



PHMSA

Pipeline and Hazardous Materials
Safety Administration

Pipeline Transportation: Hydrogen and Emerging
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Corrosion of Pipelines: from Machine Learning- Guided Damage Detection to Prevention/Mitigation

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Acknowledgment

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Outline

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- 2. Proposed Concept**
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1. Background

- Corrosion of oil/gas metallic pipelines

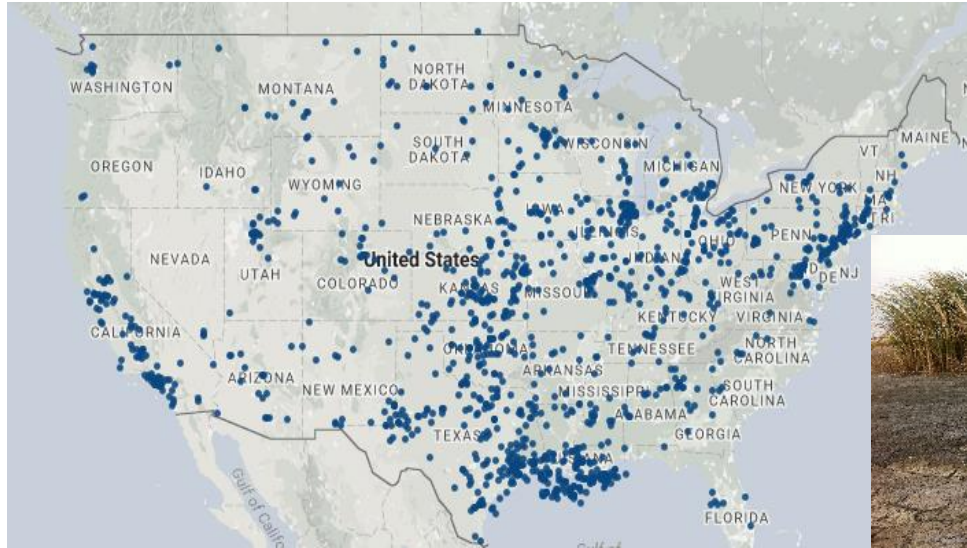


Fig. a Pipeline incidents in the United State¹



Fig. b Pipeline spill²

[1]. Photos from <http://projects.propublica.org/pipelines/>

[2] http://www.occupy.com/article/20000-barrels-spilled-north-dakota-pipeline-rupture?qt-article_tabs=2

1. Background

○ Corrosion of oil/gas metallic pipelines



Fig. 1 Internal corrosion: a) localized pits¹, b) fouling² and c) wear/erosion³

Table 1. Pipeline accidents in recent years at North Dakota (Pan et al., 2017⁴).

Accident	Location	Year	Loss
Pipeline spill	Tioga	2014	One gas pipeline exploded and burned
Pipeline spill	Tioga	2013	865,000 gallons (one of the largest to happen onshore in U.S. history)
Pipeline spill	Sargent County	2011	Spilling 400 barrels of crude oil
Pipeline spill	Neché	2010	Releasing 3,784 barrels of crude oil
Pipeline spill	Mantador	2004	Residents were evacuated, and a rail line was shut down
Pipeline spill	Barnes County	2003	Releasing 9,000 barrels of propane
Pipeline ruptured	Bottineau	2001	1.1 million US gallons (4,200 m ³) of gasoline burned
Pipeline spill	Harwood	2001	Spilling 40 barrels of fuel oil

[1]. Photos from <http://www.flickrriver.com/photos/59127492@N07/5416927808/>

[2]. Photos from <http://www.icorr.org/news/180/index.phtml>

[3]. Photos from <https://sites.google.com/site/metropolitanforensics/root-causes-andcontributing-factors-of-gas-and-liquid-pipeline-failures>

[4]. Pan, H.; Ge, R.; Xingyu, W.; Jinhui, W.; Na, G.; Zhibin, L. Embedded Wireless Passive Sensor Networks for Health Monitoring of Welded Joints in Onshore Metallic Pipelines. In *ASCE 2017 Pipelines*; 2017.

