CAAP Annual Report

Date of Report: *09/31/2024*

Prepared for: *U.S. DOT Pipeline and Hazardous Materials Safety Administration*

Annual Period: **From** *(10, 1,2023)* **to** *(10, 01, 2024)*

Contract Number: *693JK32250007CAAP*

Project Title: *Accelerating Transition towards Sustainable, Precise, Reliable Hydrogen Infrastructure (Super-H2): Holistic Risk Assessment, Mitigation Measures, and Decision Support Platforms*

Prepared by: Zhibin Lin (PI), Kevin Wang, Jace Anderson, Hong Pan, Xingyu Wang

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Section A: Business and Activities

(a) Contract Activities

- Contract Modifications: N/A
- Educational Activities:
  - Student mentoring:

Mohsin Ali Khan, a Ph.D. student in Civil Engineering at North Dakota State University, began working on the project in the second quarter.

Student internship: N/A

Zahoor Hussain, partially collaborating on Dr. Ying Huang's CAAP project, is a Ph.D. student in Civil Engineering at North Dakota State University. He also joined the project in the second quarter.

Student internship: N/A

Xuanyu Zhou, a master's student in Civil Engineering at North Dakota State University, started contributing to the project in the second quarter.

Student internship: N/A

Allison Fleck, an undergraduate student in Civil Engineering at North Dakota State University, began working on the project in the second quarter.

Student internship: Related to pipelines and water during Summer 2024.

Wentao Ma, a Ph.D. student in the Department of Aerospace and Ocean Engineering at Virginia Tech, commenced work on the project in the first quarter.

Student internship: N/A

Noah Eilers, an undergraduate student in the Department of Aerospace and Ocean Engineering at Virginia Tech, started working on the project in the second quarter.

Student internship: N/A

  - Educational activities:

During the spring semester of 2024, Dr. Lin (PI) and his team organized an engineering series for high school students (approximately 100 students), introducing them to various engineering structures, including pipelines. This series is scheduled to continue through the spring and into the summer semester of this academic year.

  - Career employed: N/A
  - Others: N/A

- Dissemination of Project Outcomes:

Publications (+ advised student, * corresponding author)

Li Shang+, Zi Zhang+, Fujian Tang, Qi Cao, N. Yodo, Hong Pan+, Zhibin Lin* (2024). "Deep Learning Enriched Automation in Damage Detection for Sustainable, Resilient Operation in Pipelines with Welding Defects under Varying Embedment Conditions." *Computation*; accepted.

Li Shang+, Zi Zhang+, Fujian Tang, Qi Cao, Hong Pan+, Zhibin Lin* (2024). "Signal Processing of Ultrasonic Guided Waves for Damage Detection of Localized Defects in Plates: From Shallow Learning to Deep Learning." *Journal of Data Science and Intelligent Systems*; accepted.

- Citations of The Publications: N/A
- Others:

(b) Financial Summary

- Federal Cost Activities:
  - PI/Co-PIs/students involvement:

  Meeting Schedule: The research team, including PI Dr. Lin, Co-PIs Dr. Wang, Dr. Pan, and Mr. Anderson, along with the students, meet bi-weekly during the first year.

  Task Supervision: Each PI supervises their respective teams to ensure the tasks are executed as planned.

  - Materials purchased/travel/contractual (consultants/subcontractors):

  Testbed Development: Co-PI Mr. Anderson from EERC is responsible for planning and designing the testbed for accelerated pipeline testing in hydrogen environments, which also includes securing the required materials.

- Cost Share Activities:
  - Cost share contribution:

  The cost share is covered by contributions from NDSU and Virginia Tech, such as faculty academy hours (from Dr. Lin and Dr. Wang) and RA tuition waivers for several Ph.D. students.

  Budgetary Considerations:

  A detailed cost breakdown by category is presented in the budget proposal (refer to Table 1). However, due to delays in budget processing from Virginia Tech and EERC, actual expenses may vary from the initially planned budget.

Table 1 Cost breakdown during the reporting period (second year)

Category	Amount spent during the second year
Personnel	
Faculty	$10400
Postdoc	$40,800
Students (RA and UR)	$18,500
Benefits	$24,015
Operating Expenses	
Travel	$4,000
Materials and Supplies	$0
Recharge Center Fee	$0
Consultant Fee	$0
Subcontracts	Subawards issued
Indirect Costs	$93,515

(c) Project Schedule Update

- Project Schedule:

Table 1. Schedule of the proposed project and progress.

Tasks (Milestones)	Year 1				Year 2				Year 3			
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Task 1 (Milestone 1)	√											
Task 2 (Milestone 2)	√	√	√	→								
Task 3 (Milestone 3)		√	√	√	√	√	√	√				
Task 4 (Milestone 4)		√	√	√	√	√	→					
Task 5 (Milestone 5)					√	√	√	√				
Task 6 (Milestone 6)						√	√	√				
Task 7 (Milestone 7)	√	√	√	√	√	√	√	√				

√ Finished, → Ongoing.

Building on the proposed methods, we are continuously refining Task 2 to further explore research-oriented avenues, aiming to enhance the robustness of decisions regarding the repurposing of existing pipelines. This will not affect the progress of other tasks. Our multi-scale simulation model Task 4 is nearing completion; however, we are still actively conducting simulations for validation purposes, both for experimental results and mitigation strategies.

- Corrective Actions: N/A

(d) Status Update of the 8th Quarter Technical Activities

Task 2.1: Develop a risk assessment model for the pipeline under hydrogen effects.

During this quarter's research period, we concentrated on refining the entire framework for evaluating the suitability of pipelines for hydrogen transport. Given the diverse perspectives on suitability evaluation, we have developed a comprehensive framework that integrates these perspectives as shown in Figure 1. Each perspective is represented as an expert model, and we employ a mixture of expert gating mechanisms to dynamically adjust the selection and importance of each model. This approach provides a holistic evaluation of the existing pipelines' potential for repurposing to hydrogen transportation.

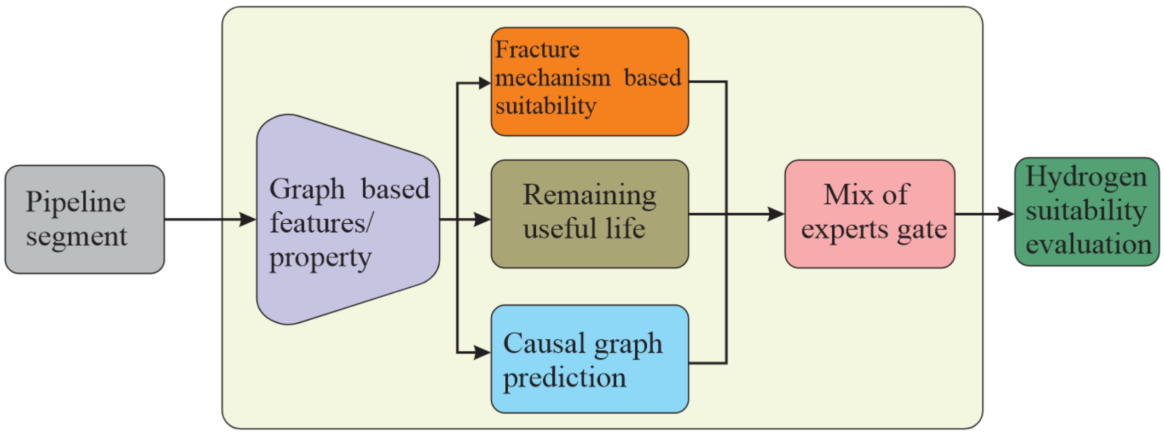


Figure 1. The robust framework for suitability evaluation

Task 3.1: Build Near real-world testbed.

During this quarter, the team led by Mr. J. Anderson from EERC has made significant progress in preparing the near real-world testbed for hydrogen testing. The design and manufacturing of material-level testing coupons are still in progress. These coupons will be crucial for assessing the performance and durability of materials under hydrogen exposure, providing vital insights for the broader implementation of hydrogen-based technologies.

In addition, the key equipment and infrastructure necessary for the testing setup have been successfully installed, and additional safety-related assessments are being finalized to ensure full compliance with rigorous safety standards.

Task 4.1: Understanding of long-term hydrogen impacts on materials and welding requirements in realistic environments through experimental study

During this reporting period, the Virginia Tech team, led by Dr. K. Wang, has made considerable strides in several critical areas of their research. First, the team has been actively developing and validating an advanced incompressible fluid dynamics solver. This solver is designed to enhance the precision of simulations involving incompressible fluids, a key aspect in understanding the behavior of gases like hydrogen under various flow conditions. The successful validation of this solver ensures its reliability and sets a foundation for further applications in hydrogen-related studies.

In addition, the team is conducting an in-depth review of the existing hydrogen transport computational model. This review aims to refine the model to better capture the complexities of hydrogen transport, particularly under conditions that may affect material performance, such as diffusion, permeation, and adsorption. By improving this model, the team hopes to gain deeper insights into the interactions between hydrogen and pipeline materials, which is crucial for predicting potential degradation mechanisms.

Moreover, the Virginia Tech team is addressing the long-term effects of hydrogen on materials. Specifically, they are simplifying the simulations of hydrogen's impact by focusing on fracture mechanics. This approach involves streamlining the modeling process to better understand how hydrogen contributes to fracture propagation and other structural failures over time. By reducing the complexity of these simulations, the team will efficiently evaluate the long-term risks posed by hydrogen to infrastructure, particularly in scenarios where hydrogen embrittlement and stress corrosion cracking may be concerns.

Task 5.1 Determine the impacts on component- and system-level pipelines.

