Digital Twin of Pipeline Corrosion Management Using Artificial Intelligence

Bingyan Cui[1] and Hao Wang[2]*

1. PhD student, 2. Professor, Department of Civil and Environmental Engineering , Rutgers University, USA (*hwang.cee@rutgers.edu)

INTRODUCTION

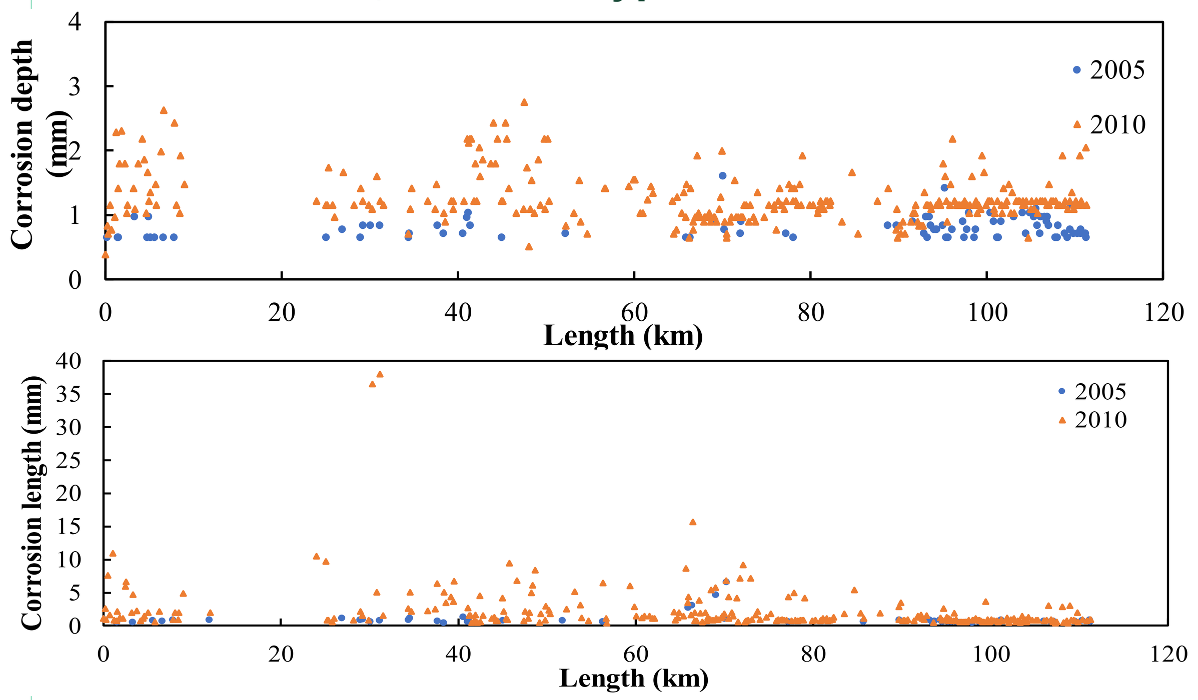
- Pipelines are crucial for transporting essential resources but are vulnerable to corrosion damages.
- Digital twin of pipeline corrosion management can visualize inspection data, establish prediction model, and perform data-driven decision-making.
- Early detection and prediction of corrosion are important to prevent catastrophic outcomes.
- Current prediction models oversimplify complex and dynamic interactions between soil and corrosion.

OBJECTIVES

- Use machine learning to identify corrosive soil environments based on In-line Inspection (ILI) data.
- Establish a probabilistic corrosion growth model considering soil environment using Bayesian Neural Network.
- Propose a reinforcement learning-based method to optimize pipeline maintenance strategy.

