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Predictive Modelling of Hydrant Piping Corrosion Rates

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Abstract

This study develops an Ordinary Least Squares (OLS) multiple linear regression model to estimate corrosion rates in hydrant piping systems using ultrasonic wall-thickness measurements. Field inspection data from 147 pipeline segments at PEM Akamigas were analyzed using two thickness measurements as independent variables to examine their contributions to corrosion rate estimation. The regression model achieved a coefficient of determination (R^2) of 0.874, indicating that the predictor variables collectively explain 87.4% of the observed variation in corrosion rates. The regression coefficients reveal different contributions from the two thickness measurements, with Thickness 1 exhibiting a stronger negative coefficient (−0.297) than Thickness 2 (−0.078). The estimated corrosion rates ranged from 0.0226 to 0.0343 mm/year, with ten segments identified as requiring priority maintenance attention, particularly within segments 53–108. These findings demonstrate the potential of regression-based analysis of ultrasonic inspection data to support pipeline condition assessment and maintenance prioritization. The proposed approach provides an interpretable statistical framework for identifying vulnerable pipeline segments and improving the management of industrial hydrant piping integrity.

Keywords: *Hydrant piping; Corrosion rate; Ultrasonic thickness testing; Multiple linear regression; Predictive modelling.*

INTRODUCTION

Hydrant piping systems play a critical role in industrial fire protection by ensuring the reliable distribution of water during emergency situations. Their structural integrity is therefore essential to maintaining operational safety and preventing failures that could compromise fire suppression capabilities. More broadly, piping systems play an essential role in the oil and gas industry, serving as a critical component of the supply chain and logistics network for the transportation and distribution of petroleum products. The reliability of these systems is vital to ensuring the continuity of industrial operations, maintaining distribution efficiency, and supporting operational safety. Therefore, maintaining the integrity of piping infrastructure is an important aspect of asset management in the oil and gas industry. However, prolonged exposure to environmental conditions, moisture, and internal water flow can progressively deteriorate pipe materials through internal and external corrosion. If left undetected, corrosion may cause localized wall thinning, reduce pressure-bearing capacity, and eventually lead to leakage or structural failure. Consequently, monitoring corrosion progression and identifying vulnerable pipeline segments are important aspects of asset integrity management, particularly in industrial facilities where the reliability of fire protection infrastructure must be continuously maintained (Handoko & Widiyanto, 2025; Subawi & Hakim, 2014).

One of the principal approaches to evaluating pipeline integrity is ultrasonic thickness testing (UTT), a non-destructive inspection technique that enables the measurement of remaining pipe-wall thickness without disrupting system operations. The resulting inspection data provide valuable information for assessing material degradation and determining the condition of individual pipeline segments. Nevertheless, collecting thickness measurements alone does not necessarily provide sufficient information for

establishing maintenance priorities. A more systematic analytical approach is required to transform inspection records into meaningful estimates of corrosion behavior, enabling maintenance personnel to identify potentially vulnerable segments and make more informed decisions regarding inspection, repair, and replacement. In this context, quantitative corrosion assessment becomes particularly important for supporting preventive maintenance and improving the reliability of industrial piping infrastructure.

Corrosion rate prediction has received considerable attention in engineering research, particularly through the application of statistical regression and computational modeling techniques. Jung and Lee (2024), for example, demonstrated the application of regression modeling to predict carbon steel corrosion rates using data obtained from commercial linear polarization resistance (LPR) sensors. Similarly, Varbai et al. (2024) employed regression models to evaluate corrosion degradation in a crude oil distillation unit, highlighting the potential of statistical approaches for interpreting corrosion-related data in industrial environments. Other studies have explored more advanced predictive techniques, including artificial neural networks and optimization-based approaches, to estimate material degradation and damage progression (Chen et al., 2023; Han et al., 2026). These developments indicate that predictive modeling can support the interpretation of corrosion characteristics and provide a quantitative basis for engineering assessment.