During this quarter's research, we focused on aggregating the system-level impact of individual components. While system performance is often evaluated by summing the effects of each component, the overall system is influenced by more than just the sum of its parts. Complex interactions between components, operational conditions, and external factors play a significant role. As a result, it is essential to adopt a comprehensive modeling approach that integrates multiple variables at both the component and system levels. This model should incorporate a Remaining Useful Life (RUL) framework, accounting for the degradation and performance of individual components while capturing system-level dependencies and emergent properties. By doing so, we can achieve a more accurate and holistic evaluation of pipeline integrity and performance over time, enabling a robust risk assessment and informed decision-making process for pipeline maintenance and repurposing.

The RUL can be defined as the number of working Cycles, or the time left at a particular operating time as shown in Figure 2. RUL *is the time between the point of measurement and the Functional Failure of the asset.* P-F Curve is the graphical representation of an item's Resistance to Failure against Time. The curve expresses two effects (i) Each failure is preceded by a symptom (In case of a pipeline, what would be these symptoms, like what would be the measurable factors that can be considered as a symptom); (ii) Resistance degrades over time. As presented in Figure 2, on the P-F curve the potential failure point (PF) indicates the point where the symptoms of a future failure are detected. The age of the system goes into the functional failure (FF) stage where the resistance becomes unsatisfactory. The age of the component between PF and FF is known as **P-F interval**.

After the functional failure point the unsatisfactory performance of the pipeline starts and thus the time taken by the pipeline to reach FF is their useful life. In other words, it is the time for which the pipeline functions satisfactorily.

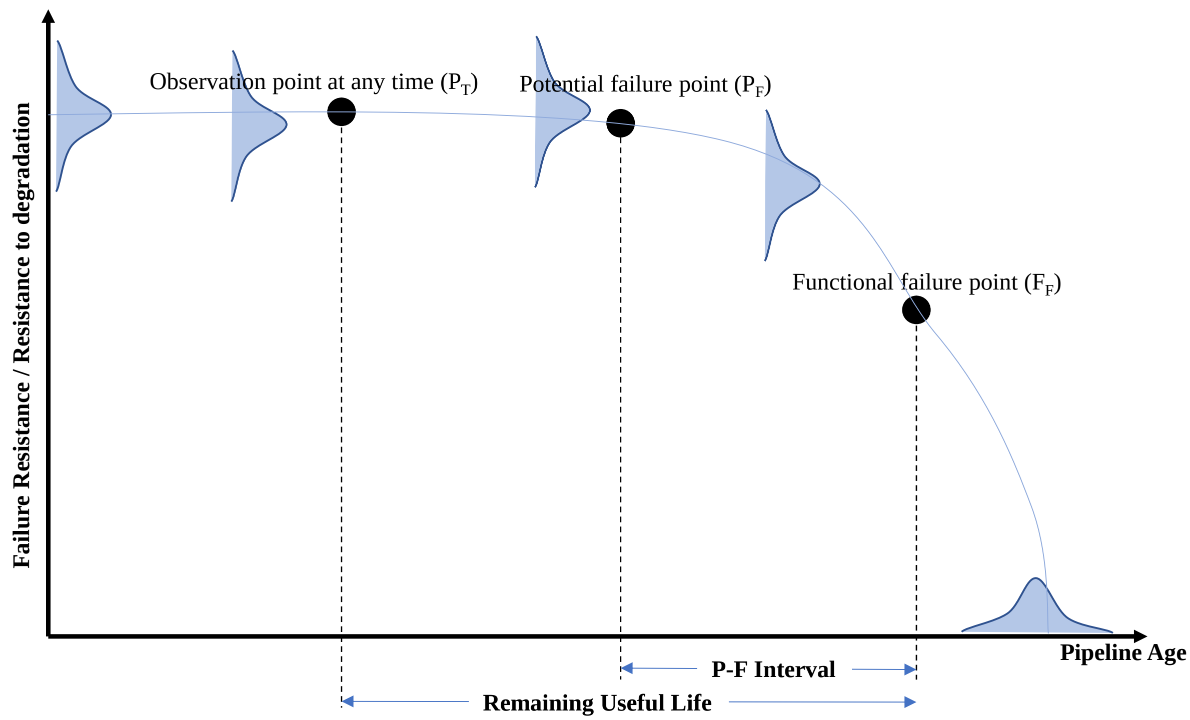


Figure 2. Graphical analysis of resistance to degradation of a system with respect to pipeline age

In case, we measure the useful life of a pipeline left (till it functions satisfactorily - FF) from a different point on the curve instead of the PF, then the P-F interval becomes RUL. For example, the RUL of a pipeline (whose life is 30 years), can be measured from the currently observed time (t) until the unsatisfactory working condition starts (FF point). RUL and P-F interval converge when the observation point indicates the start of the potential failure of the pipeline.

Because of the variations in historical data raised from different conditions, operational factors, and design parameters, every point on the P-F curve indicates the probability distribution (PDF). Therefore, when the P-F curve is repeated, it will show the distribution of curves, and thus the functional failure point will also be the distribution. The measurement of the time interval between two distributions results in another distribution. As a result, the RUL of the pipeline asset can be characterized by a range of possible values associated with a certain probability of occurrence.

Predictions inherently include uncertainty, and the curves illustrated above show the quantification of this uncertainty. The benefit of using predictive algorithms is that as the availability of data increases over time, the level of uncertainty diminishes. Therefore, the RUL prediction is uncertain at the beginning of a pipeline's lifecycle but becomes precise as the pipeline approaches functional failure. Concisely, it is advantageous to use the median of the RUL distribution as a single representative value of the estimate. Considering the probabilistic distribution, the RUL can be defined as “The probabilistic estimate of the duration over which the pipeline is expected to continue performing its intended function under specified conditions.” An accurate estimation of RUL is the first step in effective asset management. It is highly recommended that the maintenance strategies must incorporate RUL estimates along with other operational factors to align with a broader framework aimed at optimizing the pipeline performance and lifecycle management.

The temperature versus time chart is shown in the Figure 3, several data points can be observed, represented by dots. These data points allow for the extrapolation of the trend in temperature progression. If the critical temperature threshold is known, it can be easily anticipated when the system is approaching a critical event. This method facilitates the extrapolation, estimation, or prediction of the pipeline end-of-life (EOL) and the RUL is simply the difference between the current time and the predicted EOL. It is noteworthy that RUL can be estimated at multiple time intervals, which means that there is not a singular RUL but rather a series of RUL estimates over time, which evolve when fresh data becomes available.

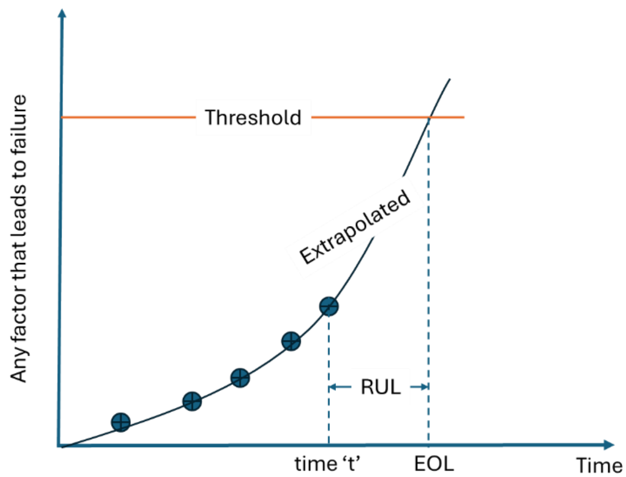


Figure 3. Generalized flow diagram of RUL estimation of a component/system

The generalized flow diagram for the RUL estimation is presented in Figure 3. Which involves several steps, which are explained in the next sections.

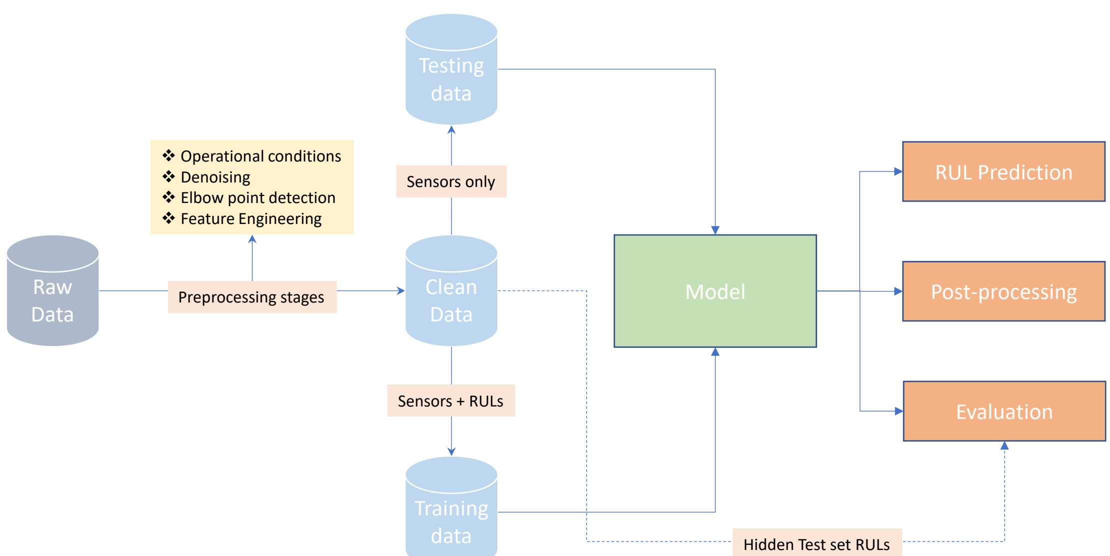


Figure 4. Different stages involved in the RUL estimation of component/system using artificial intelligence-based modeling

Task 6.1 Propose guidelines/best practices

To provide effective guidance on best practices for repurposing existing pipelines for hydrogen transportation, our team conducted a comprehensive literature review and summarized the key considerations as follows:

