17th International Conference on Probabilistic Safety Assessment and Management &
Asian Symposium on Risk Assessment and Management (PSAM17&ASRAM2024)
7-11 October, 2024, Sendai International Center, Sendai, Miyagi, Japan

External Corrosion Assessment of Oil and Gas Pipelines using 1D Convolutional Neural Network

Fengyi Lan[a,b], Taotao Zhou[a,b*], Bingcai Sun[c], Yuntao Li[a,b], Qingqing Xu[a,b], Laibin Zhang[a,b]

[a]College of Safety and Ocean Engineering, China University of Petroleum-Beijing, Beijing, China
[b]Key Laboratory of Oil and Gas Safety and Emergency Technology, Ministry of Emergency Management, Beijing, China
[c]CNPC Research Institute of Safety and Environment Protection Technology, Beijing, China

Abstract: Pipelines play a key role in ensuring safe and economical oil and gas transportation. However, pipelines are typically operated under harsh working conditions and are hence vulnerable to various failure causes, of which corrosion accounts for around 20 percent. Moreover, the consequences of pipeline failures may lead to serious production losses, environmental pollution, and even injuries. Therefore, an effective method for pipeline corrosion assessment is important to maintain the integrity of oil and gas transportation systems. This paper presents a novel method for the assessment of external corrosion in oil and gas pipelines using a 1D Convolutional Neural Network (1D-CNN). Our method leverages the ability of 1D-CNNs to automatically extract and learn features from pipeline inspection data, enabling effective corrosion prediction. The proposed method was demonstrated using real-field pipeline inspection data, and validated by a comparative study with conventional machine learning-based methods. This study underscores the potential of deep learning techniques, particularly 1D-CNNs, to enhance the accuracy of pipeline corrosion assessment.

Keywords: External Corrosion; Oil and Gas Pipelines; 1D Convolutional Neural Network; Deep Learning.

1. INTRODUCTION

External corrosion in oil and gas pipelines refers to the deterioration of pipeline materials due to electrochemical reactions with their immediate surroundings on the outer surface of the pipeline, potentially leading to metal loss from pipe walls and structural weaknesses [1]. According to the Pipeline and Hazardous Materials Safety Administration (PHMSA), approximately 8% of reported incidents on gas transmission, gas gathering, and hazardous liquid pipelines were caused by external corrosion in the U.S. from 2013 to 2017 [2]. Therefore, it is pivotal to establish effective management of external corrosion in oil and gas pipelines to prevent leaks, spills, and structural failures, thereby preserving pipeline integrity and ensuring safe and reliable operation.

As a foundation for corrosion management, corrosion assessment involves identifying, evaluating, and monitoring the severity of corrosion in pipelines, guiding proactive efforts to prevent corrosion-related failures, and extending the service life of oil and gas pipelines. The essential task of corrosion assessment is to develop predictive models for corrosion rate or depth by exploiting pipeline characteristics, environmental parameters, and operational factors [3]. In general, the external corrosion assessment models can be broadly categorized into three types:

(1) Physical models are based on a mechanistic understanding of corrosion behavior by referring to the fundamental principles of chemistry, physics, and material science, such as the De Waard carbonic acid corrosion model [4]. However, physical models often rely on simplifying assumptions and cannot fully capture the complexity of the real-world corrosion environment. This leads to discrepancies between model predictions and actual observations in the field, restricting their practical applicability.
(2) Empirical models are based on statistical analysis of historical corrosion data (e.g., multivariate regression analysis) to establish relationships between corrosion rates and various influencing factors such as environmental conditions, pipeline characteristics, and operating parameters [5, 6]. These models offer simplicity and interpretability to predict corrosion behavior, while they have limited flexibility in capturing nonlinear relationships or complex interactions between variables.
(3) Data-driven models aim to take advantage of machine learning methods' greater flexibility and accuracy in modeling complex relationships and patterns in data, making them particularly well-suited for corrosion

* Corresponding author. Email address: zhoutt@cup.edu.cn (T. Zhou).

assessment in oil and gas pipelines, where the relationships between variables may be nonlinear and multifaceted [7]. As a result, data-driven models have recently drawn growing attention for corrosion assessment in oil and gas pipelines, balancing accuracy with practicality and efficiency in field applications [8]. Some of the most widely used machine learning methods are support vector regression [9], random forest [10], and back-propagation neural networks [11]. Notably, neural network-based models can outperform most conventional machine learning methods in pipeline corrosion prognostics [12-14].