Among the available statistical approaches, ordinary least squares (OLS) multiple linear regression offers a relatively straightforward and interpretable method for examining relationships between predictor variables and a continuous response variable. The method estimates regression coefficients by minimizing the sum of squared differences between observed and predicted values, thereby allowing researchers to evaluate the direction and magnitude of individual predictor contributions (Zdaniuk, 2023; Burton, 2021). Its interpretability is particularly relevant to engineering applications,

where understanding the relationship between measured physical parameters and predicted degradation is important alongside model performance. Nevertheless, the reliability of an OLS model depends on the characteristics of the dataset and the fulfillment of relevant statistical assumptions, including linearity, independence, homoscedasticity, and the absence of problematic multicollinearity.

Despite the growing application of predictive modeling in corrosion assessment, further investigation is needed into the use of routinely collected ultrasonic thickness measurements for estimating corrosion rates in hydrant piping systems. In particular, the predictive value of two wall-thickness measurements obtained from individual pipe segments requires systematic examination within an integrated regression framework. This issue is relevant because hydrant piping networks consist of multiple segments that may exhibit different thickness conditions and degradation characteristics, making segment-level assessment important for identifying potential maintenance priorities. The application of regression modeling to such inspection data may therefore provide a practical analytical framework for supporting pipeline condition evaluation.

To address this research need, the present study develops an OLS multiple linear regression model using inspection data from 147 hydrant piping segments. Two wall-thickness measurements for each segment are incorporated as predictor variables to examine their statistical relationships with the recorded corrosion rate. The study aims to (1) quantify the individual contributions of the two thickness measurements to corrosion rate prediction, (2) evaluate the statistical significance and predictive performance of the developed regression model, and (3) identify pipeline segments that warrant priority attention based on their estimated corrosion conditions. By integrating ultrasonic thickness inspection data with an interpretable statistical modeling approach, this study seeks to contribute a practical

framework for data-driven corrosion assessment and maintenance prioritization in industrial hydrant piping systems.

RESEARCH METHOD

Dataset and Field Inspection

Field inspection data were collected from the hydrant piping system at PEM Akamigas to evaluate the existing wall-thickness conditions and estimate the corrosion rates of individual pipeline segments. The inspection covered 147 accessible pipeline segments. However, segments 148–154 were excluded from the inspection campaign because they were located underground beneath a road crossing, where direct ultrasonic thickness testing (UTT) could not be performed without excavation. Consequently, the analysis was limited to pipeline segments for which direct thickness measurements were available.

The spatial distribution of the inspected pipeline segments is illustrated in Figure 1, providing an overview of the inspection locations within the hydrant piping network.



Figure 1. Spatial distribution of field inspection points along the hydrant piping system.

Based on the field inspection, two ultrasonic wall-thickness readings were obtained for each of the 147 pipeline segments. These measurements, designated as Thickness 1 and Thickness 2, represent readings taken at different orientations or measurement positions on the pipe wall. The

resulting thickness profiles provide an indication of wall-condition variations across the inspected pipeline network, as presented in Figure 2.

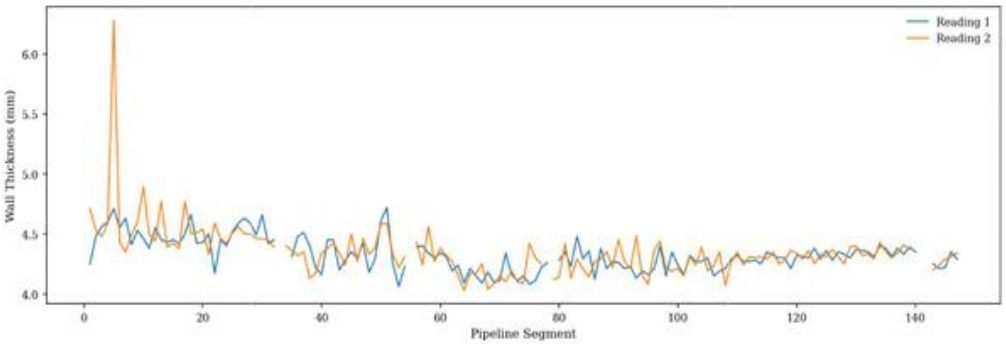


Figure 2. Distribution of Thickness 1 and Thickness 2 measurements across the inspected pipeline segments.

