# A Model-based Approach to Reliability Assessment of Corroded Pipelines

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#### Abstract

Corrosion is a main cause of failures in the gas pipeline. Both predicting pipeline failures and designing a maintenance plan play a key role in effective use of energy and security of civil life. This paper deals with model-based reliability estimation of corroded pipelines. Because a pipeline includes uncertainty in its operation, a statistical method called first-order and second- moment (FOSM) is adopted in this paper. One of distinctions in our work is to divide the whole pipeline into several clusters. Because magnitudes and likelihoods of metal corrosion defects depend on the pipeline commission environment, such a feature makes it easier to obtain practical reliability predictions. To this end, a fuzzy logic based clustering technique is employed. Numerical experiments are conducted based upon a modified field dataset. The result indicates that our proposed scheme provides more advisory predictions on the pipeline failure which is useful for preventive maintenance.

# **Keywords**

Corroded Pipeline, Reliability, First-Order Second Moment, Fuzzy Clustering, Coefficient of Variation

## 1. Introduction

In Korea, the natural gas for citizen living became widespread since 1980s and now there is much attention in safety assessment of the underground gas pipeline. One of major causes in the pipeline failure is a metal corrosion. It is known that about fifteen percent of failures in the corroded gas pipeline is due to corrosion. By this reason, many researches have been conducted for predicting residual lifetimes of the corroded gas pipeline. Those works can be divided into deterministic and probabilistic approaches. However, a recent attention focuses on the latter because it provides more realistic predictions as described by Li *et al.* (2009).

Yang and Younis (2005) investigated some probabilistic methods such as first order second moment (FOSM), first order reliability method (FORM), and second order reliability method (SORM). Both FOSM and FORM use a first order Taylor series expansion to derive a limit state function. FORM gives a better accuracy of approximation because it has a feature to find most probable point for the expansion. On the other hand, SORM employs the second order Taylor series expansion to better approximate the limit state function. Monte Carlo simulation (MCS) is one of popular methods for probabilistic reliability estimations. Once the reliability is provided as the form of numeric value, the remaining lifetime can be straightforwardly obtained by field standards, for example, ISO 16708.

A pipeline failure due to corrosion defect can be modeled by parameters such as pipe diameter, wall thickness, operating pressure, tensile strength, and metal corrosion rates. However, those failure models suffer from accommodating non-uniform corrosion growth. This difficulty can be overcome by pipeline segmentation as pointed out in Lecchi (2011). Besides, variability in defective occurrence should also be incorporated into the failure model

because it is readily encountered throughout the pipeline. This paper presents a model based procedure for pipeline reliability assessment. An FOSM is adopted for calculating defect failure probabilities from the failure model. Further, a fuzzy logic based clustering is also incorporated to deal with uncertainty involved in corrosion growth and occurrence likelihood. An illustrative example is given as well by using a modified field dataset. Results of the numerical example indicate that our method produces more advisory predictions on the pipeline failures.

The rest of this paper is organized as follows. Section 2 introduces several works related with reliability methods developed for residual lifetime prediction of the corroded gas pipeline. In Section 3, our proposed framework for model-based reliability prediction is described. The proposed method is illustrated by numerical example in Section 4. Finally, our works are concluded with summary in Section 5.

# 2. Related Works

Ahammed (1998) developed a pipeline reliability model based upon ASME B31G which is a popular code to calculate failure pressures. Sensitivity of some parameters on pipeline reliability was studied as well. He showed that radial growth rate of corrosion is most significant to pipeline failures. Teixeira *et al.* (2008) used FORM and MCS to predict explosion pressures in the pipeline. In this study, Gumbel distribution was employed in order to illustrate statistical variations in operating pressure.

Similarly, for the purpose of residual lifetime prediction, an extreme value distribution was adopted by Noor *et al.* (2008). Further they proposed a cut-off scheme to exclude low-ranked observations. This is motivated from the fact that most pipeline failures would occurred from relatively bigger defects of corrosion. By conducting a simulation study based upon DNV RP 101, they suggested that excessive cut-off should be avoided in terms of prediction accuracy.