1. Background

○ Challenges:

- **Detection:** Sensing and assessing corrosion-induced damage (early-stage, data process of collected data with high variances, e.g., noise interference for signals)
- **Prevention/Mitigation:** Conventional coating systems (low-damage tolerance, inaccessible for repair)

2. Proposed Concept

○ Solutions:

Failure Mechanism

Removal of corrosive agents

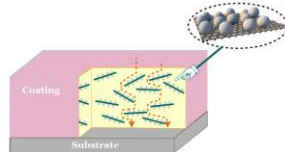


Corrosion of pipeline systems

Mitigation and Protection

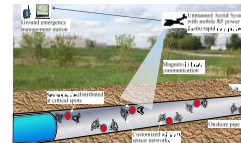
New nanocomposite coatings

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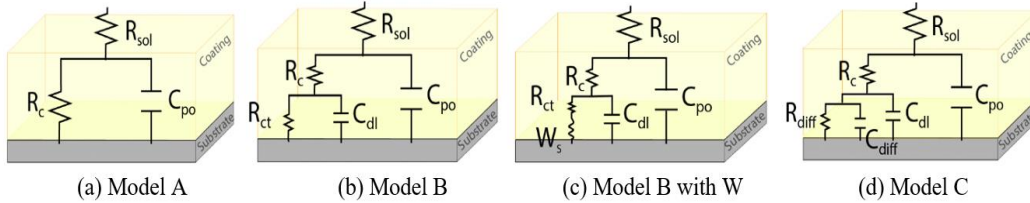
Monitoring and Diagnosis

Machine-learning guided damage detection

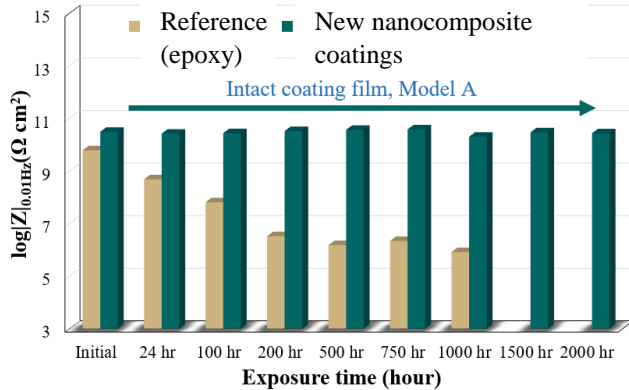
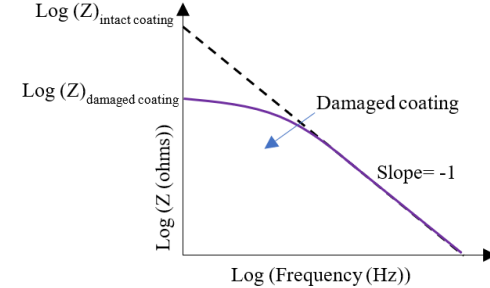


3. Case study—*New nanocomposite coatings*

○ Performance in terms of corrosion resistance:



Equivalent electrical circuit models at four stages: (a)-(d)

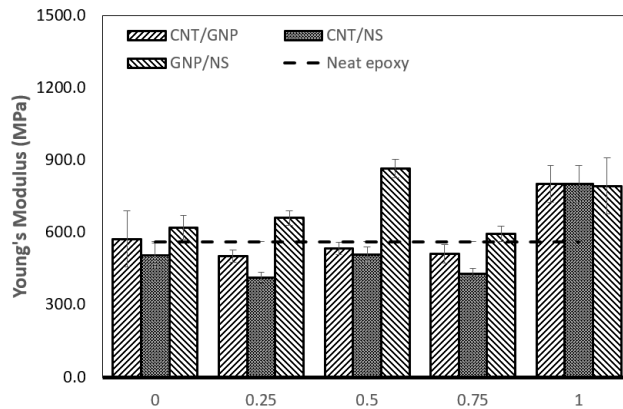
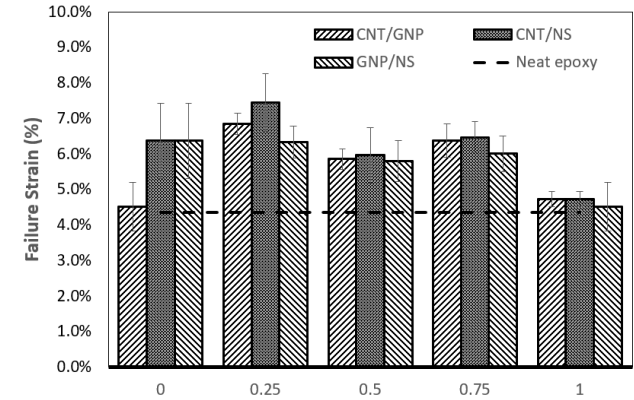
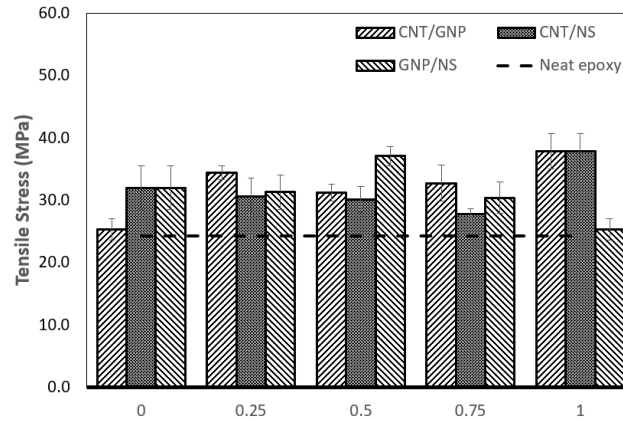