The methods for hydrogen mitigation when transforming existing pipelines primarily focus on addressing hydrogen's unique properties, such as material vulnerabilities and associated safety risks:

a) Material Compatibility: Evaluate the pipeline materials for susceptibility to hydrogen embrittlement, which can lead to material degradation through hydrogen-induced cracking. Apply protective coatings or replace vulnerable sections with materials that are resistant to hydrogen permeability and degradation.

b) Flow and Pressure Adjustments: Due to hydrogen's lower density compared to natural gas, pipeline pressure and flow dynamics must be adjusted to ensure both efficiency and safety. This includes implementing measures to prevent over-pressurization, which could compromise pipeline integrity.

c) Safety Enhancements: Given hydrogen's propensity to leak, advanced leak detection systems such as infrared, ultrasonic, or fiber-optic sensors should be employed. Additionally, fire suppression systems and explosion-proof designs are critical to mitigating hydrogen's high flammability risk.

d) Control Systems: Implement hydrogen-specific sensors and real-time monitoring systems for key parameters like pressure, temperature, and leak detection. Upgrades to SCADA systems should include automatic shut-off mechanisms to enhance safety in the event of leaks or other issues during hydrogen transport.

e) Testing and Certification: Begin with hydrogen blending (a hydrogen-natural gas mix) to test and assess pipeline integrity before transitioning to pure hydrogen. Follow established standards, such as ASME B31.12, which are specifically designed for hydrogen pipelines to ensure system safety and reliability.

f) Regulatory and Environmental Compliance: Conduct thorough environmental assessments to monitor potential hydrogen emissions and ensure compliance with regulatory standards. Collaborate with relevant authorities to align the pipeline transformation with hydrogen transportation safety regulations.

g) Personnel Training and Maintenance: Provide specialized training for personnel to handle hydrogen safely and effectively. Additionally, develop enhanced maintenance protocols, as hydrogen can accelerate wear and tear on pipeline materials, requiring more frequent inspections and upkeep.

This structured approach will help ensure that pipelines repurposed for hydrogen transport are both safe and efficient, while adhering to the necessary technical and regulatory standards.

Section B: Detailed Technical Results in the Report Period

1. Background and Objectives in the 2nd Annual Report Period

1.1. Background

The global transition towards a low-carbon future has placed hydrogen at the forefront of sustainable energy strategies, particularly as a key enabler for decarbonizing sectors that are challenging to electrify. Green hydrogen, produced through electrolysis powered by renewable energy sources such as wind and solar, is gaining momentum as a crucial vector for reducing carbon emissions in heavy industries like steel and cement manufacturing, as well as aviation, maritime transport, and long-term energy storage solutions. In line with the European Union's goal of achieving climate neutrality by 2050 [1], hydrogen is anticipated to play a substantial role in supplying clean energy to sectors that are resistant to conventional electrification due to technical and economic constraints [2].

A critical bottleneck in realizing a hydrogen-based economy is the creation of an efficient, scalable hydrogen transportation and distribution network [3]. Given the immense costs and logistical challenges associated with building a dedicated hydrogen pipeline infrastructure, the repurposing of existing natural gas pipelines has emerged as an attractive and economically viable solution. This approach leverages the existing pipeline infrastructure, significantly reducing capital expenditures and preventing the obsolescence of assets that would otherwise become stranded.

However, the technical complexity of this approach cannot be overstated. Hydrogen has unique physical and chemical characteristics that differ markedly from natural gas, and these properties introduce a range of engineering challenges [4]. Hydrogen molecules are much smaller than methane molecules, increasing the likelihood of leakage through even minute imperfections in the pipeline material. More critically, hydrogen is highly prone to embrittlement, a phenomenon in which the interaction of hydrogen with certain metals, particularly pipeline-grade steels, degrades the material's mechanical properties, making it more susceptible to crack initiation and propagation under stress [5].

To ensure the safe and efficient transport of hydrogen through repurposed pipelines, several key technical issues must be addressed. First, the pipeline materials must be assessed for hydrogen compatibility. This requires an in-depth evaluation of the microstructural properties of the steels currently used in natural gas pipelines, with particular attention to their susceptibility to hydrogen-induced cracking (HIC) and hydrogen embrittlement (HE) [5]. Advanced metallurgical analysis, including fracture mechanics studies, fatigue testing, and accelerated aging simulations under hydrogen exposure, are necessary to predict the long-term performance of these materials.

In addition to material compatibility, the repurposing process must account for operational parameters such as pressure, flow rate, and pipeline diameter, all of which impact the economic viability of hydrogen transport. Hydrogen's lower volumetric energy density compared to natural gas means that higher flow rates or increased pressure may be required to deliver the same energy output, potentially stressing pipeline systems beyond their original design specifications. Computational fluid dynamics (CFD) simulations, coupled with thermodynamic and mechanical stress analyses, are essential tools for optimizing the operational conditions of repurposed pipelines while ensuring structural integrity.

Another layer of complexity arises from the need to ensure safe pipeline operation in varying environmental conditions. Pipelines traversing regions with fluctuating temperatures or seismic activity may experience differential stress, exacerbating the risks associated with hydrogen embrittlement. Incorporating real-time monitoring systems using advanced sensors for detecting leaks, pressure drops, and material fatigue can provide early warnings of potential failures, allowing for proactive maintenance and risk mitigation.

Economic considerations also play a significant role in the decision-making process. The cost-effectiveness of repurposing versus constructing new hydrogen pipelines must be evaluated through a comprehensive life-cycle cost analysis (LCCA) [6]. This analysis involves not only upfront capital expenditures but also long-term maintenance, retrofitting costs, and operational efficiency. Public acceptance, regulatory frameworks, and environmental considerations further complicate the repurposing process, necessitating stakeholder engagement and policy alignment to ensure the project's long-term success.

Our current efforts are focused on developing an integrated decision-support framework that synthesizes these technical, economic, and regulatory factors. This framework leverages machine learning algorithms and data-driven risk models to evaluate the fitness of pipeline segments for hydrogen transport. By incorporating real-time data from monitoring systems and simulations, the framework will enable dynamic risk assessments and optimize decision-making for pipeline repurposing projects. Furthermore, we are exploring the use of knowledge graph-based approaches to map the relationships between material properties, environmental conditions, and operational factors, providing a more comprehensive understanding of the risks and opportunities involved in repurposing natural gas pipelines for hydrogen transport.

In summary, the transition to a hydrogen economy hinges not only on the production of green hydrogen but also on the development of a robust, efficient, and safe transportation infrastructure. Repurposing existing natural gas pipelines offers a cost-effective solution, but it requires overcoming significant technical challenges related to hydrogen's unique properties. Through a multidisciplinary approach that combines advanced materials science, computational modeling, real-time monitoring, and economic analysis, we aim to build a comprehensive framework to guide the safe and efficient transformation of existing pipeline infrastructure for hydrogen transport, thus accelerating the global shift towards a sustainable energy future.

1.2. Objectives in the 2nd Annual Report Period

In the second year of our project, we successfully met several key objectives as outlined in the 2nd annual report. Our primary focus was to assess the feasibility of utilizing existing pipelines for hydrogen transport through an extensive evaluation that incorporated theoretical modeling, simulation studies, and experimental testing. The following milestones were achieved:

a) Completed Development of the Decision Model Framework and Formulated a Comprehensive Decision Model (Task 2.1):

During this phase, we finalized the construction of the decision model framework, which integrates key parameters essential for evaluating the repurposing potential of existing pipelines for hydrogen transport based on graph-based feature properties. This comprehensive model incorporates a wide range of factors, including material properties, hydrogen-induced risks, operational conditions, and economic considerations. By leveraging a mix of expert gates and different "experts" perspectives, including, fracture mechanics, statistical remailing useful life, and causal graph-based model, the framework provides a robust, multi-criteria decision-making tool that facilitates the assessment of pipeline fitness for hydrogen use. The model will be instrumental in guiding future decisions on retrofitting pipelines and optimizing safety, cost efficiency, and performance.

b) Summarized and Building a Machine Learning-Based Remaining Useful Life Model for Repurposing Pipelines for Hydrogen (Task 2.1):

We have summarized various methodologies for predicting the remaining useful life (RUL) of pipelines repurposed for hydrogen transport. These methodologies include machine learning models, statistical models, and first-principles logic-based approaches. We are also working on developing a comprehensive model that integrates historical data, material degradation characteristics, operational stress factors, and the specific impact of hydrogen on pipeline integrity. The RUL model is intended to support proactive maintenance strategies, facilitating more accurate lifecycle management and reducing the likelihood of unexpected failures.

c) Designed and Implemented an Advanced Near-Real-World Testbed for Hydrogen Effects Analysis (Task 3.1):

We have designed and implemented an advanced near-real-world testbed aimed at analyzing the effects of hydrogen on pipeline infrastructure. This testbed simulates operational conditions to assess material degradation, stress responses, and the overall performance of pipelines repurposed for hydrogen transport. By closely replicating real-world scenarios, the testbed provides valuable insights into the long-term impacts of hydrogen exposure on pipeline materials. The results from these tests will inform the development of safer and more reliable pipeline systems, ultimately contributing to the optimization of hydrogen transport infrastructure.

d) Developed Multi-Scale Simulation Models for Fundamental Understanding of Hydrogen Effects (Task 4.1, Task 4.2):

Complex simulation models were successfully developed and validated during this reporting period, providing deeper insights into how hydrogen impacts pipeline integrity. Under the leadership of Dr. K. Wang, the Virginia Tech team focused on Tasks 4.1 and 4.2, which involved developing an incompressible fluid dynamics solver and reviewing existing hydrogen transport computational models. These intricate models allow for the exploration of hydrogen's behavior within the pipeline structure, contributing to a more profound understanding of long-term material degradation and enabling more accurate predictions and mitigation strategies for hydrogen transport systems')

e) Determine the impacts on component- and system-level pipelines (Task 5.1, Task 5.2):

During this phase, the research team developed a comprehensive framework to assess the impact of hydrogen on existing pipelines, focusing on critical factors like stress corrosion cracking (SCC) and hydrogen embrittlement (HE). The knowledge graph-based model evaluates both component- and system-level risks, considering material properties, weld quality, and surface conditions that influence susceptibility to hydrogen-related degradation. At the system level, corrosion and HE can lead to cascading failures, highlighting the need for robust monitoring and risk mitigation. This framework equips stakeholders with tools to optimize pipeline retrofitting for hydrogen transport, balancing safety, cost, and performance.

f) Propose guidelines and best practices for transitioning existing pipelines to support hydrogen transportation. (Task 6.1, Task 6.2):

We have synthesized essential guidelines and best practices to ensure a safe, efficient, and cost-effective transition of existing pipelines for hydrogen transport, anchored in a comprehensive integrity-driven framework. This approach emphasizes thorough assessments of mechanical properties, material integrity, and defect susceptibility, addressing critical risks such as stress corrosion cracking (SCC) and hydrogen embrittlement (HE). Key control measures, integrating mechanical, metallurgical, and environmental strategies, are recommended to mitigate these risks, along with regular inspection regimes and advanced nondestructive testing for early vulnerability detection. Additionally, tailored conversion roadmaps and integrity management plans are designed to balance safety, operational performance, and economic feasibility, optimizing the use of existing infrastructure for hydrogen transport while addressing emerging integrity challenges.