PIPELINE DATA

- Pipeline information: 112 km, X52 steel, 18-in. diameter, 0.25-in. wall thickness.
- In-Line-Inspection data: corrosion depth and length in 2005 and 2010.
- Soil parameters: soil redox potential, resistance, resistivity, pH, CO_3^{2-} concentration, HCO_3^- concentration, Cl^- concentration, SO_4^{2-} concentration, soil moisture, and soil type.



pipeline length for the zone-based ILI dataset.

DETECTION OF CORROSIVE SOIL ENVIRONMENT

- Soil moisture has the highest impact on corrosion defects. Higher moisture levels significantly increase corrosion potential.
- Lower soil resistivity values correlate with increased corrosion risk.
- Lower pH values and higher soil redox potentials accelerate corrosions.

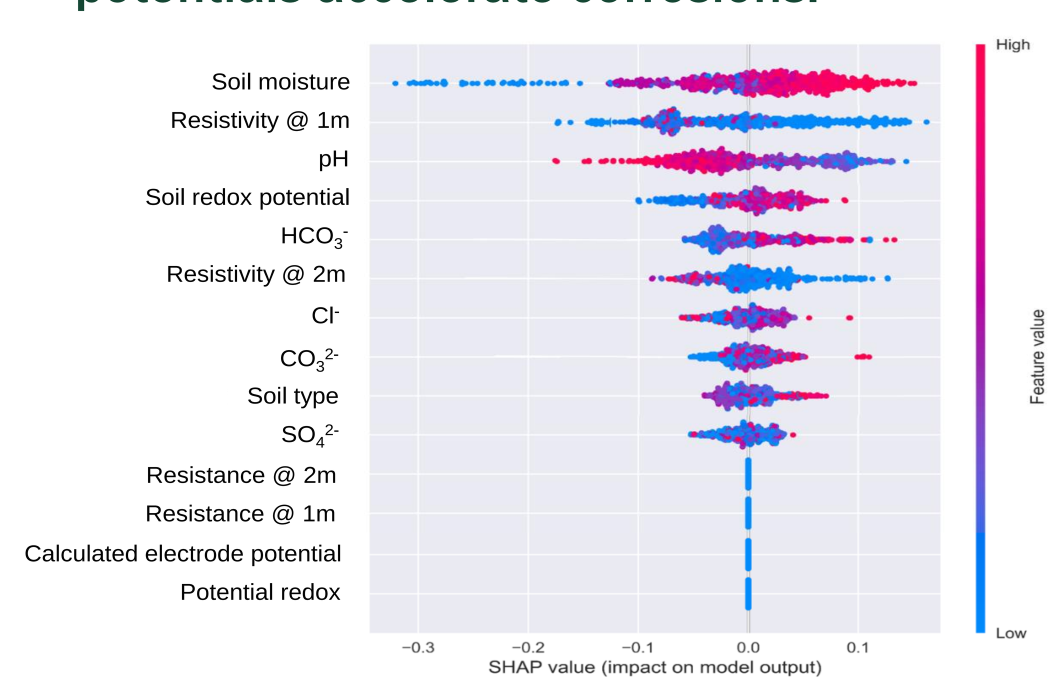


Figure 2. Importance of soil parameters on corrosion detection based on SHAP plot.

CORROSION PREDICTION WITH BNN (BAYESIAN NEURAL NETWORK)