In this paper, we present a 1D Convolutional Neural Network (CNN)-based model for external corrosion assessment that automatically extracts and learns a representation directly from the field dataset of oil and gas pipelines. Several convolutional layers are employed to capture the data structure and learn various filters essential for the predictive task. Ultimately, we illustrated the proposed framework using a real-field dataset acquired at dig sites over three years for onshore buried pipelines operating in southern Mexico for up to 50 years. The performance of the proposed model was also demonstrated by a comparison to 13 other machine learning methods.

The remainder of the paper is organized as follows: Section 2 describes the real-field corrosion dataset of onshore buried pipelines and details the data preprocessing. Section 3 presents the proposed 1D-CNN-based model and discusses the results with a comparative study of 13 machine learning models. Section 4 provides concluding remarks and future directions.

2. DATA DESCRIPTION AND PREPROCESSING

This study adopts a real-field corrosion dataset acquired at dig sites over three years for onshore buried pipelines operating in southern Mexico for up to 50 years [15, 16]. The dataset has 259 data samples; 9 outlier samples were removed, leaving 250 data samples for this study. As displayed in Table 1, the corrosion severity is represented by the maximum pit depth as the target variable of the predictive model; the inputs are the 12 influencing variables consisting of the local soil properties and operating parameters. Figure 1 shows the maximum pit depth distribution and trend over the pipeline age. Figure 2 shows the distribution of the local soil properties and operating parameters.

Table 1. Corrosion severity and influencing variables for corrosion assessment

	Variables	**Notation**	**Type of Variables**
Corrosion Severity	Maximum pit depth	d_{max}	Continuous
Operating Parameters	Pipeline age	t	Continuous
	Coating type	ct	Ordinal
Local Soil Parameters	pH	ph	Continuous
	Pipe-to-soil potential	pp	Continuous
	Soil resistivity	re	Continuous
	Water content	wc	Continuous
	Bulk density	bd	Continuous
	Dissolved chloride	cc	Continuous
	Bicarbonate	bc	Continuous
	Sulfate ion concentrations	sc	Continuous
	Redox potential	rp	Continuous
	Soil textural class	class	Nominal

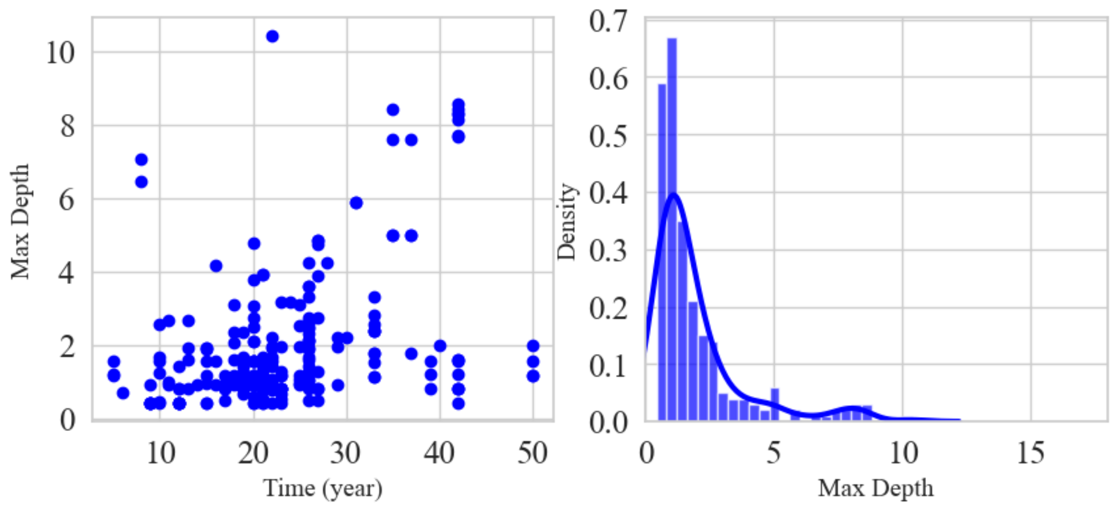

Figure 1. Trend of maximum pit depth over pipeline age and distribution of maximum pit depth