3. Case study—*New nanocomposite coatings*



○ Performance in terms of mechanical-tensile:

- Tensile strength
- Ultimate strain
- Young's modulus



3. Case study— *New nanocomposite coatings*



○ Performance in terms of mechanical-abrasion resistance:

- Mass loss after abrasion
- SEM image of abraded surface

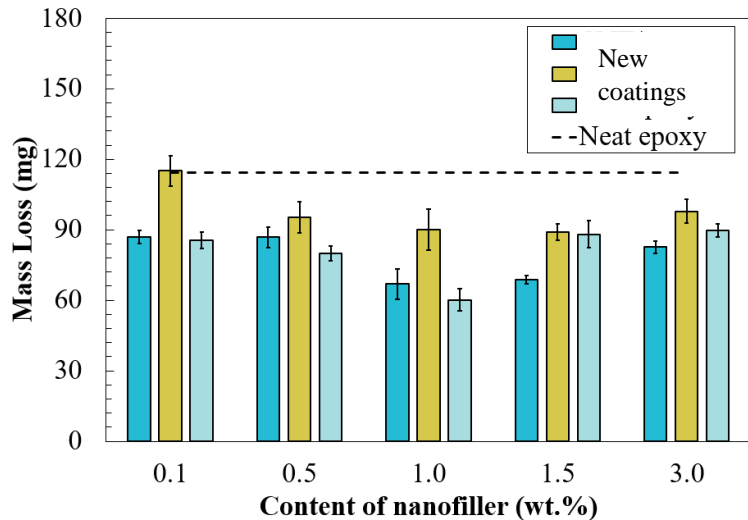


Fig. a Mass loss of nanocomposites

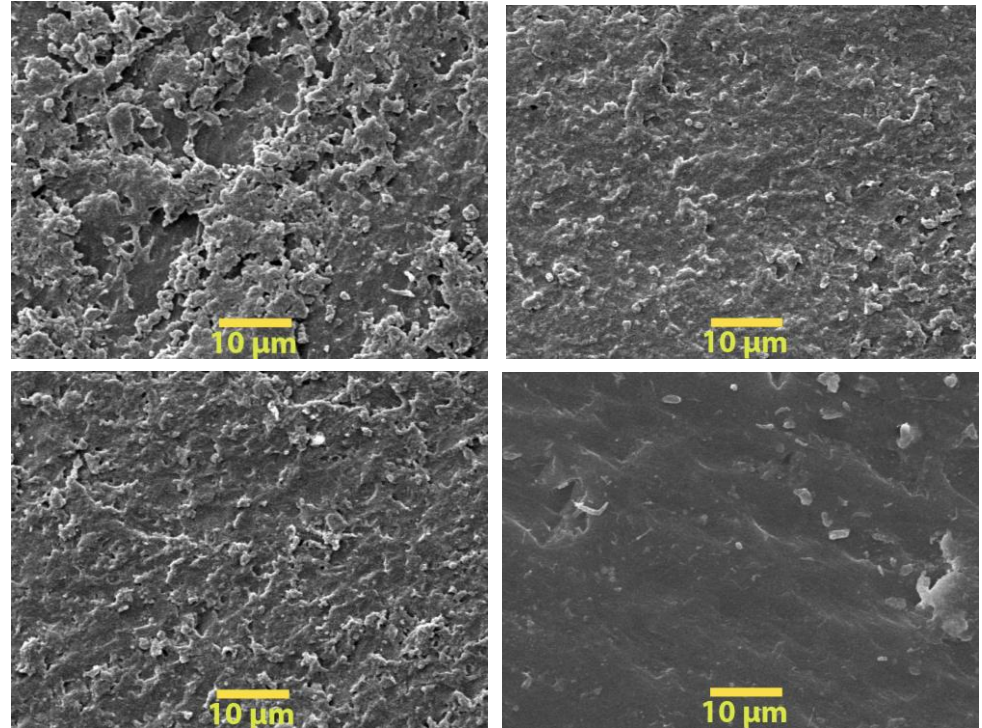