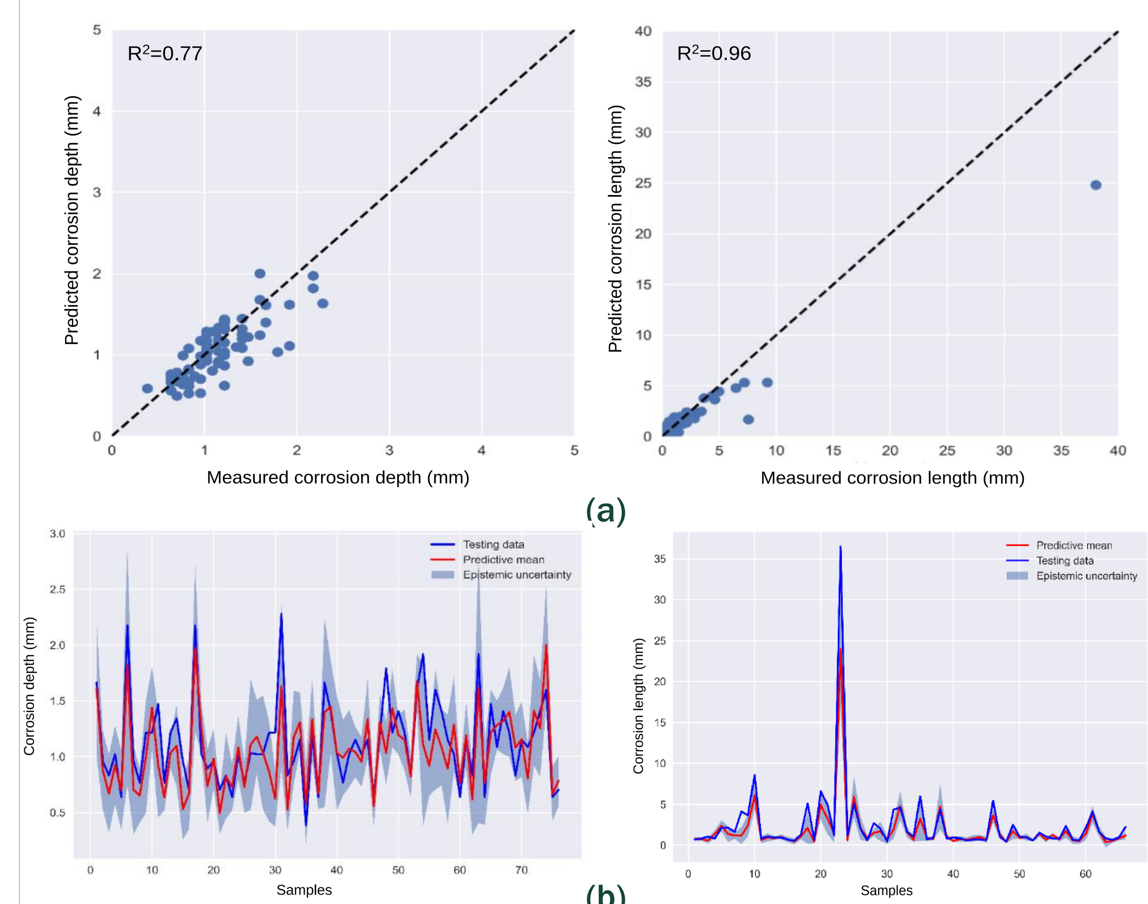


Figure 3. BNN fitting results of (a) predicted vs. measured corrosion depth and length; (b) predictions with uncertainty bound.

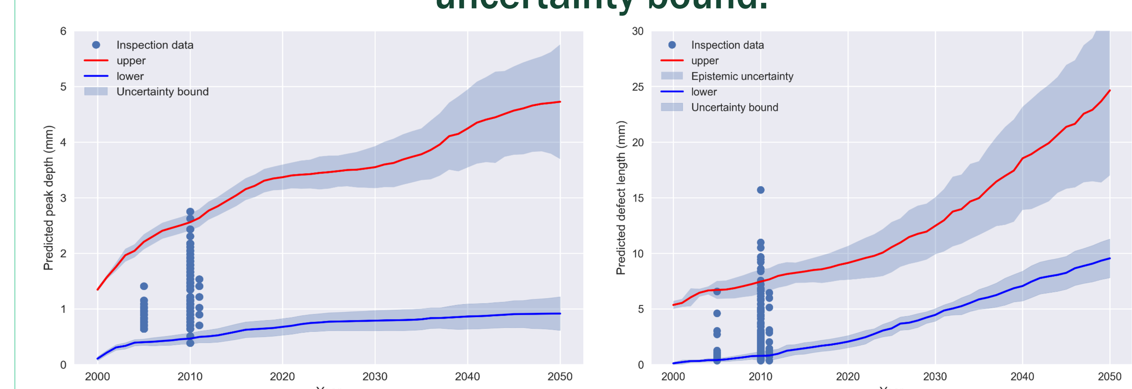


Figure 4. Prediction of future corrosion depth and length growth.

