Modeling Slow Crack Growth under Thermal and Chemical Effects and Accurate NDT of Cracks for Fitness Predictions of Polyethylene Pipes

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Srivastava Lab







Team

- Sponsor: USDOT PHMSA (CAAP Award# 693JK32050001CAAP)
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- Cost Share and Support: Brown University School of Engineering and Brown Graduate School

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PI energy industry work

ExxonMobil Upstream Research, Offshore (Houston, TX)	
Subsea and Arctic Senior Research Engineer	2010
Worldwide Deepwater Drilling Coordinator	2011 – 2012
Marine Team Lead	2013 – 2014
ExxonMobil Corporate Strategic Research (Clinton, NJ)	
Advanced Research Associate	2015 – 2016
ExxonMobil Upstream Research, Offshore & Environment (Spring, TX)	
 Mechanics Team Lead and Fitness for Service Area Lead 	2017 – 2018
Senior Technical Professional Advisor - Mechanics of Materials	2018



Objectives

Plastic pipes are increasingly used due to their lightweight, low installation costs, ease of maintenance, and corrosion resistance, with **8.3 billion feet of plastic pipeline** (4.4 billion feet Main and 3.9 billion feet service) transporting natural gas and 55 million residential and commercial gas lines (service). High-density PE (HDPE) is preferred polymer for gas transport lines. *2022 data

Non-visible flaws can grow over time and can cause catastrophic failure.

Objective 1: Develop a slow crack growth model for HDPE that accounts for the effects of stress loading with the *thermal and chemical effects*.

Objective 2: Develop a method using computational finite element simulations for convolutional neural network (CNN) to accurately predict embedded hidden crack's key characteristics for HDPE. (*The key is to be able to quantify crack using a fast microsecond raw ultrasound wave data that is essential to scan long pipelines*)

Objective 2 helps detect and quantify existing cracks using a proposed new NDE approach, and Objective 1 is aimed to provide a better assessment of HDPE pipeline integrity by helping predict the remaining life when a crack is detected and sized.



Research tasks performed

Objective 1 research activities

- Experimental work to study creep, very slow strain rate, and rate-dependent response of HDPE.
- Studied, analyzed and compiled relevant experimental data from published long-term creep tests of HDPE samples under different chemical and thermal exposures.
- Developed a new slow crack growth model incorporating the stress, thermal and chemical effects.
- Calibrated the model parameter using experimental data
- Checked the model's predictive abilities using independent experimental data.

Objective 2 research activities

- Developed and proposed an automatic crack characterization ultrasonic non-destructive evaluation (NDE) method using neural network models to eliminate human involvement.
- Develop finite element simulations for ultrasound NDT of HDPE.
- Applied high-fidelity synthetic data from finite element simulations to train a CNN for two critical crack parameters of various lengths and locations for embedded hidden cracks.
- Built an experimental set-up and conducted ultrasound NDT on HDPE specimens to independently validate the performance of FEA-trained CNN in accurately predicting both the location and size of embedded cracks simultaneously in real-life HDPE test specimens.



Research Outcomes 1:

A new slow crack growth model for highdensity polyethylene under thermal and chemical environment



Failure in polyethylene pipes



H. Hamouda et al, *Polymer* 42 (12), 2001 Almomani et al., *Materials & Design* 227, 2023



Crack-tip opening distance (COD) in slow crack growth







COD versus time for a typical PE material

$$\dot{\delta} = \frac{\delta_b - \delta_0}{t_b - t_0}$$



Brown and Lu, *Polymer* 36, 1995 Almomani et al., *Materials & Design* 227, 2023



Proposed SCG model for chemical environment exposure



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Proposed SCG model for chemical environment exposure



Time to failure is based on the final failure crack length or CTOD criteria.



New SCG model

Parameter	Description	Parameter	Description
$\dot{\delta}$	COD rate (m/s)	à	crack depth growth rate (m/s)
σ_1, σ_2	fitting parameters (Pa)	σ	applied stress (Pa)
E	Young's modulus (Pa)	ν	Poisson's ratio
Y	geometric factor	a_0	initial crack length (m)
η	viscosity (Pa.s)	d_0	primordial thickness (m)
Q	activation energy (J/mol)	R	universal gas constant (J/mol.K)
T	temperature (K)	κ	chemical exposure constant
x	unit correction factor (m)	m, n	exponents

Parameters in the proposed SCG model

 $\begin{array}{l} m \;=\; 10,\; n \;=\; 5 \\ Q_{water} \;=\; 100\; kJ/mol, \; Q_{Arkopal} \;=\; 110\; kJ/mol \\ \sigma_1 \;=\; 121\; KPa, \; \sigma_2 \;=\; 67\; MPa \\ d_0 \;=\; 35\; \mu m, \; \eta \;=\; 1.13e10\; Pa\; s \end{array}$