Failure prediction depends on the choice of calculation code. In this context, a comparative study was conducted by Caleyo *et al.* (2002). Most popular codes, such as B31G, modified B31G, Battelle, DNV 99, and Shell 92 were included in the study. In that study, it was shown that Shell 92 produces relatively higher probability of failure and defect depth is more influential than defect length. In particular, radial growth rate has more impact to failures than axial growth rate.

Fuzzy techniques have also been introduced to the field of pipeline reliability predictions. For example, Jamshidi et al. (2013) presented a fuzzy inference system for the risk assessment of pipelines. Eight pipeline factors were considered as fuzzy variables. Further, a fuzzy logic method was applied to estimate corrosion failure likelihood (CFL) in the pipeline by Zhou et al. (2016). According to the case study they conducted, the accuracy of CFL estimation can be improved by fuzzy modeling. Recently, Kim et al. (2016) proposed a fuzzy inference based reliability method (FIRM) to deal with incompleteness and vagueness of corrosion data. They showed, by numerical experiments, that their fuzzy predictions are more preventive than non-fuzzy ones.

# 3. The Proposed Method

#### 3.1 Overview

This paper presents a reliability prediction method for the corroded gas pipeline. A fuzzy logic based clustering is incorporated into the study in order to improve the prediction accuracy. The proposed approach is illustrated as shown in Figure 1.

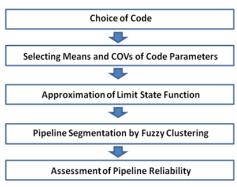


Figure 1. Flow of The Proposed Method

#### 3.2 Limit State Function

Our proposed approach to the pipeline failure prediction is based upon evaluating the probability that a limit state function is less than or equal to zero. The limit state function of pipeline pressure is defined as  $Z = P_f - P_{op}$  where  $P_f$  and  $P_{op}$  means the pressure at which a corrosion defect leads to explosion and the pipeline operating pressure, respectively. Thus, the failure probability corresponding to a single corrosion defect on the pipeline can be rewritten by:

$$F = \Pr[Z \le 0] = \Pr[P_f \le P_{op}]. \tag{1}$$

As mentioned earlier, many model codes have been used for calculating the failure pressure. Among them, PCORRC is adopted in this paper because it is well matched with field practices in Korea. According to PCORRC, the failure pressure is approximated as:

$$P_f = \frac{2St}{D} \left( 1 - \frac{d(T)}{t} M \right) \tag{2}$$

where  $M = 1 - exp(0.157L(t)/\sqrt{D(t - d(T))/2})$ .

In the above equation, S, D, and t are respectively universal tensile strength, diameter, and wall thickness of the pipe.  $P_f$  also includes time dependence as a function of corrosion defect size grown with time. Both depth and length of corrosion defects at time T are assumed by the following forms:  $d(T) = d_0 + V_r(T - T_0)$  and  $L(T) = L_0 + V_a(T - T_0)$  where  $d_0$  and  $d_0$  denote recent sizes of the defect depth and length observed at the time  $d_0$ . Note that the radial and axial growth rates  $d_0$  are assumed to be constant with time.

However, it is very difficult to obtain the probability of failure directly from (1) since pipeline parameters are random in nature and, therefore, failure pressure has a complicated probability distribution. Figure 2 below illustrates this situation based upon a load-resistance model.

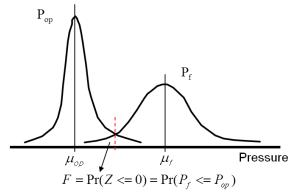


Figure 2. Load-Resistance Model for Statistical Reliability

In order to cope with this difficulty, several approximation methods have been proposed. For example, first order second moment (FOSM), first order reliability method (FORM), and second order reliability method (SORM) are widely used. Among them, FOSM is adopted in this paper. In the literature, it is reported that FOSM has an advantage of good efficiency and moderate accuracy.

