION-NATIONAL ASSOCIATION OF CORROSION ENGINEERS ANNUAL CONFERENCE-*, 2000.