1.3. Experimental Design

During this annual reporting period, the research team, led by Mr. J. Anderson from the Energy & Environmental Research Center (EERC), has made significant progress in preparing a near real-world testbed for hydrogen effects analysis. The experimental setup involves critical steps to ensure safe and reliable hydrogen testing under controlled conditions. The team has established key equipment and allocated space for the testbed, with ongoing safety checks to ensure compliance with required standards.

Procurement and Fabrication:

The EERC has secured a quote from STEFFES for the procurement and specialized welding of the pipeline. The University of North Dakota (UND) procurement team is processing the work order, which is expected to be sent to STEFFES by early July.

For gas blending, the team has opted to purchase a pre-blended hydrogen/natural gas K-bottle from a distributor, such as Airgas, to maintain precision in gas composition rather than blending gases on-site in an accumulator.

Testbed Layout and Infrastructure:

The General Arrangement Drawing (GAD) for the testbed layout has been completed in collaboration with the facilities team. The designated test site is located in Building R, within the National Center for Hydrogen Technologies (NCHT), contingent on access to natural gas lines.

The pipeline infrastructure uses API 5L X52 piping with SCH80 specifications. The primary materials for testing are API 5L X52 and 316 stainless steels, chosen for their compatibility with hydrogen transport.

Instrumentation and Safety:

The Process and Instrument Diagrams (PID) have been updated incorporating a Mass Flow Controller (MFC) to regulate flow to the thermal oxidizer (TOx). This configuration ensures safe depressurization and enables temperature control, protecting the internal refractory of the system.

Materials for pipeline fabrication are being sourced from existing stock to minimize procurement costs. To ensure safety, the team is collaborating with local welding experts to verify pressure calculations and confirm the suitability of SCH80 piping. Alternative materials are under consideration, if necessary, based on final safety evaluations.

This experimental design serves as a critical step in establishing a robust testbed for hydrogen testing, which will contribute to the comprehensive evaluation of hydrogen's impact on pipeline infrastructure.

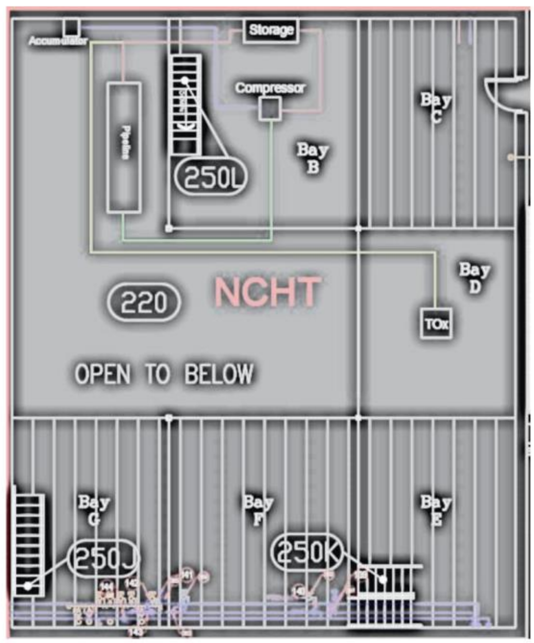


Figure 5. The layout of EERC facilities for hydrogen testing

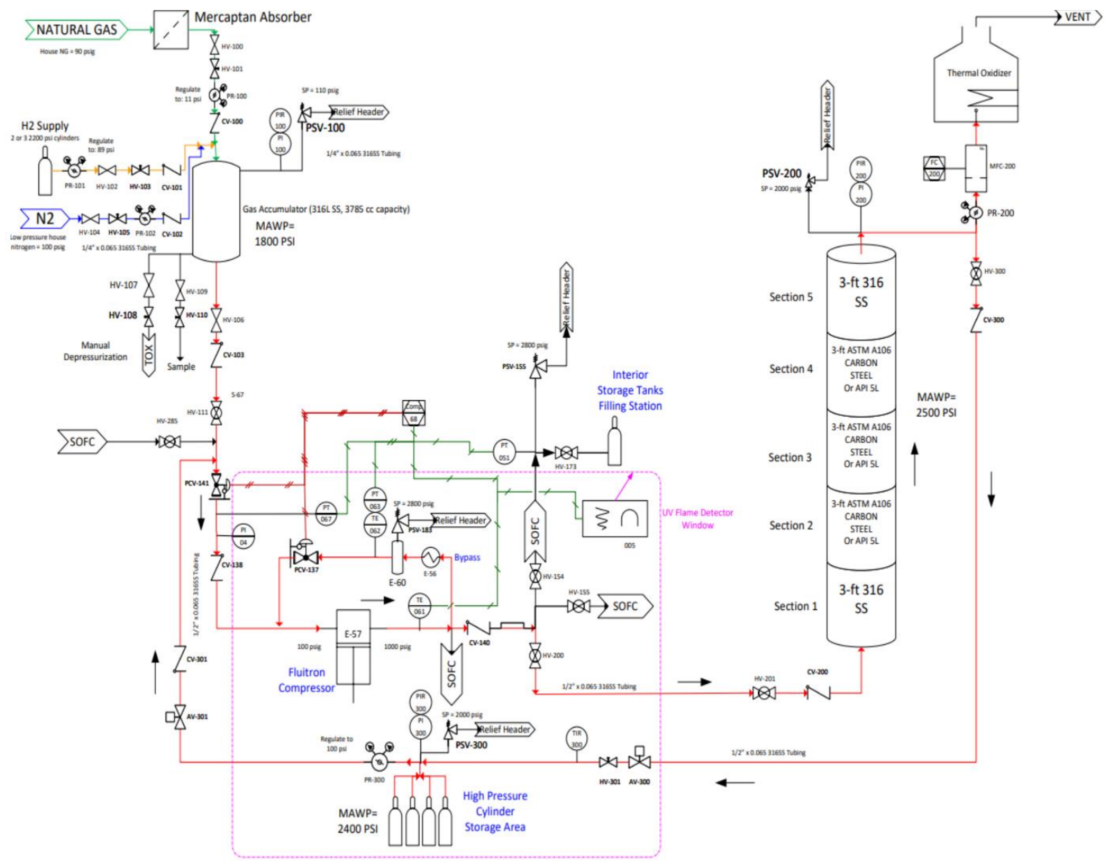


Figure 6. The updated piping and instrumentation diagram for the near real-world testbed

1.4. Testing procedure

For the testing procedure, we will conduct both pressure cycling and coupon testing. Coupon samples will be placed inside the pipeline to evaluate material degradation and response to hydrogen exposure. The following main steps outline the best approach to achieving reliable and insightful results:

a) Pressure Cycling Testing:

i. Apply pressure cycling to the system according to predetermined cycles that mimic real-world operating conditions, including pressure variations and surges commonly experienced in hydrogen transport.

ii. Continuously monitor the system's mechanical performance and behavior under varying pressure conditions, particularly focusing on stress points where hydrogen embrittlement may occur.

b) Hydrogen-Induced Stress Scenario Simulation:

i. Simulate specific hydrogen-induced scenarios such as hydrogen embrittlement, leaks, or permeation, by gradually introducing hydrogen into the pipeline at controlled levels.

ii. Monitor and record the system's response to these stressors in real time, using embedded sensors to detect early signs of material failure or degradation.

c) Comprehensive Data Collection and Analysis:

i. Collect extensive data from pressure cycles and hydrogen-specific stress scenarios using high-precision sensors, NDE tools, and wireless monitoring networks.

ii. Ensure that data includes temperature, pressure, material strain, and any detected anomalies, allowing for a multi-dimensional analysis of system performance.

d) System Integrity and Performance Evaluation:

i. Analyze the gathered data to assess the system's overall integrity, focusing on precision, sensitivity, reliability, and the material's resilience to hydrogen exposure.

ii. Compare the observed data to expected theoretical outcomes to validate the system's reliability and pinpoint areas of potential failure.

e) Industry Consultation and Expert Validation:

i. Consult with subject matter experts (SMEs) and representatives from the pipeline industry to validate the testing procedure and outcomes, ensuring practical relevance.

ii. Gather feedback on system performance and recommendations for refining the testing protocols to further optimize the testbed for future hydrogen-related research.