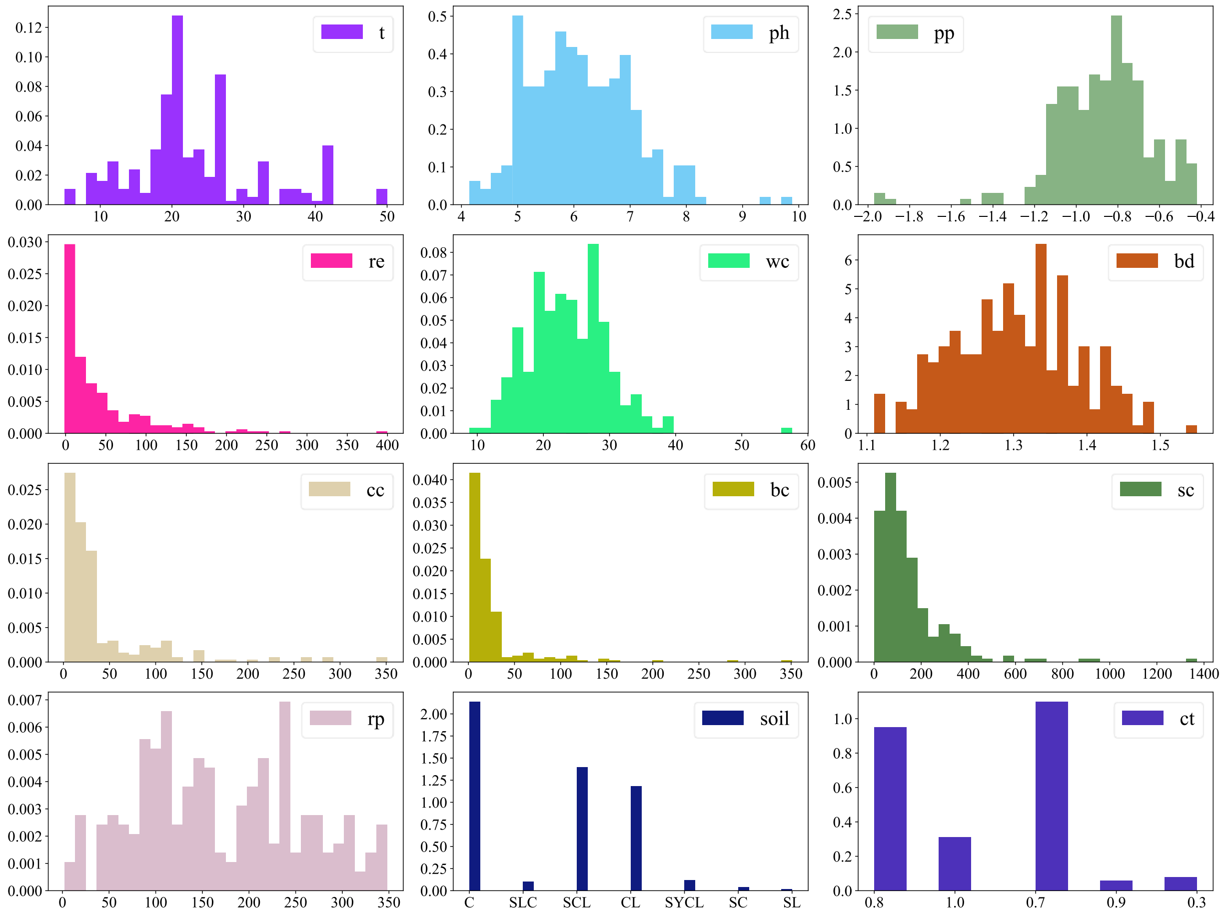

Figure 2. Distribution of local soil parameters and operating parameters

The dataset is preprocessed by the following: (a) one-hot encoding the nominal features: each nominal value is converted into a new column and assigned a 0 or 1 value to the column and the number of nominal values equals the number of columns; (b) encoding the ordinal feature: the 5 coating types are ordered by its degree of protection against corrosion and is hence converted into a numerical integer between 1 and 5; (c) standardizing the continuous features: the continuous value of the datasets are standardized to have a mean of 0 and a standard deviation of 1. Finally, there are 22 features in the preprocessed dataset, which consist of the normalized continuous features, and encoded nominal and ordinal features. It then proceeded to split the standardized dataset into a training dataset X_{train}, validation dataset X_{val} and testing dataset X_{test}, all of which account for 70%, 15%, and 15% of the total datasets.

3. MODEL DEVELOPMENT AND RESULTS