For each segment, the minimum remaining wall thickness was determined by selecting the lower value of the two ultrasonic readings. This approach was adopted to represent the more conservative wall-thickness condition at each inspected segment. Figure 3 illustrates the ultrasonic measurement positions used to obtain Thickness 1 and Thickness 2.

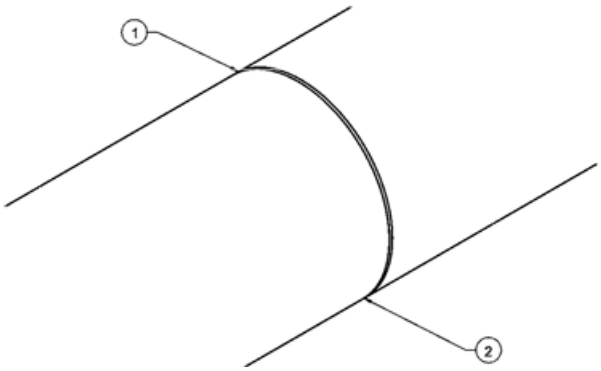


Figure 3. Schematic illustration of ultrasonic thickness measurement positions on the hydrant pipe wall.

Descriptive statistical analysis was subsequently performed to characterize the distribution of the measured thickness values and estimated corrosion rates. The analysis included the mean, standard deviation, minimum, and maximum values for each variable. As summarized in Table 1,

the mean values of Thickness 1 and Thickness 2 were 4.330 mm and 4.351 mm, respectively, while the mean minimum wall thickness was 4.289 mm.
A relatively high maximum value of 6.280 mm was observed for Thickness 2, compared with its mean of 4.351 mm. This value corresponds to segment 5 and represents an unusually high measurement relative to the overall thickness profile. However, it does not affect the determination of minimum wall thickness for that segment because the corresponding Thickness 1 reading is lower. Accordingly, the minimum thickness criterion was consistently applied throughout the dataset to provide a conservative basis for corrosion assessment.

The corrosion rate was estimated using the reduction in wall thickness relative to the nominal initial pipe-wall thickness, divided by the estimated service life of the piping system. The calculation is expressed in Equation (1):

$$Corrosion\ Rate = \frac{tin - tmeas}{Age}$$

where t is the nominal initial wall thickness of the pipe (6.02 mm), t (1) is the measured wall thickness obtained from ield inspection, and Age is the service life of the pipeline, which is 58 years.

Table 1. Descriptive statistics of the hydrant piping inspection dataset

Variable	Mean	Std. Dev.	Min.	Max.
Thickness 1 (mm)	4.330	0.141	4.060	4.720
Thickness 2 (mm)	4.351	0.221	4.030	6.280
Minimum Thickness (mm)	4.289	0.131	4.030	4.710
Corrosion Rate (mm/year)	0.02984	0.00226	0.02260	0.03430

Source: Field inspection data from the hydrant piping system at PEM Akamigas.

Multiple Linear Regression Model

An Ordinary Least Squares (OLS) multiple linear regression model was employed to examine the relationship between ultrasonic wall-thickness measurements and the estimated corrosion rates of the hydrant piping

segments. This statistical approach was selected because it enables the estimation of the individual contributions of multiple predictor variables to a continuous response variable while maintaining relatively straightforward coefficient interpretation (Zdaniuk, 2023; Burton, 2021).

The model incorporates two wall-thickness measurements, Thickness 1 and Thickness 2, as independent variables, while the estimated corrosion rate serves as the dependent variable. The general regression equation is formulated as follows:

$$Corrosion\ Rate\ =\ \beta^0 +\ \beta^1(Thickness_1) +\ \beta^2(Thickness_2) +\ \varepsilon$$

where $\beta$is the intercept term, $\beta$and $\beta$are the regression coef icients associated with the wall thicknesses of the preceding segment (Thickness) and succeeding segment (Thickness), respectively, and εrepresents the random error term. The dependent variable is the corrosion rate calculated using the measured wall thickness, an initial wall thickness of 6.02 mm, and a service life of 58 years. The predictor variables were incorporated into the model in their original form without transformation. The intercept represents the baseline corrosion rate at nominal wall thickness conditions. Pearson correlation analysis was conducted prior to regression to examine the relationships between the predictors and corrosion rate and to identify potential multicollinearity among the predictor variables.