This revised step-by-step procedure focuses on both real-world applicability and hydrogen-specific challenges, ensuring a thorough assessment of pipeline performance under varying operational conditions

2. Results and Discussions

2.1. Task 2: Repurposing decision platform formulation

a) Gaussian process for RUL:

Figure 7 presents the framework for building a Gaussian process-based machine learning model tailored for decision-making in the context of repurposing pipelines for hydrogen transport. Gaussian process (GP) regression, a non-parametric probabilistic model, is employed to predict various aspects of pipeline performance when subjected to hydrogen. This method provides predictions with well-defined uncertainty, which is crucial for making informed decisions in the high-risk domain of hydrogen repurposing.

Mathematically, let X= $\{x_1, x_2, \ldots, x_n\}$ represent the mix design or measured properties as inputs for our GP-based machine learning model, where $x_i \in \mathbb{R}^d$ is a d-dimensional vector. To reduce spurious correlations, we set $d = 1$. Let $Y = \{y_1, y_2, \ldots, y_n\}$ be the corrosion resistance measurements. The Gaussian process model assumes a function f that maps the input x_i to y_i with a mean function μ and a covariance function k (kernel function). The distribution of the functions f is given by [7]:

$$p(f|X) \sim \mathcal{N}(f|\boldsymbol{\mu}, \boldsymbol{k}) \tag{1}$$

where $f = \big(f(x_1), \ldots, f(x_n)\big)$, $\boldsymbol{\mu} = (\mu(x_1), \ldots, \mu(x_n))$ and $\boldsymbol{k}_{ij} = k(x_i, x_j)$, In our corrosion resistance prediction scenarios, we assume that the corrosion resistance is given by $y = f(x) + \epsilon$, where ϵ represents additive i.i.d measurement noise with variance σ_n^2. Thus, the prediction f^* at the new mix design point $X^*$is [8]:

$$\begin{pmatrix} Y \\ f^* \end{pmatrix} \sim \mathcal{N}\left(0 \quad \begin{bmatrix} \boldsymbol{k} + \sigma_n^2 I & \boldsymbol{k}^* \\ \boldsymbol{k}^{*T} & \boldsymbol{k}^{**} \end{bmatrix}\right) \tag{2}$$

where $\boldsymbol{k} = k(X, X)$,$\boldsymbol{k}^* = k(X, X^*)$and $\boldsymbol{k}^{**} = k(X^*, X^*)$.

The predictive distribution for Gaussian process regression is [9]:

$$\widehat{f^*}|X, Y, X^* \sim \mathcal{N}(\widehat{f^*}, COV(f^*)) \tag{3}$$

where $\widehat{f^*} = \boldsymbol{k}^{*T}[\boldsymbol{k} + \sigma_n^2 I]^{-1} Y$, $COV(f^*) = \boldsymbol{k}^{**} - [\boldsymbol{k} + \sigma_n^2 I]^{-1} \boldsymbol{k}^*$

To address the needs of our small datasets and smoothness requirements, we use a modified Radial Basis Function (RBF) Kernel, parameterized as [10]:

$$k(x, x') = \theta_0 \cdot \exp\left(-\frac{\|x - x\|^2}{2l^2}\right) + \alpha I \tag{4}$$

where $\theta_0$is the scaling parameter, l is the length scale, and α controls the noise level. The hyperparameter $\theta = (\theta_0, l, \alpha)$ can be determined by the existing data and the physical properties of the analyzer. The optimal hyperparameters are found by maximizing the regularized log marginal likelihood:

$$\theta^* = \arg\max_{\theta} p(Y|X, \theta) + R(\theta) \tag{5}$$

By combining the parameterized kernel and Equation 3, we obtain the Gaussian process-based machine learning model.

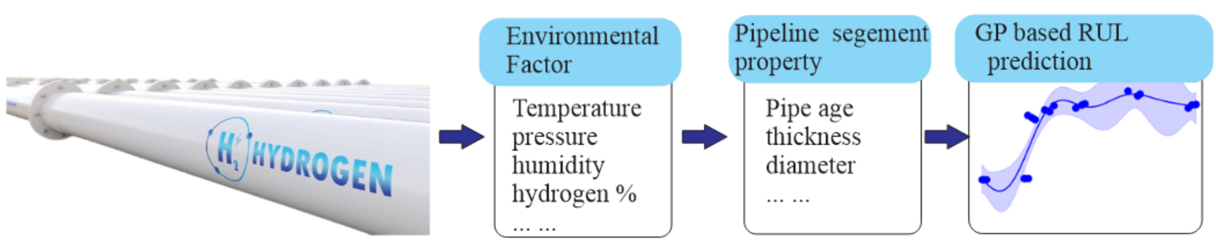


Figure 7. Gaussian process-based RUL prediction

b) General ML (shallow learning) for RUL:

For more general machine learning based prediction model, the typical ML model development includes two primary stages: training and prediction. During the training phase, the model develops inferential capabilities relying on provided datasets, and progressively enhances prediction performance. The tasks done during the training phase involve pre-processing, learning, and evaluation [11]. The pre-processing converts the inconsistent, unstructured, incomplete, and noisy raw data to machine-readable structure for learning process [12], [13]. The learning step involves the selection of an appropriate learning algorithm, the tuning of the model's hyperparameters, and training the model on the subjected pre-processed data. The evaluation phase then evaluates the model's performance using statistical metrics. After the post-processing, the prediction phase provides the most valuable model that can be further used for making predictions using new datasets.

The ML is divided into three subdomains based on the type of feedback the learning system receives: supervised learning, un-supervised learning, and semi-supervised learning [13]. Figure 8 presents the taxonomy of ML techniques.

Supervised Learning

Supervised learning maps the known independent and dependent features to learn the correlation between them. Commonly employed algorithms used in supervised learning includes NN, SVM, DT, and k-nearest neighbors. Supervised learning can be used to solve regression and classification problems. Regression solves the problems where the dependent variable is continuous such as the problems related to estimation of defect sizes and prediction of degradation rates in pipeline infrastructure. While classification is commonly employed where the variables hold the finite set of discrete value. In pipeline infrastructure classification helps in detection of leakage, identification of defect type, and prediction of risk level.

Unsupervised Learning

Unsupervised learning aims to identify trends/patterns or concealed features within the variables array data without having the prior knowledge of output variables. Clustering is an unsupervised learning task that divides the objects into separate clusters, with an aim to group the similar objects in single cluster according to the certain predefined criteria [42]. The mostly used clustering techniques include hierarchical clustering, K-means clustering, and Gaussian mixture models. In pipeline infrastructure, clustering can be used for the simplification of risk assessment task like clustering the pipeline segments according to degradation mechanisms, materials, and operating conditions.

Semi-Supervised Learning

Semi-supervised learning uses the features of both supervised and unsupervised learning and utilizes both the labeled and unlabeled data. Semi-supervised learning is recommended when a large amount of unlabeled data and less labelled data is available. Furthermore, the reinforcement learning algorithms learn the actions in the data more efficiently using a reward system, like receiving of rewards and punishments associated to the actions in the data [13]. The commonly adopted techniques in reinforcement learning include Markov decision processes, Q-learning, and Monte Carlo methods.

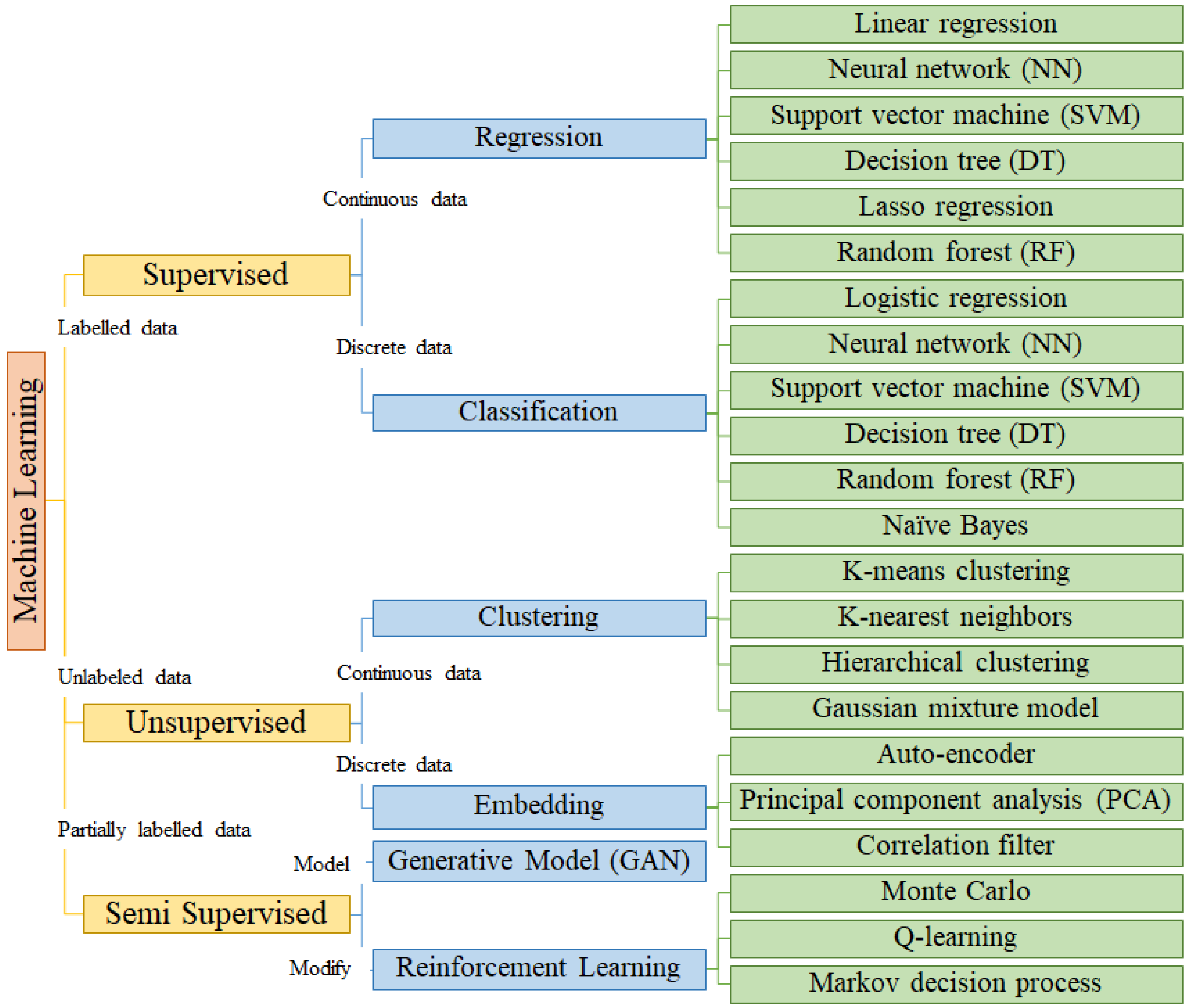


Figure 8. Overview of machine learning algorithms

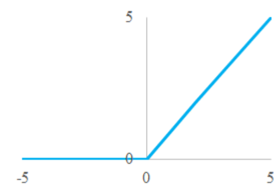
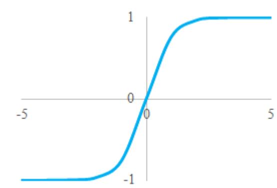
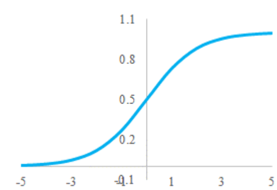
c) Deep learning for RUL:

