Reliability Analysis of Crude Unit Overhead Piping Based on Wall Thickness Degradation Process

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SUMMARY & CONCLUSIONS

Assuring the reliability of crude unit pipelines in the downstream oil and gas industry is highly essential since unexpected failures of these pipelines can result in a number of negative impacts to the business, including safety, environmental, and economic impacts. The objective of this work is to understand the degradation behavior of the piping system so we can know in advance when the degraded pipeline will reach the minimum thickness threshold.

The damage mechanisms in atmospheric crude tower overhead piping has been well researched. Hydrochloric Acid (HCL) corrosion is one major type of damage mechanisms seen in the atmospheric crude tower overhead piping. This type of corrosion is time-dependent and also influenced by different operational conditions such as temperature, adequacy of the neutralization of the formed HCL and pipeline interior protection using corrosion inhibitors. To better monitor the degradation of these pipelines and to reduce cost associated with scheduled inspections, a number of refineries are resorting to real time thickness monitoring using Ultrasonic instruments mounted at vantage locations on the pipeline, to provide continuous, non-destructive corrosion and erosion monitoring.

The focus of this paper is to use a stochastic degradation model, which is suitable for characterizing wall thickness degradation data, to estimate the failure probability of the pipeline in the midst of inadequate data. We model the degradation of the crude overhead pipeline using a stationary Gamma process. To capture the substantial heterogeneity among different thickness monitoring locations on the pipe line, random effects are incorporated in our stochastic degradation model. We illustrate the proposed random effect method using the gamma process to model pipe wall thickness degradation data observed over a period.

1 INTRODUCTION

It is important to understand piping system degradation and analyze the reliability of the piping system. As hydrocarbons and other products flow through the pipe, there is an irreversible accumulation of damage over time that ultimately reaches a certain threshold, leading to the pipe failure. Corrosion and erosion account for degradation of piping systems in downstream oil and gas industry. Piping for fluid transport is normally sized to have velocities less than certain thresholds depending on the fluid state, to eliminate the erosion damage mechanism, making corrosion the main mechanism for pipe degradation. Corrosion monitoring is typically done at time intervals during plants shutdowns where elevated piping or out of reach piping may require scaffold erection to access pipe for inspection. Piping that are insulated for heat conservation may have to be stripped at various locations to perform these non-destructive examinations (NDE). To minimize the cost of time interval inspections and optimize maintenance intervals, a number of refineries have installed on-line ultrasonic (UT) thickness probes at various locations on their Atmospheric Crude tower overhead Carbon steel piping to provide continuous, non-destructive corrosion and erosion monitoring through UT testing. The pipeline is said to be in a failed state when the pipeline thickness reaches a threshold, beyond which the integrity of the pipe cannot be guaranteed, or the piping system fails to perform its intended function safely. At the failure threshold, a leak or a pipe rapture is imminent with a wide range of negative impacts on the refinery activities. These include but not limited to (1) safety impacts due to loss of containment causing injury to personnel and damage to property; (2) environmental impacts arising from the loss of containment and release of hydrocarbons to the atmosphere with subsequent flaring events due to unit upsets; (3) business or economic impacts being the outcome of a crude unit shutdown with multiple rippling effects on other units, causing significant amounts of lost profit opportunity and maintenance cost.

1.1 Problem statement

Collecting degradation data on piping is key to maintaining the mechanical integrity of the piping. Due to variations present in UT instruments, instrument malfunction, temperature of

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piping being measured, some measurements over a period do not show consistency. This is also the case when inspection personnel are used for UT measurements. In some instances the data shows a growing pipe wall thickness which is practically not possible.

In this paper, we focus on modeling the degradation path of the pipe wall using a stationary Gamma process in the presence of inadequate data. This model can be used to compute a time dependent failure probability of the pipe. For critical piping such as the Crude atmospheric tower overhead piping, it is preferred to make the decision two Turnaround cycles ahead to replace piping that approaches the minimum threshold. The reason is that, although most Refinery Turnarounds average five-year cycles, some refineries may make a decision to run longer for various reasons such as logistics, manpower, coinciding turnarounds with sister facilities in the organization, competing with other organizations for resources. We analyze piping wall thickness data from six thickness monitoring locations, observed over a period of three years.