RESULTS AND DISCUSSION

Corelation Structure

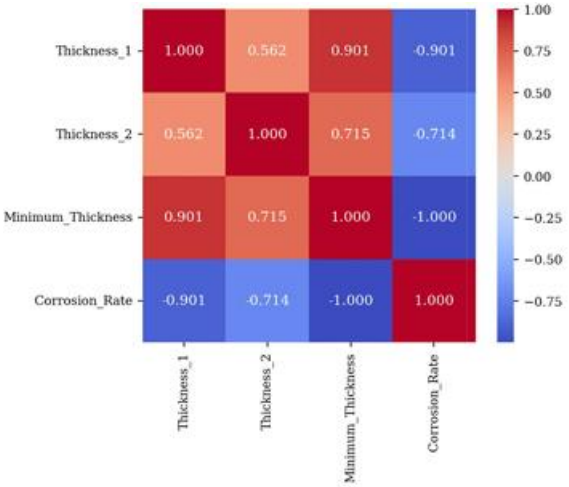


Figure 4. Pearson correlation heatmap for Thickness ,Thickness, Minimum, and Corrosion Rate.

Figure 4 indicates strong inverse relationships between wall thickness measurements and corrosion rate. Minimum thickness exhibits a near-perfect negative correlation with corrosion rate (r = −1.000), as corrosion rate is directly derived from the reduction in wall thickness. Adjacent segment thicknesses also show strong negative correlations with corrosion rate, with r =−0.901 for Thickness$_1$ and r = −0.715 for Thickness$_2$.

These relationships re lect the in luence of neighboring wall thickness measurements on local corrosion behavior. The correlation between Thickness and Thickness is moderate (r = 0.562), suggesting some degree of collinearity; however, the magnitude is below commonly accepted thresholds for severe multicollinearity, indicating that both variables can be retained in the regression model.

Regression Output The itted model produces an R^2 of 0.874 and adjusted R^2 of 0.872 across 139 observations. The F-statistic of 472.8 ($p < 0.001$) con irms overall model signi icance. Table 2 presents the full coef icient results. Table 2. OLS regression coef icients.

Table 2. OLS regression coef icients.

Predictor	Coefficient	Std Error	t-statistic	p-value
Intercept	0.0938	0.002	44.43	< 0.001
Thickness$_1$	−0.0117	0.001	−19.93	< 0.001
Thickness$_2$	−0.0031	0.000	−8.17	< 0.001

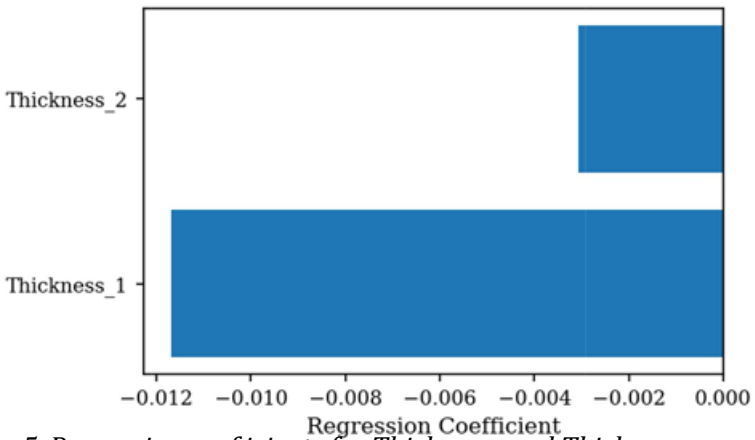


Figure 5. Regression coef icients for Thickness$_1$ and Thickness$_2$.