SCG experiments



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Sample Post-Failure



CREEP TESTS TIME TO FAILURE AT 3 MPA:

No chemical exposure (Air) - 160 days With chemical pre-exposure (Igepal) – 100 days

Scanning electron microscope (SEM) image



SEM images of creep test HDPE samples captured at 1000X



Creep/Slow crack growth experimental data

Experimental data: Elongation for various temperatures (FNCT – Full Notched Creep Test specimens)



Experimental data from Schilling et al, Polymer Testing 64 (2017)

Conversion approximation:

$$a = \frac{l}{\left(\frac{\sigma}{\sigma_{ref}} - 6.2\right)}$$

where σ_{ref} (= 1.25 MPa)

Arkopal structure

$$C_{9}H_{19} = O = O = (CH_{2} - CH_{2} - O)_{X}H$$

Nonylphenolpolyglycolether (x = number of added-on molecules of ethylene oxide)

Arkopal (also Igepal) (nonylphenolpolyglycolether), is a nuonionic surfactant used as an environment stress cracking ESC agent to accelerate SCG in polyethylene and is the standard for ESC testing under ASTM *D1693* (Standard Test Method for Environmental Stress-Cracking of Ethylene Plastics)



Calibration of new SCG model









Absolute values are approximations, but the relative values and trends are quite relevant.

Stress, Temperature and Chemical Environment Dependent SCG Predictions from the new model





SCG model prediction for single edge notched specimens



Comparison of COD rate ($\dot{\delta}$) of the single edge notch test (SENT) specimen obtained from new SCG model with experimental data of Brown and Lu. Only basic properties for the experimental material and the geometry parameter (Y) were updated. *This was intended for independent validation of the model*.



Brown and Lu, Macromolecular Symposia (1991)



Very slow strain rate and rate dependent response experimental study



MTS mechanical testing machine with temperature chamber

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SEM images of the fracture surface near the crack initiation of HDPE samples (0.0003 s–1 strain rate) for different temperatures and exposure environments

(a) Air 22 °C, (b) Air 37 °C, (c) Air 50 °C,
(d) Igepal 22 °C, (e) Igepal 37 °C, (f) Igepal 50 °C,
(g) PBS 22 °C, (h) PBS 37 °C.



Rate and temperature dependent response of HDPE under different exposure



Strain Rate =		$0.0003 \ s^{-1}$	
Treatment	Temperature	E	σ_{max}
	(°C)	(MPa)	(MPa)
Air	22	383	38
Air	37	218	26
Air	50	143	22
Igepal	22	348	33
Igepal	37	233	25
Igepal	50	165	21

Research Outcomes 2: Crack Length and Position Measurements using Ultrasound NDT and CNN

Crack length *a* is one of the most critical parameter

$$\dot{\delta} \propto a^m$$
 where $m > 0$ (Slow Crack Growth Model) (1)
 $\sigma_f \propto a^m$ where $m = -\frac{1}{2}$ (Linear Elastic Fracture Mechanics) (2)



Nondestructive evaluation (NDE)

NDE is a non-destructive evaluation inspection technique used to detect and characterize flaws in structures without damaging the material.

- Ultrasonic testing
- Infrared testing
- Electromagnetic testing
- Magnetic particle testing

Example: ILI detects flaws using smart pipeline integrity gauges (PIGs) with NDT techniques



Manual ultrasound NDT



Ultrasonic smart PIG

MEASURING DEFECTS





Willems et al., *European Conference on Non-destructive Testing*, 2010 https://www.dacon-inspection.com/pipeline-services/intelligentpigging/ultrasonic-in-line-inspection-ili-pigging/

https://www.eddyfi.com/en/product/rscan-manualultrasonic-system



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Motivation

Current HDPE pipe integrity challenges:

- Interpretation from human operator
- <u>Black line</u>: ideal interpretation (metal)
- Blue dots: real experiment data (metal)
- Lack of fast quantification NDE

Current limitations:



ML when trained can be very useful but where is the data?

"Information for the procurement and conduct of NDT," *The British Institute of Non-Destructive Testing*, 2008.



2. Lack of training data from experiments

Training data fact sheet

- Very scarce for hidden flaw
- Not well-labeled
- Extremely costly from experiments



Quantification of an embedded crack: Our methodology

Our Proposed Method:

- FEA of ultrasound NDT A scan (fast scan)
- Simulation-based, well-labeled training data
- Microseconds fast obtained unprocessed1D signal-based (Ultrasound A-scan based) CNN

(The proposed method solves the problem of a lack of a non-destructive evaluation methodology that can **rapidly and accurately** predict embedded crack length and position simultaneously in long HDPE pipes.)

• Validation with independent real-life lab experiments



Computation





3D numerical simulation representing ultrasound NDT

Abaqus/Explicit

- Dynamic analysis
- Time dependent pressure BC
- Nodal displacement



3D Geometry. Penny-shaped crack. Crack length/size to its thickness ratio varied from 2 to 12.