Deep learning (DL) [13], a fast-evolving domain within ML, refers to a deep artificial neural network comprised of multiple hidden layers. It stands out from normal neural networks due to its increased complexity and larger network size and significantly enhance the predictive performance. The key networks of DL include Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) networks.

CNN approach is commonly used for image analysis tasks, with an architecture consists of an input layer, convolutional layer, pooling layer, fully connected layer, and output layer, as presented in Figure 9. The training dataset, the types arrangements, depth and the chosen functions of network layers, define the developed model's accuracy and robustness.

The pooling (or sub-sampling) layer helps to reduce the dimensionality and compress the image information. Popular operations within this layer include average pooling and maximum pooling, which help compact the data and prevent overfitting, thus reducing the number of neurons in the network. Next, the fully connected layer combines and integrates the extracted features with the usage of multilayer perceptron (MLP) as a core network structure. Each input neuron links to an output neuron with designated weights and biases, and then an activation function is used to produce the final output. Furthermore, an activation function is a supplementary addition during forward propagation, which introduce the non-linearity to the network, and allows back propagation, which eventually enhances the image recognition capabilities of the pooling layer and convolution layer. The most common non-linear activation function that can be used in CNN are presented in Table x.

Table x. Non-linear activation function used in hidden layers of CNN network

Name and symbol	***Mathematical function***	***Purpose***	***Graphical output***
Rectified Linear Unit (ReLU)	$f(x) = \max(0, x)$	Sets all negative inputs to zero, helps with faster convergence and addresses the vanishing gradient problem.	
Hyperbolic Tangent (Tanh)	$f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$	Squeezes the input values between -1 and 1, and therefore suitable for classification tasks that require outputs in a specific range.	
Sigmoid/logistic	$f(x) = \frac{1}{1 + e^{-x}}$	Maps the input values to the range of (0, 1), and therefore suitable for binary classification tasks where probabilities need to be calculated.	

After initialization of the network parameters, CNN models go through supervised training, which allows forward propagation to extract features through different operations (convolution, pooling etc.), and backpropagation modifies the network parameters while comparing the predicted and actual values. Waibel et al., introduced the first CNN, which evolved over the decades, with various derived structures and algorithms to successfully apply for anomaly classification and defects detection in oil and gas pipeline related tasks. Bastian et al. (2019) used CNN with a dataset of 140,000 pipeline images with varying degree of corrosion to classify the intensity of corrosion. CNNs have confirmed effectiveness in training large-scale networks and tackling big data challenges. Ajmi et al. (2020) used an AlexNet based CNN architecture for the classification of defects in welds. Other notable CNN architectures include GoogleNet, and VGG.

RNNs are usually employed in time series prediction. The LSTM emerged as a popular extension due to its valuable performance in modeling large-scale data. Ahuja et al. (2021) successfully applied Bi-directional LSTM for the classification of images related to pitting corrosion in pipelines. Despite the increasing interest in deep learning for oil and gas pipeline analyses, the method is still in an exploratory phase due to the extensive data requirements involved in the modeling process.

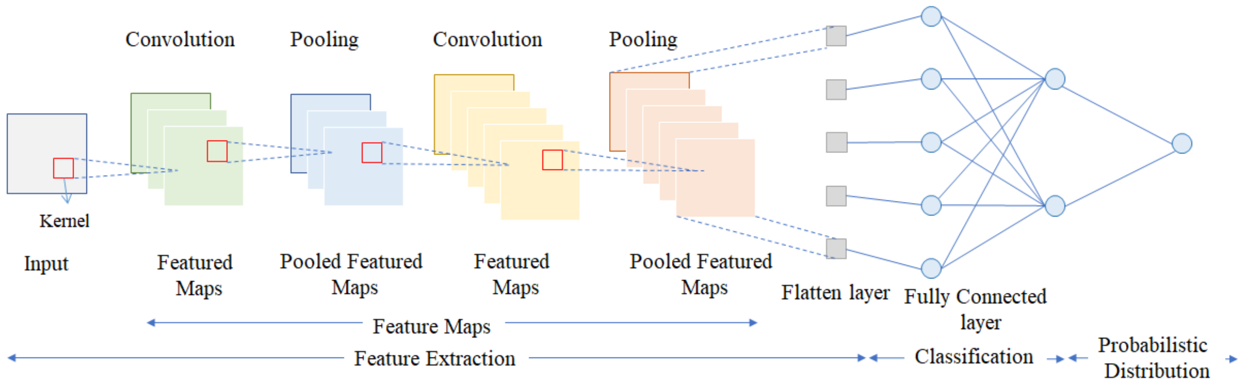


Figure 9. Typical architecture of confidently used CNN algorithm in pipeline network.

Post-processing

Post-processing involves the refinement and optimization of the predictions generated by the model. After an array of predicted RUL, like 48, 45, or 39 days until failure are obtained, various post-processing techniques can be utilized to improve these predictions. Which includes the evaluation of the model's performance to assess its accuracy and effectiveness, as well as analysis and interpretation of the predictions to ensure they are significant and consistent. Through this process, the predictions can be fine-tuned, which can eventually lead to improved reliability and better alignment with the underlying data.

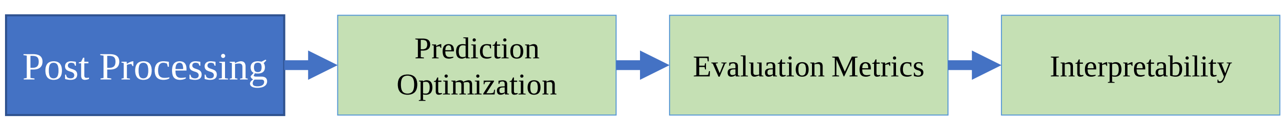


Figure 10. ***Steps involved in post-processing of the RUL models***

Prediction Optimization

Different models are applied to achieve the estimation of RUL. It is necessary to optimize the divergent results of the estimated RUL from various models. The researchers used different approaches to fuse the estimated results. Baptista et al. suggested the data-driven based Kalman-Filter solution approach. As presented in Figure 11 (a) the RUL was estimated using five different methods i.e., GLM, KNN, MNET, RF and SVM. It can be clearly observed the scatter and divergence in the estimated RUL, specifically for the KNN model (greenish yellow). To address aforementioned issue, the authors employed a Kalman filter, which helped to linearize the predictions and increases their dependency. The achieved approach smooth predictions ensures that coherence and completely reflective of temporal relationships, eventually improves overall predictive accuracy.

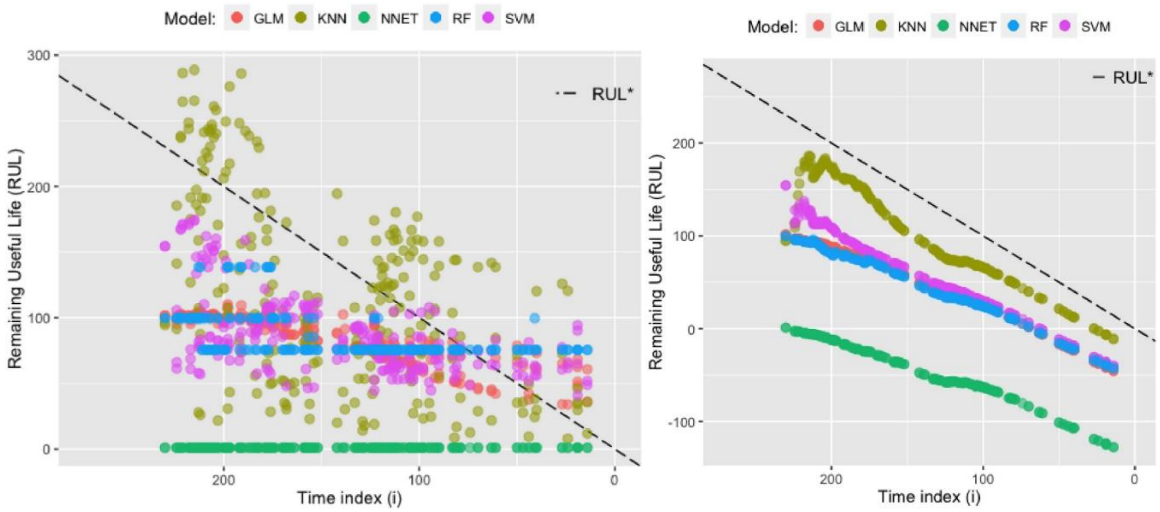


Figure 11. (a) RUL estimation using five different models i.e., GLM, KNN, MNET, RF and SVM, (b) Fused RUL estimation and linearization using Kalman Filter

Evaluation Metrics

The evaluation of the developed model is necessary to ensure that the model is not only good only on the training data but also on the testing data that was never seen. Naseer et al. provided 78 most used metrics for evaluation of classification and regression-based ML models. Although statistical metrics like MAE and RMSE are important but not the best way to see all the dimensions of the model. As presented in Figure 12, all the three plots have same MAE, but the first plot with scattered predictions, the second one with over predictions and the third one with over predictions. Only the values of statistics are not enough, and it is equally important to visualize performance in different ways.