The 1D CNN is used as the backbone model in this study as illustrated in Figure 3. The model receives data in 18×1 dimensions as an input, followed by 3 convolutional layers, whose kernel sizes are {64×1, 32×1, 16×1}, respectively, and the kernel numbers are {7, 3, 2}, respectively. A max-pooling layer with a pooling size of 2×1 is appended to each convolutional layer. After the convolution and pooling operations, the extracted features are flattened as the input to a dense layer of 64 units and then an output layer of 1 unit, indicating the corrosion severity. The activation function used is the rectified linear unit (ReLU) function, except the softplus function in the output layer, imposing the positive requirement of pit depth values. The network is trained using the loss function of mean square error (MSE) and the Adam optimization algorithm with a learning rate as 1×10^{-3}, and the number of training epochs is 200. Once the model is well trained, the corrosion severity (i.e., maximum pit depth) can be properly estimated through a forward pass of the proposed model.

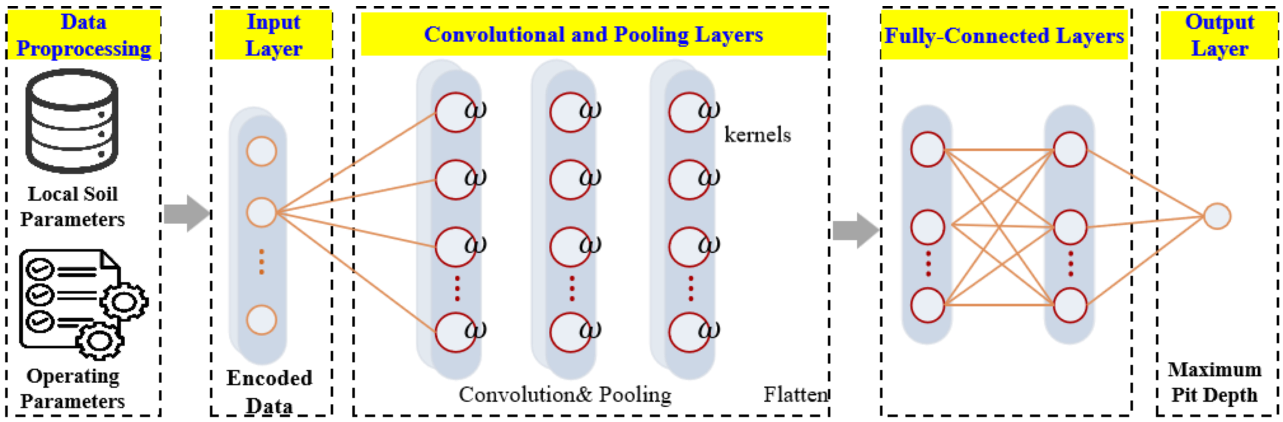

Figure 3. Configuration of a 1D convolutional neural network-based model for external corrosion assessment