Fig. b SEM image of abraded surface

3. Case study— *New nanocomposite coatings*

- Performance in terms of wettability:

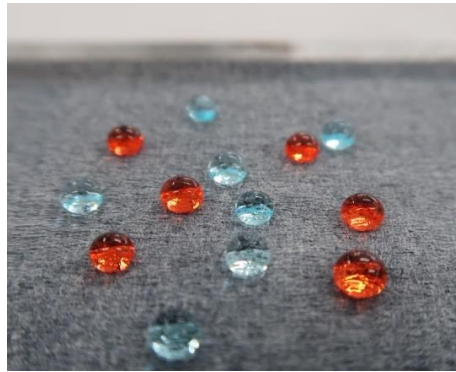


Fig. a Picture of water (blue) and hexadecane (red) on new coating

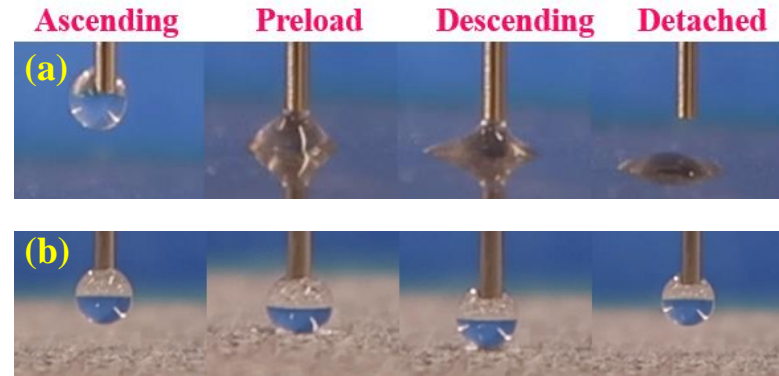
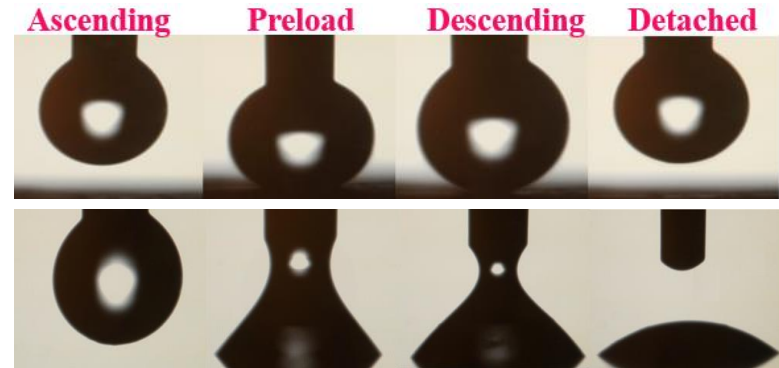
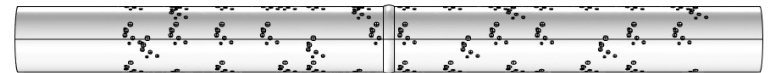
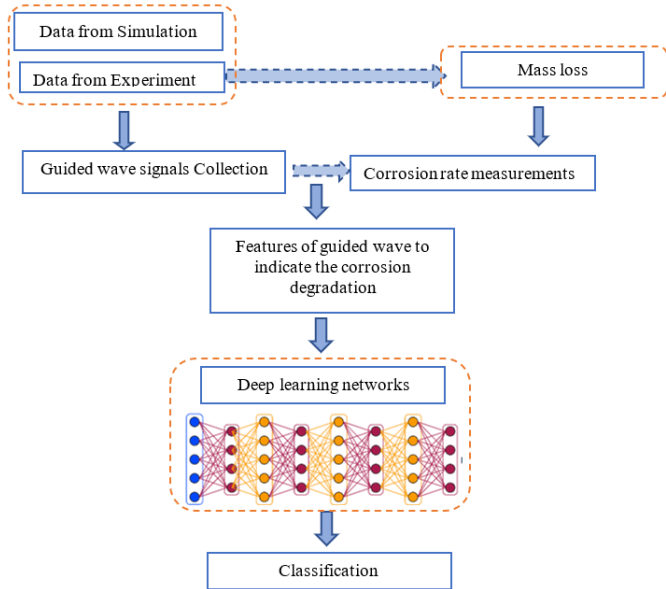