MAINTENANCE STRATEGY WITH REINFORCEMENT LEARNING

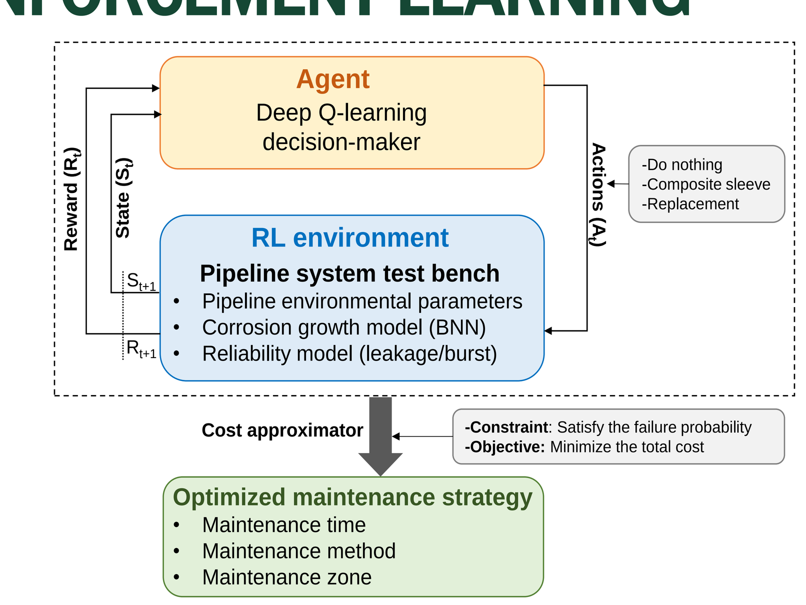


Figure 5. Framework of pipeline maintenance strategy using RL method.

Table 1. Comparison of RL-based and non-RL-based maintenance strategies.

Scenarios	Maintenance plan		Total cost ($)	P_f threshold
1	RL	[8, composite wrap]	7543.84	Pass
	Random #1	[7, composite wrap]	7937.14	Pass
	Random #2	[11, composite wrap]	10345.54	Fail (0.011)
2	RL	[16, composite wrap]	5955.43	Pass
	Random #1	[10, composite wrap]	7110.79	Pass
	Random #2	[19, composite wrap]	17596.18	Fail (0.053)
3	RL	[7, composite wrap]	7770.16	Pass
	Random #1	[4, composite wrap]	8490.66	Pass
	Random #2	[13, composite wrap]	54818.79	Fail (0.178)
4	RL	[3, composite wrap], [47, composite wrap]	11127.73	Pass
	Random #1	[2, composite wrap], [21, composite wrap]	14145.10	Pass
	Random #2	[7, composite wrap], [44, composite wrap]	60024.18	Fail (0.157)

CONCLUSIONS

- Pipeline corrosion is more likely to occur in soil environments with high moisture content, low pH, and high redox potential.
- The BNN model demonstrates robust predictions of corrosion with uncertainty.
- RL can dynamically optimize decision-making based on pipe condition and prediction model, contributing to reduced life cycle costs and lower failure risk.
- Integrating advanced AI tools into pipeline integrity management can enhance the realization of digital twins by enabling defect monitoring, degradation prediction, and intelligent maintenance planning.

ACKOWLEDGEMENT

USDOT PHMSA Competitive Academic Agreement Program (CAAP)

RUTGERS
THE STATE UNIVERSITY OF NEW JERSEY