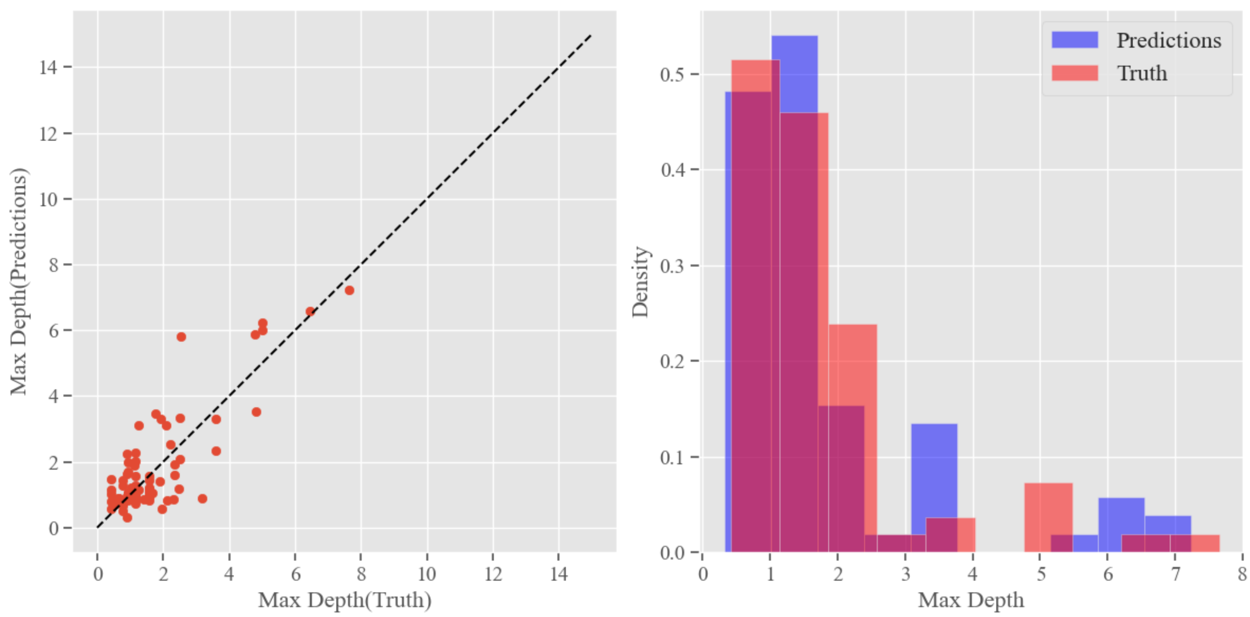

Figure 4. Predictive Results Using 1D Convolutional Neural Network

Figure 4 displays the results based on our proposed model. To further corroborate our proposed model's performance, we compared 13 other widely used machine learning-based regression models. The results of the comparative study are summarized in Table 2. Note that we use the parameter settings of those ML models in Python to keep the reproducibility of the results. The models' performance is evaluated using the metrics of root mean square error (RMSE), mean absolute error (MAE), and the coefficient of determination (R-Square).

Table 2. Performance of pipeline corrosion assessment using the proposed model and 13 other models

Method	**RMSE**	**MAE**	**R-Square**
Proposed	**0.60**	**0.81**	**0.65**
Linear regression	0.84	1.10	0.36
Lasso regression	1.06	1.40	-0.04
Elastic Net regression	0.97	1.29	0.12
K-Nearest neighbors regression	0.77	1.14	0.30
Decision tree regression	0.77	1.13	0.32
Gradient boosting regression	0.61	0.92	0.55
Support vector regression	0.67	0.98	0.49
Ridge regression	0.83	1.10	0.36
Multi-layer perceptron regression	0.69	0.94	0.53
Extremely randomized tree regression	0.94	1.37	0.01
Random forest regression	0.66	0.97	0.50
Adaboost regression	0.62	0.85	0.62
Bagging regression	0.59	0.93	0.54

4. CONCLUSION

In this study, we have demonstrated the efficacy of using a 1D-CNN-based model for external corrosion assessment in oil and gas pipelines. Through extensive training and testing on a real-field onshore pipeline inspection dataset, the proposed model exhibited superior performance for corrosion assessment against conventional machine learning techniques. The results highlight the ability of the 1D-CNN to automatically learn and extract relevant features from raw data. This research underscores the transformative potential of deep learning techniques in the field of pipeline integrity management. Future work will focus on enhancing the model's accuracy and explainability, along with its integration with other data sources and broader application to other pipeline types and corrosion scenarios. Adoption of such advanced technologies can result in more proactive and reliable pipeline integrity management, ultimately safeguarding critical infrastructure.