2 LITERATURE REVIEW

Corrosion is material degradation due to environmental effects [1]. Hydrochloric acid (HCL) corrosion is the main type of corrosion that causes degradation in Crude Unit overhead piping systems [2]. Although dewatering, desalting and caustic injections are used to minimize the amounts of hydrolysable salts making it onto the crude unit heaters, some of these salts make it through. HCl is generated in crude heaters when salts like magnesium chloride and calcium chloride are heated up enough to become hydrolyzed [2]. When HCl finds water in the crude overhead it becomes corrosive to most metals. To help minimize HCl acid corrosion, neutralizers are injected into the overhead. However, the overhead still sees some level of corrosion. Sahraoui et al. [3] discussed the use of power law as a model to account for wall loss due to uniform corrosion with the corrosion power law given as $t_C = kT^n$ where $t_C =$ Thickness of corroded layer, $T =$ elapsed time, k and n are the corrosion parameters. This approach was also used by Lawless and Crowder as they replaced a shape function $\eta(t)$ with $\eta(te^{x^T\beta})$ in an accelerated life model, where β is an unknown vector [4].

Mahmoodian and Alani [5] used the power law as a means to estimate the shape parameter in the gamma degradation process in concrete piping. Ahammed [6] used a probabilistic approach rather than a deterministic approach to assess the safety, integrity, and predict the remnant life of a pipeline with active corrosion.

Degradation over time is usually a stochastic process which often possesses a monotone, non-decreasing degradation path and independent increments. Measurements of degradation has variations due to process conditions, imperfect instruments etc. Lu and Meeker [7] used a parametric model, the General Path Model of degradation to estimate time to failure considering measurement errors. They used the two-stage method to estimate parameters of the Path model; some fixed and some random. Whitmore [8] employed the Wiener diffusion process with measurement errors to capture randomness of degradation as well as measurement error due to imperfect instruments, procedures, and environments. Ye et al. [9] discussed the Wiener process with positive drift or measurement errors as a favorable candidate to degradation modeling. They proposed two models in this process; the simple model with measurement errors to capture homogeneity and mixed effects model to capture heterogeneity in the population. This process was successfully used to investigate the wear behavior of a magnetic head of a Hard disk Drive (HDD). Ye and Chen [10] proposed the Inverse Gaussian process as an alternative to the Wiener process of degradation modeling as it has the capability of modeling monotone paths. They compared the Inverse Gaussian process to the Gamma process as both being limiting Poisson processes with the Inverse Gaussian process having more flexibility than the Gamma process in terms of incorporating random effects. Peng [11] explored the Inverse Gaussian process to model degradation from accelerated degradation test data with random effects and explanatory variables such as Temperature, Voltage etc. Bagdonavicius and Nikulin [12] however used the Gamma process to model degradation under the influence of covariates which includes the dependency of intensity of traumatic events on degradation. Lawless and Crowder [4] explored the use of an extended Gamma process to incorporate random effects or covariates where the random effects represent the heterogeneity of the degradation paths of individual units. Park and Padgett [13] used the Gamma Process with acceleration degradation test data to model degradation considering the difficulty in observing failures due to the slow rate of degradation. Timashev and Bushinskaya [14] described the Markov process as a more universal approach and adequately described wall-thinning in pipelines. Ye et al. [15] introduced the use of semiparametric estimation of the Gamma process for degradation modeling. They combined the use of non-parametric and parametric methods of the Gamma process to model degradation.

3 CASE STUDY

In this case study, we reviewed thickness readings from a refinery in the Mid-West. These readings were obtained at seventeen thickness monitoring locations at various points on the crude overhead line logged every twelve hours. The locations are normally determined based on history of degradation as well as expectation of degradation. Since the visual degradation trends were minimal, we used yearly averages at each of the seventeen locations. Six locations were used in this analysis. Table 1 shows pipe wall thickness data from seventeen thickness monitoring locations over the period of observation. Six locations – 2,7,9,10,11 and 14 were used in this analysis based on the continuous logging of three years of thickness data without any interruptions and the annual average data showed a trend of degradation. The other locations show either increments in pipe wall thickness which is practically not possible or readings for only one or two years. We used the stationary gamma process with random effects to model pipe wall thickness degradation. The pipeline sizes that were analyzed included four 12” pipe segments, one 14” pipe segment, and one 10” pipe segment. All of them had a minimum wall thickness threshold of 0.11". It is important to note that the cumulative degradation to reach the minimum wall thickness from the initial wall thickness of a 12" pipe is 0.39" or 390mils. Figure 1 shows a cumulative corrosion rate in milli-inches (mils) per year (mpy) for the six locations.