Based on Figure 5, Thickness shows a coef icient magnitude approximately four times greater than that of Thickness, consistent with its stronger correlation with the minimum wall thickness observed across the dataset. The Durbin–Watson statistic of 1.836 suggests the absence of signi icant autocorrelation in the residuals along the pipeline segment sequence. However, the Omnibus and Jarque–Bera tests indicate that the residuals deviate from normality ($p < 0.001$), as evidenced by a positive skewness of 1.527 and a kurtosis value of 5.775, re lecting a right-skewed distribution with heavier tails than a normal distribution.

Model Fit

The predicted-versus-observed plot demonstrates a strong overall agreement between the model predictions and the measured corrosion rates, indicating satisfactory predictive performance within the central range of the data. However, the model tends to underestimate corrosion rates at the lower end of the distribution and exhibits a slight increase in prediction variability at higher corrosion rates. This behaviour is consistent with the positive residual skewness identi ied by the Omnibus and Jarque–Bera normality tests. The predicted-versus observed relationship is shown in Figure 6.

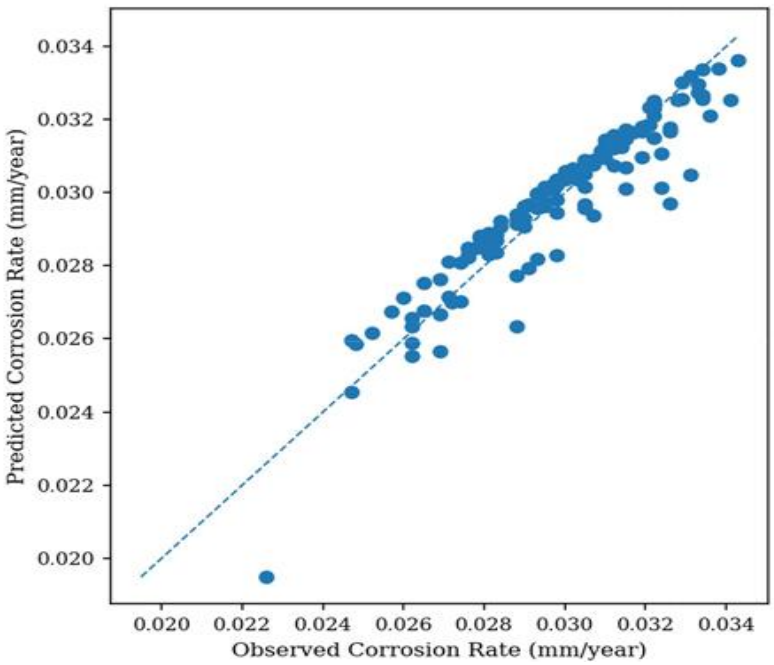


Figure 6. Predicted vs. observed corrosion rate scatter plot with 1:1 reference line.

Corrosion Rate Distribution

The corrosion rate distribution is centred around approximately 0.030 mm/year and exhibits a moderate positive skew. Most pipeline segments have corrosion rates within the range of 0.027 to 0.033 mm/year, indicating relatively consistent wall loss across the system. A smaller subset of nine segments exhibits corrosion rates below 0.025 mm/year, representing areas with comparatively lower material degradation which is shown in Figure 7.

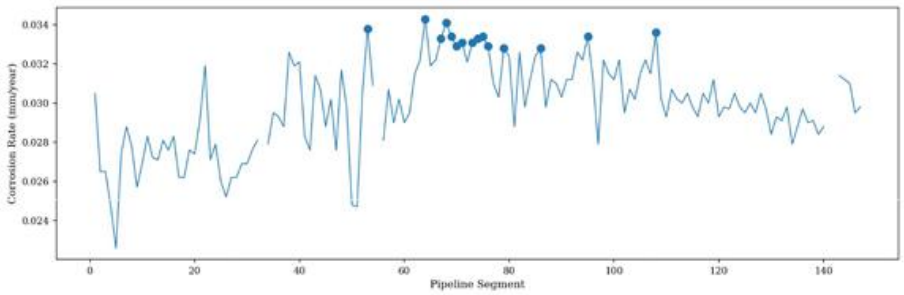


Figure 7. Corrosion rate pro ile across all 147 pipeline segments with high-risk segments marked.