Fig. b Water droplet ascending and descending of (a) neat epoxy, (b) high-performance coating

3. Case study— *Machine-learning guided damage detection*

○ Machine learning guided damage detection:



Time: 5E-5 s



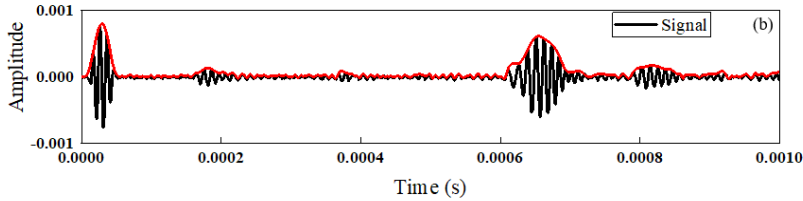
Time: 1E-4 s



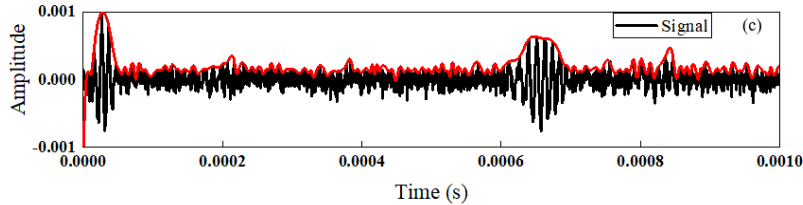
3. Case study—*Machine-learning guided damage detection*

○ Machine learning guided damage detection:

-Noise interference



(a) SNR=100 dB



(b) SNR=80 dB

Accuracy: 100.00%

	S1	S2	S3	S4	S5	S6
S1	100.0% 100	0.0% 0	0.0% 0	0.0% 0	0.0% 0	0.0% 0
S2	0.0% 0	100.0% 100	0.0% 0	0.0% 0	0.0% 0	0.0% 0
S3	0.0% 0	0.0% 0	100.0% 100	0.0% 0	0.0% 0	0.0% 0
S4	0.0% 0	0.0% 0	0.0% 0	100.0% 100	0.0% 0	0.0% 0
S5	0.0% 0	0.0% 0	0.0% 0	0.0% 0	100.0% 100	0.0% 0
S6	0.0% 0	0.0% 0	0.0% 0	0.0% 0	0.0% 0	100.0% 100
	S1	S2	S3	S4	S5	S6

Target State

(a) SNR=100 dB

Accuracy: 91.17%

	S1	S2	S3	S4	S5	S6
S1	99.0% 99	0.0% 0	0.0% 0	0.0% 0	0.0% 0	0.0% 0
S2	0.0% 0	96.0% 96	2.0% 2	1.0% 1	0.0% 0	0.0% 0
S3	0.0% 0	2.0% 2	88.0% 88	1.0% 1	3.0% 3	5.0% 5
S4	0.0% 0	2.0% 2	2.0% 2	91.0% 91	8.0% 8	8.0% 8
S5	1.0% 1	0.0% 0	4.0% 4	4.0% 4	86.0% 86	0.0% 0
S6	0.0% 0	0.0% 0	4.0% 4	3.0% 3	3.0% 3	87.0% 87
	S1	S2	S3	S4	S5	S6