Table 1. Average wall thickness readings per year for three years at seventeen locations

Thickness Monitoring Location	Year 1 Pipe wall thickness (inches)	Year 2 Pipe wall thickness (inches)	Year 3 Pipe wall thickness (inches)
1	0.5089	0.50934	0.5096
2*	0.5090	0.5052	0.5041
3	0.5082	0.5091	0.5101
4	0.4793	0.4833	0.4842
5	0.5570	0.5573	0.5573
6	0.3866	0.3885	0.3888
7*	0.3571	0.3555	0.3551
8	0.5293	0.5314	0.5319
9*	0.3978	0.3978	0.3966
10*	0.3652	0.3638	0.3635
11*	0.5076	0.5065	0.5060
12	0.3687	0.3719	0.3731
13	0.4135	0.4136	-
14*	0.4641	0.4633	0.4631
15	-	0.5096	0.5097
16	-	0.4915	0.4912
17	-	-	0.4811

**Locations used for analysis and model development*

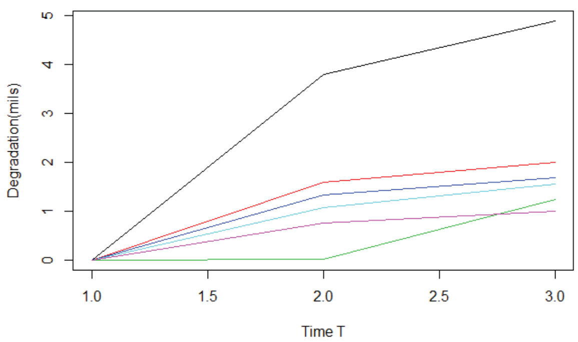

Figure 1: Cumulative degradation decrements of pipe wall thickness per year over three years at six locations. Each color indicates one of the locations

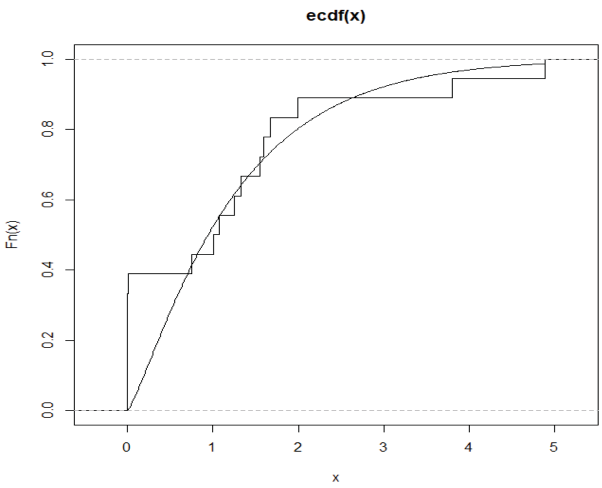

Figure 2: Empirical cumulative (Step ladder line) pipe wall thickness increments vs the fitted model (Curvilinear line).

4 ILLUSTRATIONS

The parameter estimation yielded shape parameter $\widehat{\Delta\eta} = \alpha = 1.26$ and a rate parameter γ following Gamma (λ, k) with $\hat{\lambda} = 11.66$ *and* $\hat{k} = 14.99$. Since the degradation process is based on a homogeneous Gamma process, the estimated parameters are the same for each of the observed readings. With the parametric estimation of α, λ *and* k, we compare the empirical and the fitted distributions by plotting the empirical cumulative distribution function associated with the data set together with the fitted gamma distribution (Figure 2). We also used the Kolmogorov-Smirnov test as the statistical test for goodness of fit with a $p - value = 0.01$. Following this model, we are able to calculate the probability of failure.