Acknowledgements

The research of the author Taotao Zhou was supported by the National Natural Science Foundation of China (No. 72301294), the Young Elite Scientist Sponsorship Program by the Beijing Association for Science and Technology (BAST) (No. BYESS2023323), and the Program for Youth Talents by the China University of Petroleum-Beijing (No. 2462023BJRC016).

References

[1] Farh, H. M. H., Seghier, M. E. A. B., & Zayed, T. (2023). A comprehensive review of corrosion protection and control techniques for metallic pipelines. Engineering Failure Analysis, 143, 106885.
[2] Pipeline and Hazardous Materials Safety Administration. Fact Sheet: External Corrosion. Retrieved May 28, 2024, from https://primis.phmsa.dot.gov/Comm/FactSheets/FSExternalCorrosion.htm
[3] Wasim, M., & Djukic, M. B. (2022). External corrosion of oil and gas pipelines: A review of failure mechanisms and predictive preventions. Journal of Natural Gas Science and Engineering, 100, 104467.
[4] De Waard, C., Lotz, U., & Milliams, D. E. (1991). Predictive model for CO2 corrosion engineering in wet natural gas pipelines. Corrosion, 47(12), 976-985.
[5] Velázquez, J. C., Caleyo, F., Valor, A., & Hallen, J. M. (2009). Predictive model for pitting corrosion in buried oil and gas pipelines. Corrosion, 65(5), 332-342.
[6] Heidary, R., & Groth, K. M. (2021). A hybrid population-based degradation model for pipeline pitting corrosion. Reliability Engineering & System Safety, 214, 107740.
[7] Soomro, A. A., Mokhtar, A. A., Kurnia, J. C., Lashari, N., Lu, H., & Sambo, C. (2022). Integrity assessment of corroded oil and gas pipelines using machine learning: A systematic review. Engineering Failure Analysis, 131, 105810.

[8] Ma, H., Zhang, W., Wang, Y., Ai, Y., & Zheng, W. (2023). Advances in corrosion growth modeling for oil and gas pipelines: A review. Process Safety and Environmental Protection, 171, 71-86.

[9] Naserzadeh Z, Nohegar A. Development of HGAPSO-SVR corrosion prediction approach for offshore oil and gas pipelines[J]. Journal of Loss Prevention in the Process Industries, 2023, 84: 105092.

[10] Imran M M H, Jamaludin S, Ayob A F M. A critical review of machine learning algorithms in maritime, offshore, and oil & gas corrosion research: A comprehensive analysis of ANN and RF models[J]. Ocean Engineering, 2024, 295: 116796.

[11] Ossai, C. I. (2020). Corrosion defect modelling of aged pipelines with a feed-forward multi-layer neural network for leak and burst failure estimation. Engineering Failure Analysis, 110, 104397.

[12] Wang, Q., Song, Y., Zhang, X., Dong, L., Xi, Y., Zeng, D., ... & Luo, H. (2023). Evolution of corrosion prediction models for oil and gas pipelines: From empirical-driven to data-driven. Engineering Failure Analysis, 146, 107097.

[13] Seghier, M. E. A. B., Keshtegar, B., Tee, K. F., Zayed, T., Abbassi, R., & Trung, N. T. (2020). Prediction of maximum pitting corrosion depth in oil and gas pipelines. Engineering Failure Analysis, 112, 104505.

[14] Chou, J. S., Ngo, N. T., & Chong, W. K. (2017). The use of artificial intelligence combiners for modeling steel pitting risk and corrosion rate. Engineering Applications of Artificial Intelligence, 65, 471-483.

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

[16] Velázquez, J. C., Caleyo, F., Valor, A., & Hallen, J. M. (2010). Field study—Pitting corrosion of underground pipelines related to local soil and pipe characteristics. Corrosion, 66(1), 016001-016001.