FOSM uses the first order Taylor series expansion to approximate the limit state function Z as the following:

$$Z(\underline{x}) \cong Z(\underline{\mu}) + \sum_{i=1}^{k} \left(\frac{\partial Z}{\partial x_i}\right)_{\underline{x} = \underline{\mu}} (x_i - \mu_i)$$
 (3)

where  $\underline{x} = (x_1, x_2, \dots, x_k)$  and  $\underline{\mu} = (\mu_1, \mu_2, \dots, \mu_k)$  respectively denote vectors of the pipe variables and the corresponding means in Equation (2). Thus, from Equation (3), mean and variance of the limit state function are approximately obtained as:

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$$\mu_Z = Z\left(\mu\right) \tag{4}$$

and

$$\sigma_Z^2 = \sum_{i=1}^k \left(\frac{\partial Z}{\partial x_i}\right)_{\underline{x}=\mu}^2 \sigma_i^2 \tag{5}$$

By using Equations (4) and (5), the failure probability for individual corrosion defect can be rewritten as:

$$F = \Pr[Z \le 0] \cong \Phi(-\frac{\mu_Z}{\sigma_Z}) \tag{6}$$

where  $\Phi(\cdot)$  is the cumulative Gaussian distribution function.

## 3.3 Fuzzy Logic based Clustering

As explained earlier, for the proposed method to be operational, pipeline parameters should be configured a priori. In this paper, means and coefficients of variation (COV) of pipeline variables in Equation (2) are provided from specification documents and field dataset. However, a field dataset contains a variety of corrosion data and this implies that there would be two or more corrosion populations. In order to deal with such problem, this paper proposes to use a fuzzy logic based clustering method. As a result, the entire pipeline can be segmented into two or more sub-pipelines.

The proposed clustering proceeds with three steps. First, fuzzy variables are defined. By considering variability and vagueness, we choose 3 fuzzy variables in this study. Growing speeds of corrosion depth and length (GS1 and GS2) and occurrence likelihood (OL) are chosen. Second, a fuzzification on the fuzzy variables is conducted. This study uses Gaussian membership function to find the corresponding fuzzy values. Third, k-means algorithm is applied for clustering populations. We will show the benefit of pipeline clustering by example.

# 4. Numerical Example

#### 4.1 Dataset

A case study is now presented for illustrating potential application of the proposed method. This example is based on the data obtained from a natural gas pipeline which has commissioned since 1993. In 2014, an in-line inspection was conducted to collect corrosion data. However, in this study, a modified dataset is used at a confidential reason and it is illustrated by the following figure.

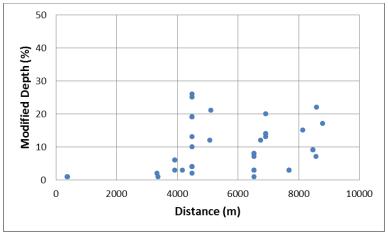


Figure 3. Modified Data of Corrosion Depth

There are 41 cases of corrosion defect identified in the dataset. As shown in the figure, magnitudes and occurrences of corrosion depths are non-uniform throughout the pipeline. This indicates that the dataset should be partitioned into two groups. Figure 4 illustrates Weibull probability plots generated by MINITAB. We can see that distribution parameters are significantly different each other. Note that the steeper slope means the higher rate of failures. For more details on Weibull reliability analysis, readers can refer to Li and Mobin (2016).

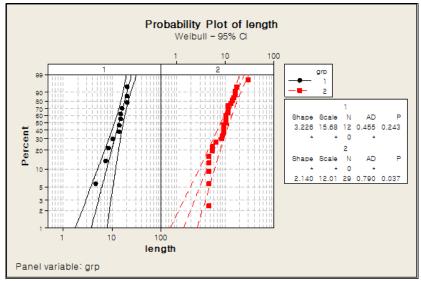


Figure 4. Weibull Probability Plots by Group Depicted in MINITAB

## 4.2 Experimental Results

Once a corrosion size is provided, the corresponding failure probability can be approximated as described in Figure 1. Means and COVs of pipeline variables are determined as shown in Table 1.

