Public Quarterly Report

Date of Report: 3rd Quarterly Report – June 30, 2025
Contract Number: 693JK32410002
Prepared for: DOT PHMSA
Project Title: Developing Safety Models for Potential Impact Radius (PIR) Determination in Hydrogen and Hydrogen-Natural Gas Pipeline Systems Using Computational and Experimental Methods
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For the quarterly period ending: June 30, 2025

1. Items Completed During this Quarterly Period:

Item #	Task #	Activity/Deliverable	Title
7	5	Perform literature review activities to perform industry outreach.	Document existing PIR prediction methods, limitations, and industry experience using PIR.
8	2	Submit monthly updates on PRIMIS.	Monthly Updates
9	3	3rd Quarterly Status Report	Submit the 3rd Quarterly Status Report

2. Items Not Completed During This Quarterly Period:

The project is currently on schedule. All planned tasks up to this point have been completed.

3. Project Financial Tracking During this Quarterly Period:

This information is included in the Internal Quarterly Report.

4. Project Technical Status:

Item #4, Task #4: Perform literature review activities to identify the state of the art
The first sub-task of this project involves conducting a comprehensive literature review to support the primary goals of the project: build on the existing Potential Impact Radius (PIR) prediction framework for natural gas, to include hydrogen, and blended-gas pipelines. During the literature review, the team investigated studies detailing experimental programs, numerical analyses, and machine learning approaches. Further, the team worked with industry to understand the state of the art for gaseous pipelines. Over the last quarter, the team placed a particular focus on existing hydrogen and hydrogen/natural gas blended pipeline applications and experimental studies. These two elements help inform the design of a realistic and practical setup for future model validation. The review findings also highlight that most published research studies emphasize dispersion scenarios, with fewer studies addressing fire, explosion, or buried pipeline conditions. The team has initiated documentation of the literature review, with particular attention directed toward completing the assessment of numerical and machine learning approaches. This effort will continue into the next quarter.

This section of the quarterly report includes a brief overview of hydrogen and hydrogen/natural gas blended pipeline installations and a summary of the literature available for experimental methods.

Hydrogen and Hydrogen/Natural Gas Blended Pipeline Installations:
To support the development of a PIR prediction framework for hydrogen pipelines, it is important to first understand the geographic context in which these pipelines operate. Figure 1 shows the hydrogen pipeline centerlines (in black) across the Texas Gulf Coast region, along with high population areas (in red). This highlights the proximity of hydrogen infrastructure to densely populated regions, reinforcing the need for accurate PIR estimation to support risk management and safety assessments.