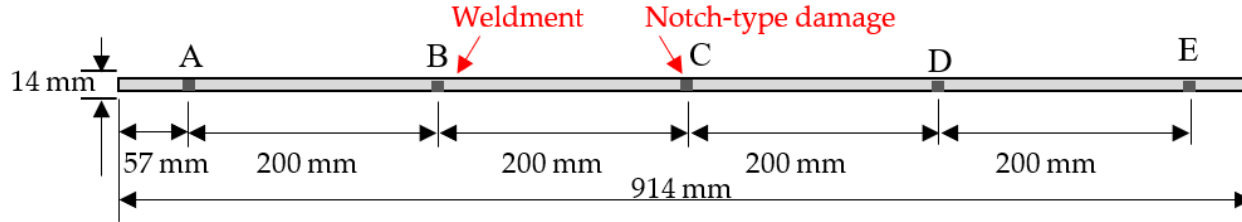
Target State

(b) SNR=80 dB

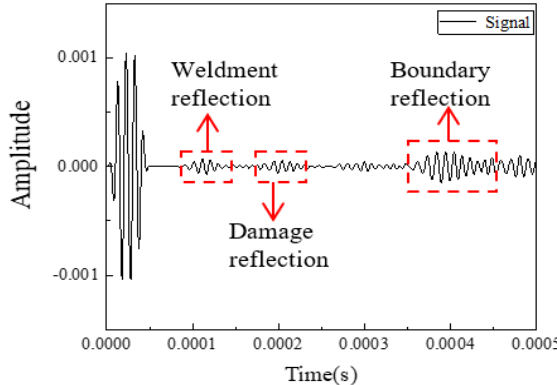
3. Case study—*Machine-learning guided damage detection*

○ Machine learning guided damage detection:

-Material discontinuity



(a) Plate with a butt welded joint at point B and a 6-mm long notch-type damage at point C.



(b) Signal collected from point A

Table 1, Comparison of accuracy in two cases

Noise level	120 dB	110 dB	100 dB	90 dB	80 dB
Without weldment	100.00%	100.00%	100.00%	100.00%	56.4%
With weldment	100.00%	100.00%	80.00%	73.10%	65.71%

3. Case study— *Machine-learning guided damage detection*

○ Machine learning guided damage detection:

-Shallow learning

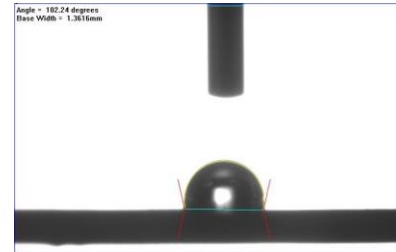
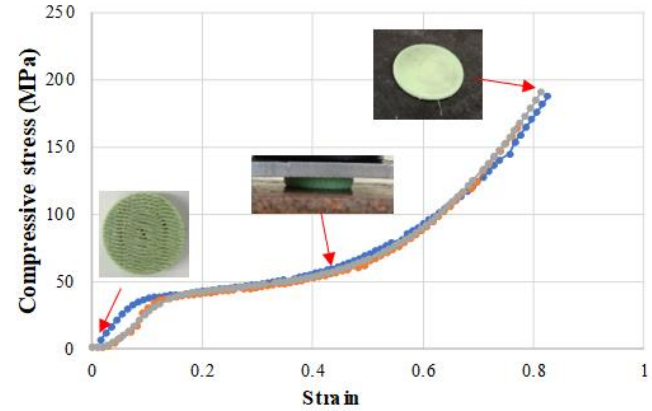
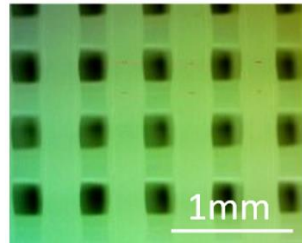
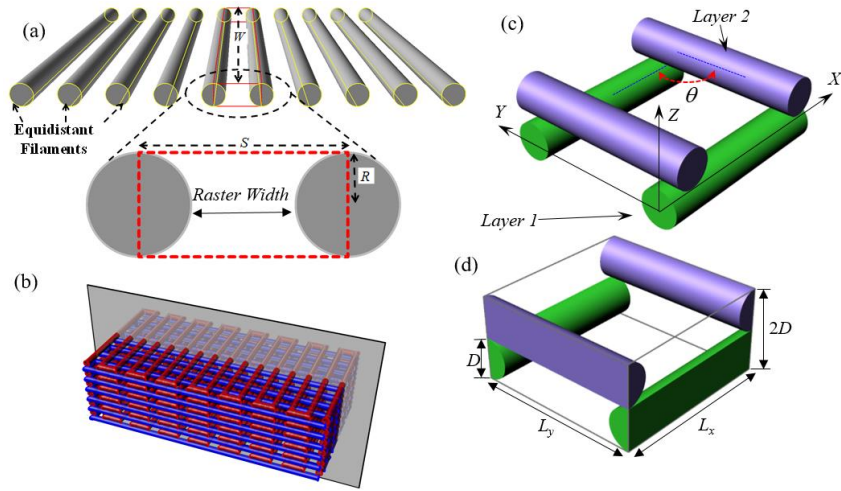
Method		Classification by physics-based			Classification by SVM		
Features		Amp	Frq	RMS	No feature selection		Feature selection
					Physics based Features	All Features	Selected features
Noise level	120dB	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
	110dB	97.71%	100.00%	98.86%	98.86%	98.86%	100.00%
	100dB	81.14%	86.29%	84.00%	92.00%	84.00%	95.43%
	90dB	44.00%	64.00%	72.00%	80.00%	72.00%	86.29%
	80dB	19.43%	34.86%	39.43%	53.71%	39.43%	56.00%