Parameter	Length	Position
Min	$1 \mathrm{mm}$	$3 \mathrm{mm}$
Max	$6 \mathrm{mm}$	$11 \mathrm{~mm}$

Pulse amplitude

$$A = \begin{cases} \cos(2\pi ft) \left[1 - \cos\left(\frac{2\pi ft}{m}\right) \right], & 0 \le t \le \frac{m}{f} \\ 0, & \text{otherwise.} \end{cases}$$

Averaged 3-direction displacement

Signal (t) =
$$\frac{1}{n} \sum_{i=1}^{n} u_3^i(t)$$

Normalization





FEA mesh





1 MHz Ultrasound

1D Convolutional neural network (CNN)



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Results: Training and testing of a CNN

CNN was trained for 2000 epochs for a learning rate of 0.0005

1600 training data, 100 testing data



Embedded crack characterization	Crack feature	Length	Location
	Error (MAPE)	3.2%	2.5%



Validation using HDPE samples: sample preparation





Validation using physical ultrasound NDE experiments

Ultrasound transducer

- Single element
- Straight beam
- 1 MHz
- 12.7 mm diameter



Olympus Epoch 650 Ultrasonic Flaw Detector



Ultrasound sensor with a hydrogel couplant on a material sample



Accurate quantification of multiple crack features

- The CNN that was pre-trained only by simulation signals
- Results are shown for crack feature predictions on 25 experimental signals;









The methodology can be applied to curved geometries such as pipelines.

Closing remarks

1. SCG Model:

A new model for Slow Crack Growth in HDPE that incorporates thermal and chemical effects has been developed.

2. Chemical Exposure Effects:

Findings show significant differences in failure times between chemically exposed and unexposed HDPE, underscoring the importance of including chemical exposure in the SCG model.

3. Machine Learning in Non-Destructive Evaluation (NDE):

The study successfully applies machine learning to process fast microsecond acquired unprocessed ultrasound time signals for measuring embedded cracks in HDPE, offering a faster, feasible and more accurate alternative to traditional NDE methods.



Closing remarks (Continued)

4. Industry Implications:

- Future recommendations include further tests and work for SCG model validation, parameter calibrations and model modifications *as needed for specific materials, chemical environments and applications*.
- It is recommended to customize the proposed FEA and CNN-based NDE method for plastic pipeline NDE considering key field variables and flaw types.
- The proposed method should be considered for further development and deployment of advanced NDE units equipped with machine-learning (ML) analysis chips for field use (e.g., an ultrasonic detector with NN in an ILI).
- The proposed method of physically accurate simulations to train ML for NDE can also be applied to other NDE techniques.



Closing remarks (Continued)

5. Current and Future Critical Research Needs:

- Need strong support and leadership from federal agencies, industry partners and university researchers to work together to develop robust understanding and 3D models for polymer damage under stress, thermal and chemical exposure.
 - Scientifically and carefully study *microstructural damage mechanisms* in important polymers and develop physics-based continuum scale (practical length scales) 3D damage and failure theoretical frameworks and constitutive models for broader applicability.
- Polymer failure research is critical for onshore (pipelines) and offshore (pipelines, flexibles, risers, etc.) structures where polymers are subjected to long-term exposure degradation and stress.
 - Continued commitment towards (polymer) structural safety from DOT, industry and academia is greatly appreciated.



Closing remarks (Continued)

5. Relevant Publications:

- Sijun Niu, Venkatsai Bellala, Daanish Qureshi, and Vikas Srivastava, A machine learning method to characterize the crack length and position in high-density polyethylene using ultrasound, *arxiv.org*, 2023. <u>https://doi.org/10.48550/arXiv.2304.11497</u>
- Sijun Niu and Vikas Srivastava, Simulation trained CNN for accurate embedded crack length, location, and orientation prediction from ultrasound measurements, *International Journal of Solids and Structures*, 242, 111521, 2022. <u>https://doi.org/10.1016/j.ijsolstr.2022.111521</u>
- Sijun Niu and Vikas Srivastava, Ultrasound classification of interacting flaws using finite element simulations and convolutional neural network, *Engineering with Computers*, 1-10, 2022. <u>https://doi.org/10.1007/s00366-022-01681-y</u>
- Sijun Niu, Enrui Zhang, Yuri Bazilevs, and Vikas Srivastava, Modeling finite-strain plasticity using physicsinformed neural network and assessment of the network performance, *Journal of the Mechanics and Physics of Solids*, 172, 105117, 2023. <u>https://doi.org/10.1016/j.jmps.2022.10517</u>



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The project Page with the Final Report and debrief presentation can be found here.

https://primis.phmsa.dot.gov/matrix/PrjHome.rdm?prj=893

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