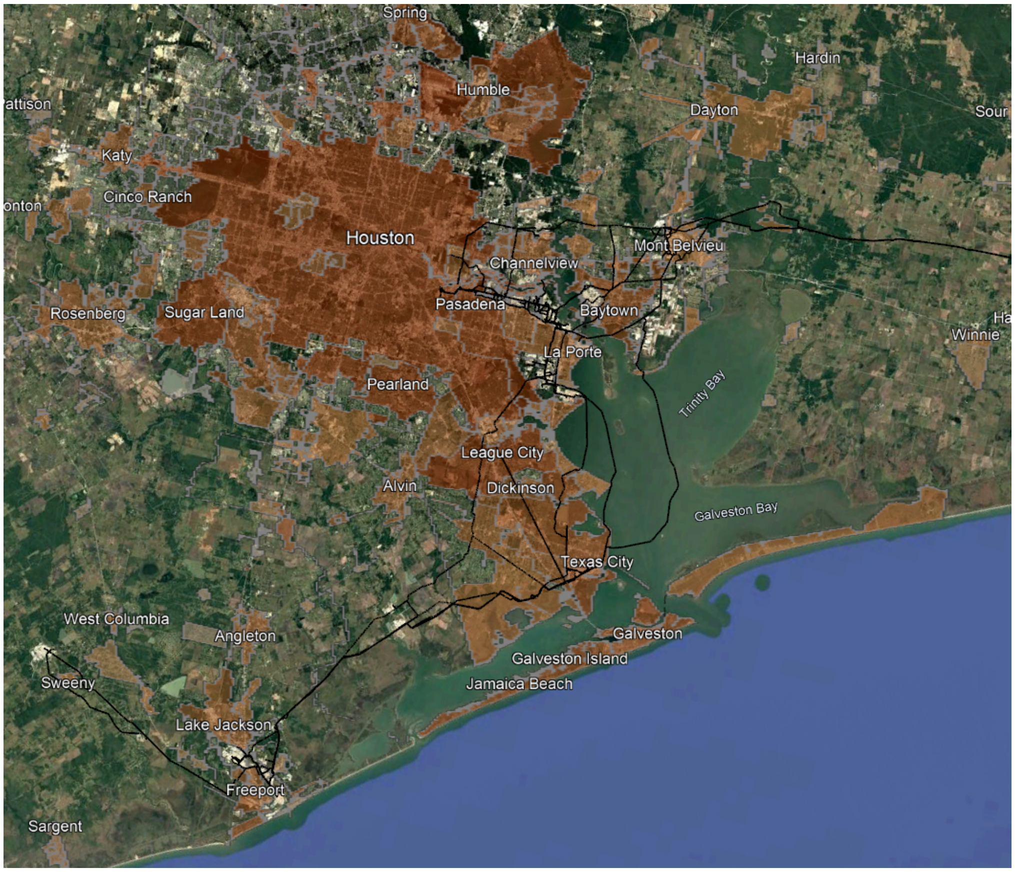

Figure 1. Map Showing Hydrogen Pipeline Centerlines and High Population Areas in the Texas Gulf Coast Region.

This map displays the hydrogen pipeline network in the Texas Gulf Coast region. The pipeline centerlines are shown in black, representing the routes the pipelines traverse. High population areas are indicated in red, providing a clear visualization of the pipelines' proximity to densely populated regions. This geographic context underscores the importance of accurate PIR estimation and risk assessment for hydrogen pipelines operating in areas where potential impacts could affect nearby communities.

A map of hydrogen/natural gas blended pipelines does not yet exist, but trial applications are taking place across the U.S. Some cities, such as Corpus Christi in the Gulf Coast region, have been periodically supplying blended gas to the local distribution grid for decades when the hydrogen production in the area reaches a critical threshold. Further, Canada has several ongoing blended-gas local distribution grids in operation.

Technical Review of Publications Supporting PIR Prediction - Analysis by Gas Type, Incident Scenario, and Research Approach:

Over the last quarter, an extensive literature review was conducted to assess the current state of knowledge related to hydrogen, natural gas, and blended-gas pipelines. The review considered a range of factors from which the team developed a classification framework. This framework organizes the studies by the type of gas, incident scenarios studied (such as dispersion, fire, explosion, and whether pipelines are buried or aboveground), and the research approach used (experimental, numerical modeling, machine learning, or incident analysis). Figure 2 presents a summary of this classification framework. This structured approach ensures that the analysis covers the full spectrum of relevant studies and technical considerations necessary to inform the PIR prediction model.

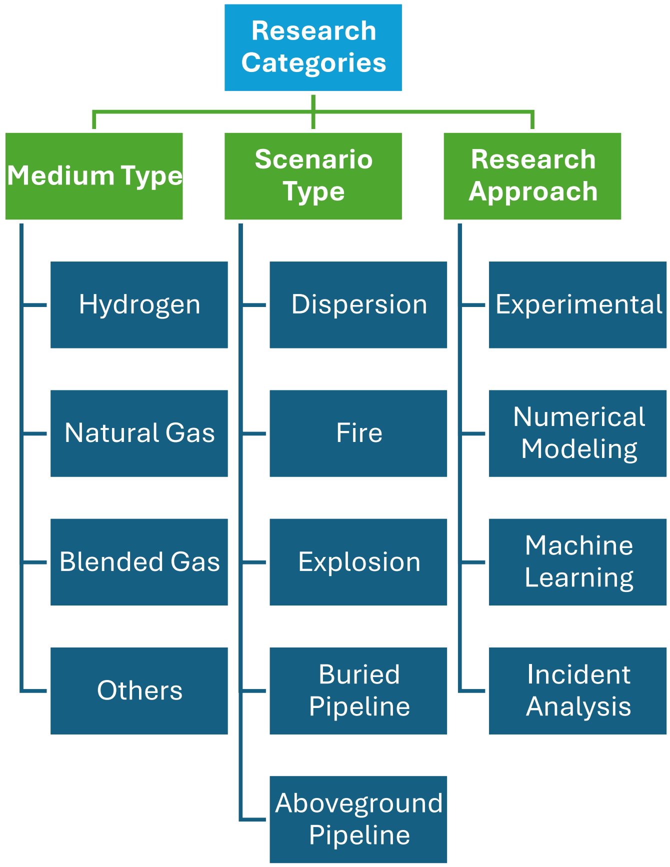

Figure 2. Classification of Collected Publications Based on Medium, Scenario Type, and Research Approach.