-Deep learning

	100 dB	90 dB	80 dB	70 dB	60 dB
SVM_WT	98.5%	84.1%	57.3%	31.4%	26.5%
SVM_PH	100%	91.1%	64.9%	42.2%	26.5%
SVM_ALL	100%	100%	100%	84.00%	46.4%
SVM_FS	100%	100%	98.4%	77.9%	49.9%
CNN	100%	100%	100%	88.75%	62.5%
Resnet	100%	100%	100%	93.19%	67.69%

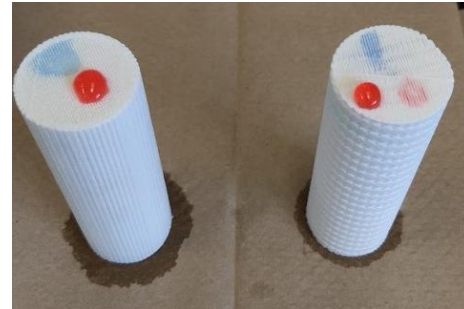
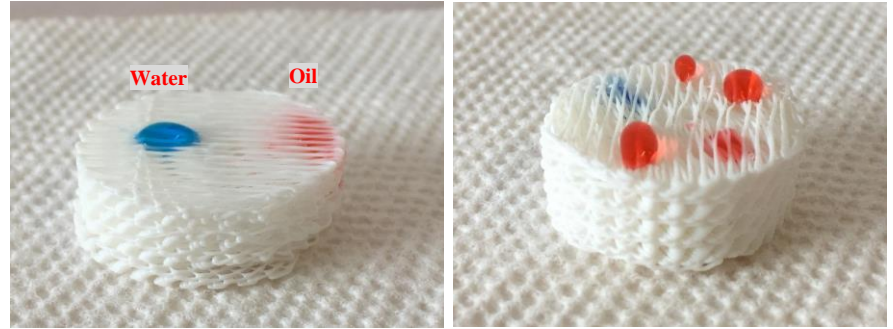
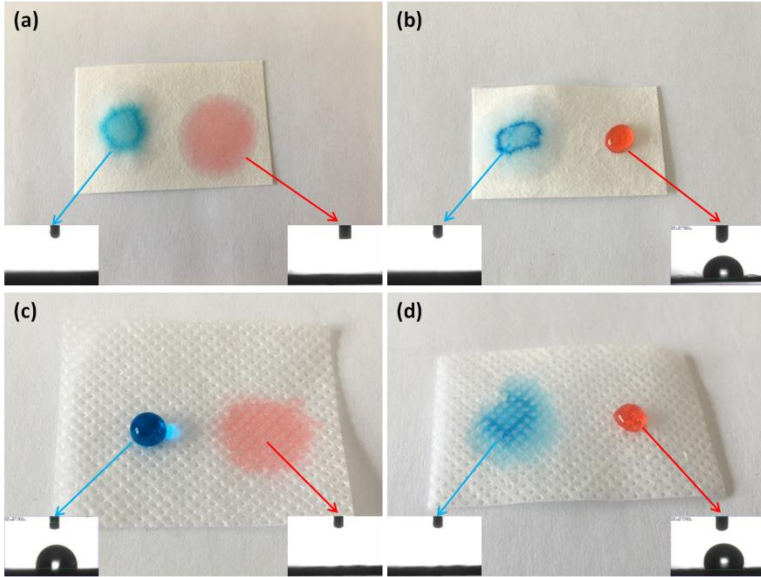
3. Case study—*Removal of corrosive agents*