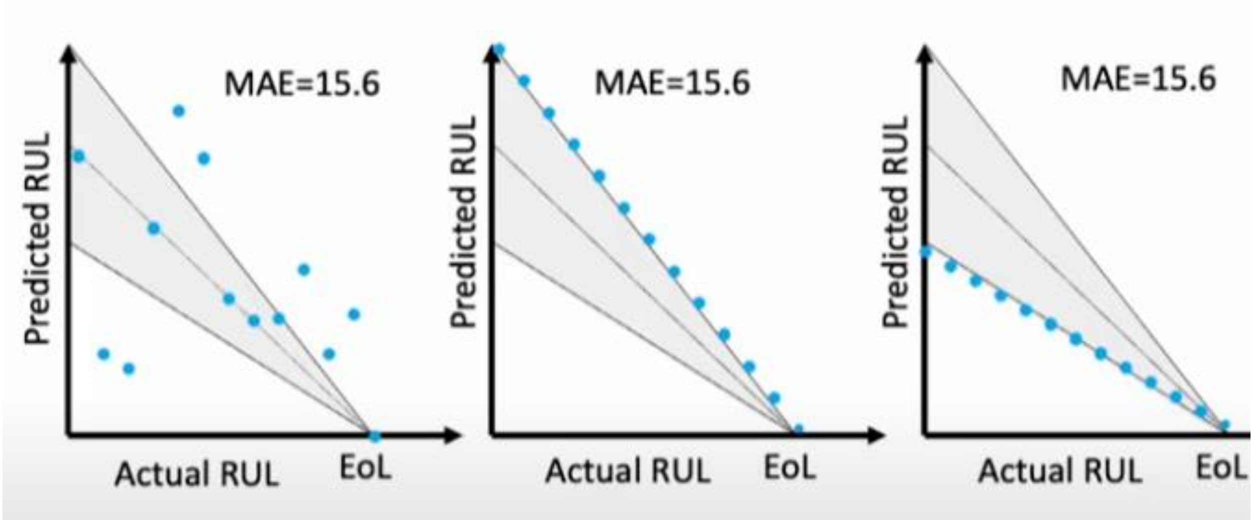


Figure 12. Importance of visualization considering the same MAE with different visualization.

Interpretability

In terms of interpretability, ML models, mainly data-driven models, present challenges. These models provide predictions, like "40 days to failure", deprived of how the result was obtained. The lack of transparency makes it tough to know the reasons behind such estimations. To address this issue, the authors worked on application of explain-ability techniques, like the SHAP (Shapley Additive Explanations) model, to improve interpretability through the generation of explanations for the predictions. For instance, if the model estimated RUL of 30 or 50 days, SHAP can find the factors that contributed to the prediction. It might specify that a temperature of 20°C was a significant feature, or that pressure accounts for 80% of the prediction's outcome, Such approach can provide a notion of what is going on inside the model, providing a clear understanding of the factors that influence the predictions.

2.2. Task 3: Near real world testing

The EERC has discussed two potential siting spots for the fabrication of the pipeline. The spot has been decided upon and deconstruction and cleanup of the unused equipment in the space will begin to clear way for the new system.

An initial HAZOP review has been done, which determined the sitting was adequate, but called for some redesigning on the system itself to ensure proper recycling of the gas blend so the system won't inefficiently consume the hydrogen supply to run. Once the PID has been updated again, a final HAZOP will occur.

Material purchasing will begin shortly once the sitting location is cleaned up enough to properly store the materials.

The material to be used for the pipeline is being discussed, as it may end up being a result of availability. The original plan is API 5L X52, but the availability of obtaining the small amount needed has proven difficult. After consulting with a few members from the EERC with experience in pipeline infrastructure, a suitable material used in natural gas transmission could also be ASTM A106 SCH40 carbon steel or ASTM A53 SCH40 carbon steel (however, this seems to be more for on-site distribution). If possible, the EERC would like to stick with the original plan of API 5L.

2.3. Task 4: Long-Term Hydrogen Impacts on Transportation Pipelines

The Virginia Tech team, led by Dr. K. Wang, has developed a computational model to simulate long-term hydrogen absorption in transportation pipes, focusing on the effects of surface roughness and defects on hydrogen absorption and material degradation. Key tasks include:

Model Development and Implementation: The team has implemented part of the model in their in-house research code, M2C, which utilizes C++, MPI, PETSc, and Eigen. The model adopts computational fluid dynamics (CFD) to predict how surface roughness, particularly small defects, can act as hydrogen traps that accelerate absorption and material degradation.

Code Verification: They conducted a verification study for the incompressible viscous flow solver in the M2C code, comparing results with OpenFOAM and COMSOL for a benchmark test case involving fluid flow past a square cavity. The study confirmed good agreement between M2C results and reference software, verifying the accuracy of the solver.

Hydrogen Transport Modeling: The model was extended to account for the transport of gas mixtures (hydrogen, air, impurities), utilizing diffusion coefficients for each species. This required extending the conventional Navier-Stokes equations to handle species-specific diffusion.

Benchmark Simulations and Defect Modeling: The team designed various model problems by varying the size and shape of pipe defects. Simulations revealed vortex-dominated microflows within these cavities, with results validated against previous findings.

Further Extensions: Plans to incorporate multi-component gas mixtures into the M2C code were discussed, allowing the model to handle hydrogen transport in more realistic conditions, such as mixtures of hydrogen, air, and impurities.

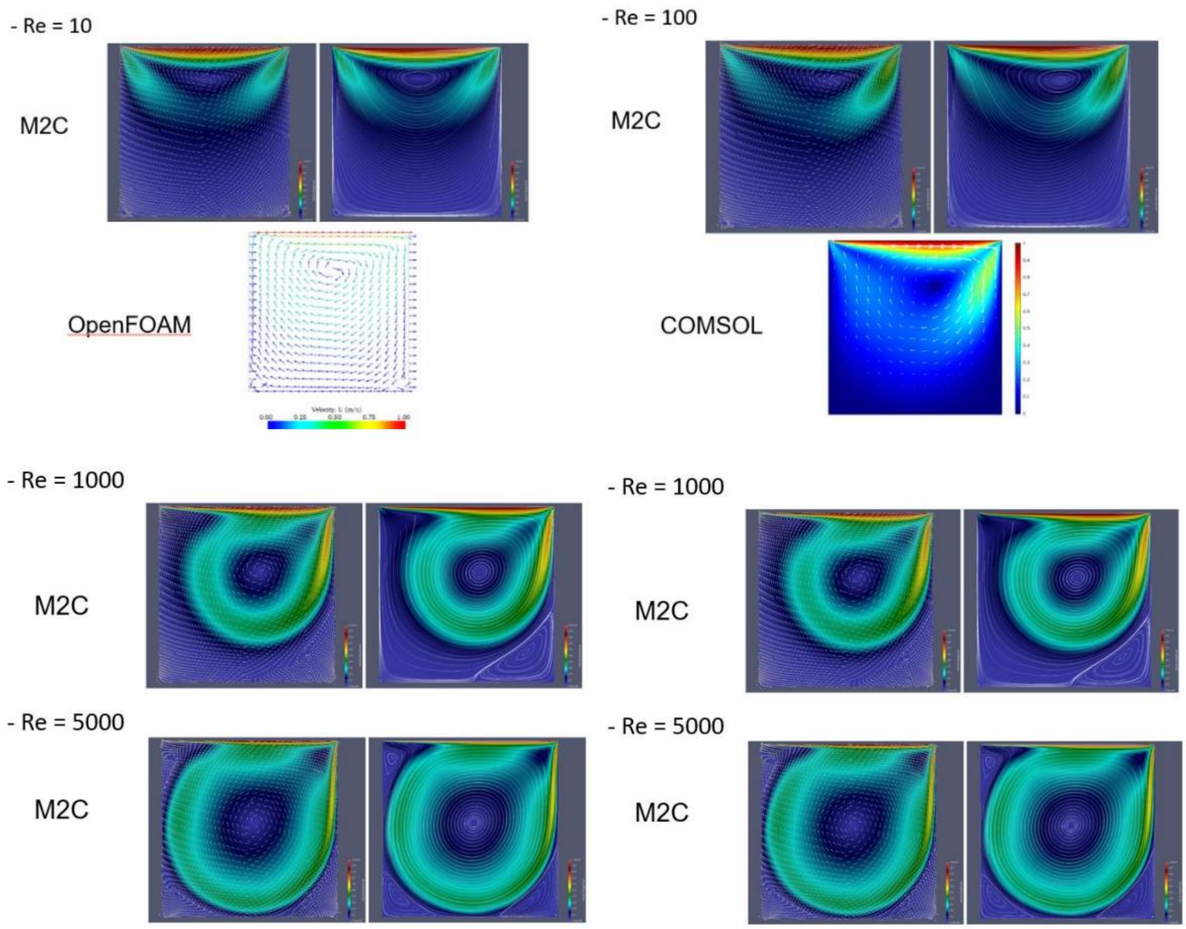


Figure 13. Simulation results obtained from the verification study. Good agreement is obtained between results of our in-house research code (M2C) and references obtained using OpenFOAM and COMSOL.