This figure summarizes the categorization of the collected publications used in this study. The classification is organized into three key aspects: medium type (hydrogen, natural gas, blended gas, and others), scenario type (dispersion, fire, explosion, buried, and aboveground pipelines), and research approach (experimental studies, numerical modeling, machine learning, and incident analysis). This framework provides a clear overview of the technical focus areas across the reviewed literature.

In the current quarterly period, our work has primarily focused on reviewing papers that include the research approach "Experimental." All medium types and scenario types were considered. So far, the team has collected 52 publications related to experimental research on hydrogen, natural gas, or blended-gas pipelines. Table 1 lists the key components of each study, including the type of scenario, gaseous medium, and the study focus. The study is listed as "Experiment" if it was based on controlled experiments investigating safety impacts, or "Incident Analysis" if it focused on the study of past accidents.

Table 1. Collected Publications for Experimental Research on Hydrogen, Natural Gas, or Blended-Gas Pipelines

This table provides an overview of the collected publications related to hydrogen, natural gas, and blended-gas pipelines. Each entry includes the reference, the type of phenomenon studied (dispersion, fire, or explosion), whether the pipeline is buried or aboveground, the gas medium involved, and the study category, distinguishing between experimental research and incident analysis

Reference	Dispersion	Fire	Explosion	Buried	Medium	Study Type
Niu (2025)	Yes	No	No	No	Hydrogen	Experiment
Zhang (2025)	Yes	No	No	No	Natural gas (95.7% methane)	Experiment
Xu (2024)	Yes	No	No	No	Hydrogen	Experiment
Jiang (2024)	Yes	No	No	No	Hydrogen	Experiment
Zhang (2024)	Yes	No	No	Yes	Methane	Experiment
Qiu (2024)	Yes	No	Yes	Yes	Hydrogen	Experiment
Cheptonui (2023)	Yes	No	No	Yes	Natural gas (85–95% methane)	Experiment

Reference	Dispersion	Fire	Explosion	Buried	Medium	Study Type
Zhu (2023)	Yes	No	No	Yes	Natural Gas The hydrogen mixing ratio varied from 0-30%	Experiment
Li (2023)	Yes	No	No	No	Methane conc.: 4% to 25% Hydrogen conc: 1% to 7%	Experiment
Cai (2022)	Yes	Yes	Yes	No	Methane	Experiment
Liu (2021)	Yes	No	No	Yes	Natural Gas	Experiment
Gao (2021)	Yes	No	No	Yes	Methane Mixture	Experiment
Yue (2021)	Yes	No	No	No	Natural Gas	Experiment
Zhang (2019)	Yes	Yes	No	No	Methane: 91.654 % Ethane: 5.423 %	Experiment
Shrivill (2019)	No	No	Yes	No	Ethane, propane, methane, and Hydrogen	Experiment
Pu (2019) **Hooker (2011)**	Yes	No	No	No	Hydrogen	Experiment
Cheng (2018)	No	No	Yes	No	Natural Gas	Experiment
Houssin-Agbomson (2018)	Yes	No	No	Yes	Methane/Hydrogen	Experiment
Wang (2017)	No	Yes	Yes	Yes	Natural Gas	Experiment
Wu (2016)	Yes	No	No	No	Air	Experiment
Deepagoda (2016)	Yes	No	No	Yes	50,000 ppm Methane and 950,000 ppm Nitrogen	Experiment
Yan (2015)	Yes	No	No	Yes	2.5vol% Methane 97.5 vol% Air	Experiment
Lowesmith (2013)	No	Yes	No	Yes	Test 1: 78 % NG, 22 % Hydrogen Test 2: Pure Natural Gas	Experiment
Mattei (2011)	Yes	No	No	No	Hydrogen	Experiment
Grune (2011)	Yes	Yes	No	No	Hydrogen	Experiment
Acton (2010)	No	Yes	No	Yes	Hydrogen	Experiment
Lowesmith (2010)	No	No	Yes	No	Various compositions of methane and hydrogen	Experiment
Royle (2007)	No	No	Yes	No	Various concentrations used (methane, pure hydrogen, or mixtures)	Experiment
Knudsen (2006)	No	No	Yes	No	Mixture of fuels (hydrogen, propane, methane)	Experiment
Inaba (2004)	No	No	Yes	No	Natural gas and methane	Experiment
Hankinson (2000)	Yes	Yes	No	No	Natural gas	Experiment
Acton (2000, 2015)	No	Yes	No	Yes	Natural Gas	Experiment
McRae (1995)	Yes	No	No	Yes	Natural Gas	Experiment
Turner (1988)	Yes	No	No	Not specified	Natural Gas	Experiment
Witkofski (1984)	Yes	Yes	No	No	Hydrogen	Experiment
Hoff (1983)	Yes	No	Yes	Yes	90 % Natural Gas, 4.4 % CO_2, 4.2% Nitrogen, 1.4% Hydrocarbons	Experiment
Burgess (1977)	Yes	No	No	No	Water	Experiment
Guise (1967)	No	Yes	No	Yes	Natural Gas	Experiment
Wang (2019)	Yes	No	Yes	Yes	94% methane, 2.8 % ethane, remaining HC's	Incident Analysis
Wang (2019)	Yes	No	Yes	Yes	92.3 % methane	Incident Analysis