Table 1. Farameter Setting for mustration		
Parameter	Mean	COV(%)
Diameter, D	508mm	0.1
Thickness, t	6.4mm	1.0
Pop	7.8Mpa	4.2
UTS	564Mpa	5.2
Radial growth rate, Vr	d0/12	40
Axial growth rate, Va	L0/12	40
d0	As measured	40
L0	As measured	40

Table 1. Parameter Setting for Illustration

An example of the failure probability evaluated at a single corrosion point is illustrated by Figure 5. Among 41 corrosion defects, No. 6, No. 30, and No. 41 are selected. It is shown, in the figure, that the failure probability over 30 years is depicted in log scale because all of values are very small. We can see that the failure probability of No. 41 is fast approaching 1.0e-5.

The probability of pipeline failure (POPF) can be calculated from individual failure probabilities. Letting  $F_j$  denote the failure probability of individual corrosion defect, we can obtain POPF as:

$$POPF = 1 - \prod_{j=1}^{n} (1 - F_j) \tag{7}$$

where n is the number of corrosion defects on the pipeline.

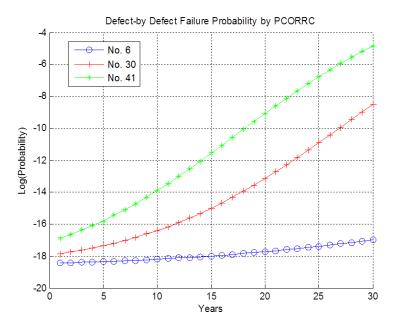


Figure 5. Defect-by-Defect Failure Probabilities Obtained by PCORRC

Figure 6 depicts POPF calculated by Equation (7) for next 30 years. The reliability target specified in ISO 16708 is provided as 2.72e-5. In other words, if POPF exceeds 2.72e-5, it should be judged that the corresponding pipeline fails. According to our numerical experiments, POPF approaches the reliability target after 30 years. This implies that the residual lifetime of the pipeline can be estimated as 30 years. In the figure, POPFs calculated by cluster are illustrated as well. The remaining lifetime for Cluster 1 is predicted by 30 years which is almost same to the whole pipeline. This is because POPF of Equation (7) heavily depends on the largest  $F_j$ . On the other hand, the remaining lifetime of Cluster 2 is much longer.

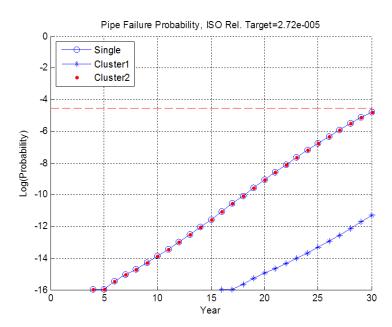


Figure 6. Probabilities of Pipeline Failure by Cluster

# 5. Conclusion

This paper presents a model based reliability estimation procedure for city gas pipeline with corrosion defects. In order to improve its accuracy, a fuzzy logic based clustering is proposed to be incorporated with the estimation process. According to our experimental result, the failure probability of the first cluster is much bigger than the one of the second cluster. This result suggests that clustering and segmentation should be helpful for more advisory prediction. This point has a practical significance in planning maintenance schedules and assessing the value of pipeline property.

As mentioned earlier, the proposed reliability analysis depends on the setting of pipeline parameters. In particular, an appropriate choice of COVs is essential in evaluating the probability of failure. In this sense, a sensitivity analysis on COV would be fruitful issue for future research. Our study has a limitation in that only corrosion is considered as the cause of failure. Interface failures pointed out by Li and Mobin (2015) would also be included for future study.

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# **Biography**

Seong-Jun Kim is a Professor of Industrial Engineering in Management Science, Gangneung-Wonju National University, South Korea. He received the B.S. degree in applied statistics from Yonsei University, Seoul, Korea in 1989, and the M.S. and Ph.D. degrees in industrial engineering from Korea Advanced Institute of Science and Technology (KAIST) in 1991 and 1995, respectively. He was a Visiting Scholar at the University of Tennessee, Knoxville, in 2006. Dr. Kim has conducted consulting services with Samsung Electronics, LG Chemicals, Korea Gas Corporation (KOGAS), and Korea Electric Power Research Institute. His research interests include quality and reliability engineering, soft computing, and big data analytics. He won the Back-Am Award from Korea Institute of Industrial Engineers in 2006.

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