The segment-wise corrosion pro ile reveals a concentration of elevated corrosion rates between Segments 53 and 108, indicating a localized region of accelerated wall degradation. The ten segments exhibiting the highest measured corrosion rates are summarized in Table 3.

Table 3. Descriptive statistics of inspection dataset

Segment	Thickness$_1$ (mm)	Thickness$_2$ (mm)	Min Thickness (mm)	Corrosion Rate (mm/year)
64	4.09	4.03	4.03	0.0343
68	4.18	4.04	4.04	0.0341
53	4.06	4.22	4.06	0.0338
108	4.21	4.07	4.07	0.0336
95	4.16	4.08	4.08	0.0334
69	4.10	4.08	4.08	0.0334
75	4.08	4.42	4.08	0.0334
67	4.09	4.25	4.09	0.0333
74	4.15	4.09	4.09	0.0333
71	4.34	4.10	4.10	0.0331

[a] Data taken from hydrant system

All of these segments have minimum wall thicknesses of 4.10 mm or less, highlighting the direct relationship between wall loss and corrosion rate. Notably, seven of the ten highest-corroding segments are located within the Segment 64 to 75, suggesting that this section of the pipeline may be particularly susceptible to corrosion and warrants further inspection and monitoring.

DISCUSSION

The regression model explains 87.4% of the variability in corrosion rate using only two wall thickness measurements per segment, demonstrating strong predictive capability with a minimal set of input variables. This level of performance is well suited for practical inspection applications, as ultrasonic thickness testing (UTT) readings can be directly incorporated into the model to estimate corrosion rates without requiring additional environmental, operational, or low-related data.

Thickness is the dominant predictor in the model. Its regression coef icient (−0.0117) is approximately four times greater than that of Thickness (−0.0031), consistent with its stronger association with the minimum wall thickness across the 143 analyzed segments. This inding suggests that the measurement location represented by Thickness more frequently corresponds to the region experiencing the greatest wall loss. Such behavior may be in luenced by localized exposure conditions, including soil contact characteristics, coating degradation, moisture accumulation, or low-induced effects speci ic to the pipeline installation.

The residual distribution exhibits positive skewness (1.527), indicating that a subset of segments may experience localized pitting corrosion rather than uniform wall thinning. Under these conditions, a segment containing a highly corroded local area and an otherwise near-nominal wall thickness may yield the same minimum thickness value as a uniformly corroded segment, despite having different structural integrity characteristics. Consequently, the current model may not fully capture the distinction between localized and

generalized corrosion mechanisms. Future model development could bene it from incorporating a wall thickness differential parameter to account for spatial variability in wall loss.

The concentration of elevated corrosion rates between Segments 53 and 108 suggests the presence of common underlying factors affecting this section of the pipeline. Potential contributors include variations in soil chemistry, differences in material properties associated with construction batches or installation periods, or increased exposure to moisture resulting from drainage patterns or groundwater ingress. Given the clustering of high-corrosion segments within this corridor, targeted ield investigation and condition assessment are recommended before the next maintenance or inspection cycle.

CONCLUSION

Wall thickness measurements obtained from two-point ultrasonic thickness testing (UTT) explain 87.4% of the variability in corrosion rates across 147 inspected segments of the hydrant pipeline. Segments 148 to 154 were excluded from the inspection campaign because the pipeline in this section passes beneath a road crossing, making direct UTT access impractical without excavation. The regression analysis identi ied Thickness as the dominant predictor of corrosion rate, re lecting its stronger association with minimum wall thickness. The highest corrosion rates were concentrated within the Segment 64–108 corridor, where the ten most severely affected segments all exhibited minimum wall thicknesses of 4.10 mm or less. These indings demonstrate that the proposed model provides a practical and ef icient tool for prioritizing inspection and maintenance activities using only routine UTT measurements. However, the observed residual non-normality suggests the presence of localized pitting corrosion in a subset of segments. Future studies may improve predictive accuracy by incorporating the wall thickness differential between measurement points as an additional predictor to better capture localized wall-loss behaviour.

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