○ 3D printing lattices for water/oil separation:



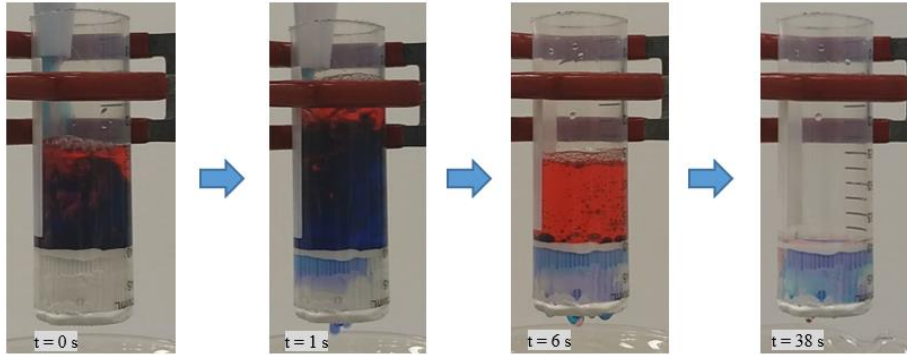
3. Case study— *Removal of corrosive agents*

- 3D printing lattices for water/oil separation:

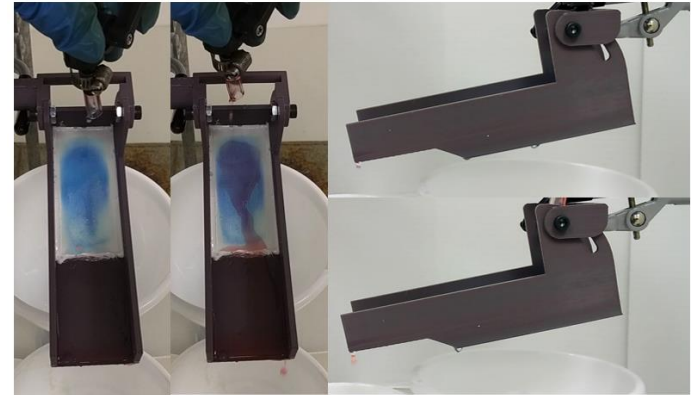
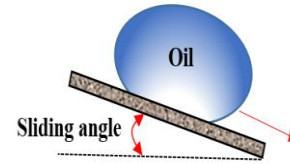
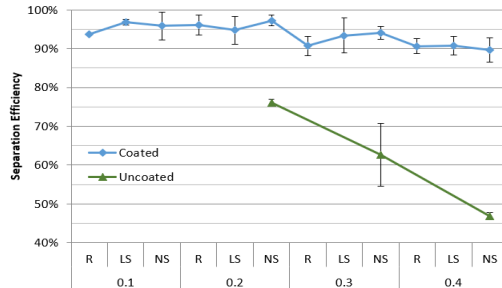


3. Case study— *Removal of corrosive agents*

○ 3D printing lattices for water/oil separation:



0.2-mm 3D printing LS type lattices



Sliding angle

4. Summary

- The projects aimed to address corrosion issues experienced in pipelines from different perspectives.
- The proposed nanocomposite coatings with high damage tolerance as well as superior corrosion resistance as one solution for pipeline corrosion control and prevention
- The proposed machine learning guided framework for early-stage corrosion-induced damage detection for pipelines
- The proposed approach for removal of corrosive agents (e.g., water) for pipeline corrosion prevention

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