2.4. Task 5: impacts on component-/system-level pipelines

During this research period, our investigation into the effects of hydrogen on existing pipeline infrastructure revealed key insights, particularly regarding component- and system-level factors. Stress corrosion cracking (SCC) and hydrogen embrittlement (HE) are recognized as significant factors influencing pipeline integrity. The team's proposed knowledge graph-based neural query framework allows for the comprehensive evaluation of these factors, providing valuable tools for stakeholders to assess and mitigate hydrogen-related risks.

a) Component-Level Impacts

At the component level, specific attributes of the pipeline material, welds, and surface finishes are critical in determining the susceptibility to hydrogen-related degradation:

Stress Corrosion Cracking (SCC): SCC is one of the primary mechanisms driving pipeline failures in hydrogen environments. It involves the combined action of tensile stress and corrosive environments, which may lead to crack initiation and propagation. The crack initiation stage is influenced by material surface quality, such as coarse machining marks or weld porosity, which can act as stress concentrators.

Hydrogen Embrittlement (HE): HE refers to the reduction in ductility and toughness caused by hydrogen absorption in metals. It is exacerbated by the presence of SCC, where hydrogen produced during corrosion further weakens the material. This phenomenon is especially prevalent in high-strength steels used in pipelines.

Crack Growth Stages: The crack growth in pipelines follows the Bathtub model, as illustrated by the five sequential stages in the SSC crack growth mechanism. Crack initiation (Stages 1a and 1b) depends largely on the material quality and external surface conditions, while Stage 2 represents mechanical forces that accelerate crack growth. Fast rupture occurs in Stage 3, emphasizing the need to prevent early crack development.

b) System-Level Impacts

At the system level, the broader implications of hydrogen presence and SCC/HE factors are considered across multiple interconnected pipeline components and their performance:

Corrosion as a Dominant Failure Mechanism: According to the Pipeline and Hazardous Materials Safety Administration (PHMSA) report (2008–2017), corrosion was responsible for 63% of pipeline failures. Material, welding, and equipment failures accounted for an additional 17%. These failures are often interrelated, as SCC and HE can occur simultaneously, weakening the entire pipeline system.

Hydrogen Embrittlement (HE) in the System: The system-level implications of HE is profound, as a single component's failure can lead to cascading failures across the entire pipeline network. System-wide monitoring of hydrogen levels and stress conditions becomes essential to prevent large-scale pipeline failures.

In conclusion, the component-level factors (such as surface quality and material defects) and system-level factors (such as overall corrosion susceptibility and hydrogen embrittlement) need to be rigorously monitored and managed to ensure the integrity of existing pipelines.

2.5. Task 6: Propose guidelines/best practices

In this research phase, we aim to summarize comprehensive guidelines and best practices from multiple perspectives to facilitate a streamlined and quantitative approach to the complex task of repurposing existing pipelines for hydrogen transportation. These guidelines are designed to ensure a safe, efficient, and economically viable transition. A holistic, integrity-driven approach is emphasized, focusing on key aspects such as mechanical properties assessment, material testing, and customized integrity management. The mechanical properties assessment evaluates how hydrogen affects pipeline steel, particularly addressing risks like embrittlement and stress corrosion cracking (SCC). Robust material testing programs help identify vulnerabilities and assess the remaining service life of the pipelines, while tailored integrity management plans are developed to address each pipeline's unique threats and operating conditions.

Stress corrosion cracking (SCC) is identified as a critical threat, especially in pipelines carrying hydrogen, due to the interaction of tensile stress and corrosive environments. Effective mitigation requires a combination of mechanical, metallurgical, and environmental control measures. Mechanical strategies include minimizing stress concentrators, relieving fabrication stresses, introducing surface compressive stresses, reducing operating pressures, and implementing regular nondestructive testing. Metallurgical strategies focus on selecting materials and optimizing alloy microstructures to resist SCC, as well as applying protective coatings to prevent corrosion and hydrogen ingress. Environmental measures involve controlling factors such as pH and moisture levels, applying electrochemical protection (e.g., anodic or cathodic protection), using corrosion inhibitors, applying organic coatings, and controlling operating temperatures to limit SCC risks.

Successful conversion of pipelines to hydrogen service requires a comprehensive and tailored approach. Key recommendations include implementing regular inspection regimes and nondestructive testing, applying a combination of mechanical, metallurgical, and environmental measures to mitigate SCC risks, and engaging in thorough material testing and defect assessment programs to evaluate hydrogen's impact on pipeline integrity. Additionally, practical guidelines and roadmaps, such as the Pipeline Repurposing Roadmap, should be provided to operators to guide them through the conversion process safely and economically. Ultimately, the success of the hydrogen economy depends on the ability to repurpose existing pipeline infrastructure while addressing key integrity threats, such as SCC. By following the proposed guidelines and control strategies, pipeline operators can ensure the safe and efficient transportation of hydrogen, optimizing pipeline performance in hydrogen service while mitigating associated risks.

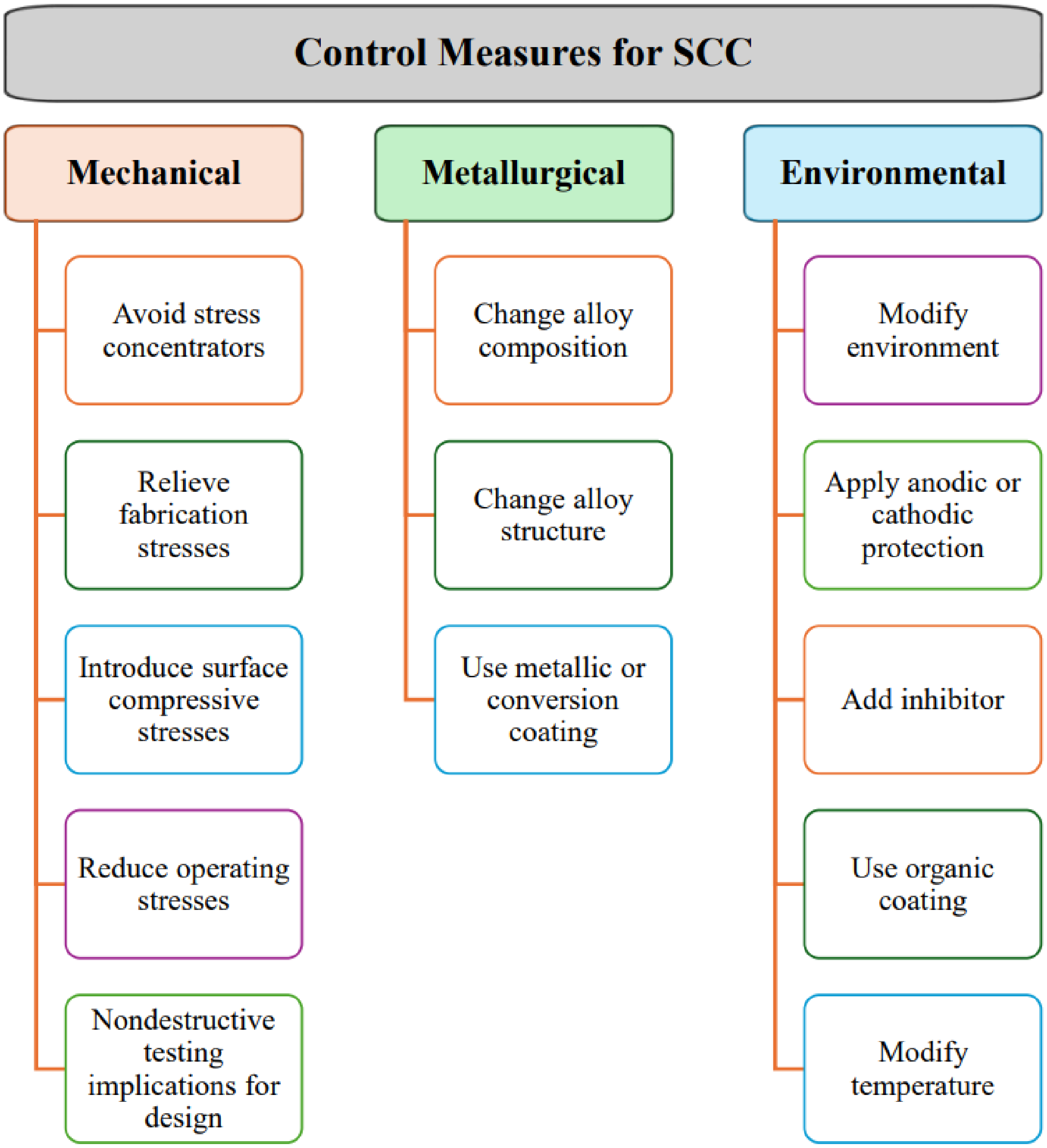


Figure 14. Main control measures for SCC.

3. Future work

In the upcoming third year, our project will encompass a broad range of activities, including experimental work, component-to-system model formulation, the development of a long-term computational tool, and the consolidation of guidance and best practices. The project team will also focus on completing delayed tasks, particularly those related to hydrogen testing, to ensure the project remains on schedule and successfully addresses all remaining objectives. Our research and development plan for the upcoming year includes the following activities:

- Continue developing a holistic Remaining Useful Life (RUL) model using the Failure

Assessment Diagram (FAD), based on existing standards and data, to formulate a comprehensive repurposing decision model as outlined in Task 2.

- Advance the construction of hydrogen test experiments, adhering to the guidelines specified in Task 3.

- Expand the multi-scale hydrogen simulation model, conduct simulations to analyze long-term effects, and validate the experimental results, as described in Task 4.

- Develop a comprehensive model that bridges component-level evaluations with system-level assessments, aligning with the framework detailed in Task 5.

- Summarize existing guidance and best practices, using our testing results to validate and refine them as necessary, as outlined in Task 6.1 and Task 6. 2..

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