5 DEGRADATION MODEL

5.1 Model Development

Considering that the carbon steel pipeline is considered failed when the wall thickness is depleted or deteriorates by the depth to get to the failure threshold T_{min}, we use the Gamma process to model the degradation of the crude overhead piping due to its independent increments property and monotonic increasing function [12]. This implies that for a process $\{Y(t); t \geq 0\}, \Delta Y(t) = Y(t+s) - Y(s)$ is independent of $Y(s)$ and $\Delta Y(t)$ follows Gamma $(\eta(t+s) - \eta(s), \gamma)$ [15] where $\Delta Y(t)$ represents the annual decrements in the pipe wall thickness for $n = 6$, given that there are six thickness monitoring locations, $\eta(t)$ is the shape function for $m = 3$, given that there are three years of observations and γ is the rate parameter. In this paper we assume the shape function is linear and for that reason stationary. This implies that $\eta(t) = \alpha t$ and $\Delta Y(t)$ follows Gamma$(\alpha t, \gamma)$ given that the thickness data is analyzed at 1 year intervals for t, i.e, $\Delta t_{i,m} = 1$.

The Gamma process as denoted by Ye et al [15] has a probability density function (PDF) of:

$$f_{\Delta Y(t)}(y\colon \gamma, \eta(t)) = \frac{\gamma(\gamma y)^{\eta(t+s)-\eta(s)-1}}{\Gamma(\eta(t+s)-\eta(s))} \exp(-\gamma y), y > 0 \quad (1)$$

Following the stationary assumption the PDF reduces to:

$$f_{\Delta Y(t)}(y\text{: } \gamma, \alpha t) = \frac{\gamma(\gamma y)^{\alpha-1}}{\Gamma(\alpha)} \exp(-\gamma y)\, , y > 0 \quad (2)$$

with a mean of $\alpha t/\gamma$ and a variance of $\alpha t/\gamma^2$. For a process with random effects, γ follows Gamma(k, λ), rerating $y(t)$ without changing the shape parameter of the gamma distribution [15].

5.2 Parameter Estimation

Expectation-Maximization (EM) Algorithm for the Random Effect Model.

In this section we use the EM algorithm for parameter estimation. This process is used to iteratively compute the maximum likelihood (ML) estimates due its ability to simplify complex ML processes. In this process the parameters are estimated with initial random values. These parameters are re-estimated and iteratively until they converge.

There are two steps in the EM algorithm process; the Expectation step or the E-step and the Maximization step or the M-step. In the E-step, we let Θ assume an initial value randomly generated for the first iteration with initial values $\alpha^0 \lambda^0 k^0$. The M-step maximizes the $Q(\Theta, \Theta^{(0)})$. The E and M-steps are repeated alternatively until the likelihoods $L(\Theta^{N+1}) - L(\Theta^N) = \delta$ where δ is an arbitrarily small value, in our case 0.01 EM algorithm is the better choice for missing data problems.

The conditional distribution of γ given the past observations up to time t is

$$\{\gamma | Y(u), u \leq t\} \sim Gamma(\alpha t + k, \lambda + Y(t)) \quad (3)$$

Given $\Theta = (k, \lambda, \alpha)$ is the parameter vector, where k *and* λ represent the rate and shape parameters respectively for γ and α the shape parameter, the log-likelihood function for the n units is [15]

$$l(\Theta) = \sum_{i=1}^{n} \{k In\lambda + In\Gamma(\alpha t_{\mathrm{m}} + k) - In\Gamma(k) - [\alpha t_{\mathrm{m}} + k] In[\lambda + y(t_{\mathrm{m}})]\} + \sum_{i=1}^{n}\sum_{j=1}^{m} \{[\alpha \Delta t_j - 1] In[\Delta Y_{i,j}] - In\Gamma(\alpha \Delta t_j)\} \quad (4)$$

<u>E-Step</u>

To estimate the parameter vector Θ, the observed data $\boldsymbol{D_{obs}} = Y_1 \cup Y_2 \cup \ldots \cup Y_n$ where $Y_i = \{y_i(t_0), y_i(t_1), \ldots y_i(t_m)\}, \forall i = 1, \ldots, n.$ and the missing data $\boldsymbol{D_{miss}} = \{\gamma_i; i = 1, \ldots, n\}$ is given by the complete data $\boldsymbol{D} = \boldsymbol{D_{miss}} \cup \boldsymbol{D_{obs}}$. γ_i is considered as missing data as they are not observable [15]. The log-likelihood function based on $\boldsymbol{D}$, up to a constant, can be expressed as:

$$L(\Theta; D) = L_1(\alpha\, ; D) + L_2(k, \lambda; D) \quad (5)$$

where

$$L_1(\alpha\, ; D) = \textstyle\sum_{i=1}^{n} \sum_{j=1}^{m} [\alpha \Delta t_j (\ln \Delta Y_{i,j} + \ln \gamma_i) - \ln \Gamma(\alpha \Delta t_j)] \quad (6)$$

$$L_2(k, \lambda; D) = \textstyle\sum_{i=1}^{n} [k \ln \lambda + (k-1) \ln \gamma_i - \ln(\Gamma(k)) - \lambda \gamma_i] \quad (7)$$

Denote the estimate at the Nth EM iteration by $\Theta^N = (\alpha^N, k^N, \lambda^N)$, the E-step at the next iteration requires computation of $\upsilon_i^N = E[\gamma_i | D_{obs}, \Theta^N]$, $\upsilon_i^N = E[\ln \gamma_i \,| D_{obs}, \Theta^N]$

Based on (4), υ_i^N can be readily obtained as

$$\upsilon_i^N = E[\gamma_i | D_{obs}, \Theta^N] = \frac{\alpha^N t_m + k^N}{\lambda^N + Y_i(t_m)} \quad (8)$$

$$\upsilon_i^N = E[\ln \gamma_i \,| D_{obs}, \Theta^N] = \psi(\alpha^N t_m + k^N) - \ln(\lambda^N + Y_i(t_m)) \quad (9)$$

The values of υ_i^N, υ_i^N obtained are used to update the Q-function

<u>M-step</u>

The objective of this step is to find Θ^{N+1} that maximizes $Q(\Theta | \Theta^N)$. Note that λ and k are involved only in $E[L_2(k, \lambda; D) | D_{obs}, \Theta^N]$, which is a simple likelihood function for a Gamma distribution. By differentiating $E[L_2(k, \lambda; D) | D_{obs}, \Theta^N]$ with respect to λ and k, setting them to zero, and then rearranging the two equations, we can obtain

$$\ln k - \psi(k) = \ln \bar{\upsilon}^N - \bar{\upsilon}^N \quad (10)$$

$$\frac{k}{\lambda} = \bar{\upsilon}^N$$

$$\lambda^{N+1} = \frac{k^{N+1}}{\bar{\upsilon}^N} \quad (11)$$

Take the first derivative of $E[L_1(\alpha\, ; D) | D_{obs}, \Theta^N]$ with respect to α and solve the corresponding equation system, which yields:

$$\frac{\partial L_1(\alpha; D)}{\partial \alpha} = \sum_{i=1}^{N}\sum_{j=1}^{m} \Delta t_j ln \Delta Y_{i,j} + \upsilon_i^N \Delta t_j - \Delta t_j \frac{\Gamma' \alpha \Delta t}{\Gamma \alpha \Delta t} \quad (12)$$

$$\alpha^{N+1} = \psi^{-1}\left(\bar{\upsilon}^N + \tfrac{1}{n}\textstyle\sum_{i=1}^{n} ln \Delta Y_{i,j}\right) \quad (13)$$

where $\psi^{-1}(\cdot)$ is the inverse function of the digamma function. The EM algorithm terminates when the increment of the log-likelihood value is smaller than a given criterion $\delta = 0.01$.

6 CONCLUSION

In conclusion the homogenous or stationary Gamma process with random effects is an appropriate process for modeling piping degradation and predicting the remaining useful life of the piping. We used random effects in our model to capture the heterogeneity of the piping, instrument errors and other effects common in real life data from industry. The Gamma process' property of independent increments and monotonic increases is consistent with wall thickness degradation in piping. The EM algorithm is also appropriate in estimating the rate and shape parameters as they are the better choice for missing data problems. Kolmogorov-Smirnov test Goodness of fit test as well as empirical and fitted model comparison is indicative that the gamma process with random effect is an appropriate process for measuring wall thinning in process plant. As the thickness probe takes continues readings, the Gamma model with random effects can be revised with the additional yearly readings to obtain a model with less uncertainty.

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