Reference	Dispersion	Fire	Explosion	Buried	Medium	Study Type
Zhu (2015)	No	No	Yes	Yes	Crude Oil	Incident Analysis
Mishra (2015)	Yes	Yes	Yes	Yes	Natural Gas	Incident Analysis
Wilkening (2007)	Yes	No	Yes	Yes	Methane or hydrogen	Incident Analysis
Manninen (2002)	No	No	Yes	No	Hydrogen	Incident Analysis
NTSB (2000)	No	Yes	Yes	Yes	Natural Gas	Incident Analysis
Mniszewski (1994)	No	Yes	Yes	Yes	Ammonium perchlorate	Incident Analysis
Jones (1993)	Yes	No	Yes	Not specified	Natural Gas	Incident Analysis
Kulyapin (1990)	Yes	No	Yes	Not specified	Natural Gas	Incident Analysis
Lewis (1980)	Yes	Yes	Yes	No	Hydrogen and naphtha mixture	Incident Analysis
Jones (1952)	Yes	Yes	Yes	Yes	Natural Gas	Incident Analysis
Watts (1951)	Yes	Yes	Yes	No	Natural Gas	Incident Analysis
Elliott (1944)	Yes	Yes	Yes	No	Natural Gas	Incident Analysis

The distribution of publications across different study types is illustrated in Figure 3(a), providing a summary of the types of research, such as experimental studies and incident analyses, derived from the detailed data presented in the table. Figure 3(b) shows the trend in publication counts over time, indicating a noticeable increase in research activity in recent years. This upward trend reflects the growing interest in pipeline failure scenarios, including studies focused on more realistic conditions such as buried pipelines.

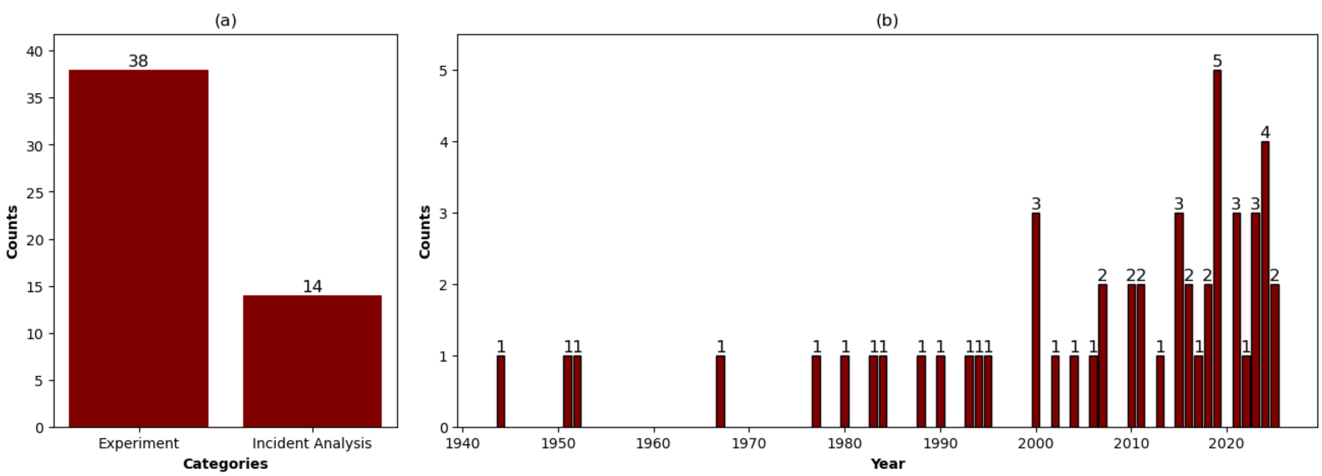

Figure 3. The Collected Publications: (a) Study Type (Category); (b) Number of Publications Per Year
The analysis indicates that the majority of publications are concentrated in experimental studies, with a smaller but significant portion dedicated to incident analysis. Notably, there has been a steady growth in the number of publications over the past decade, highlighting a rising interest and research activity within this field.

Furthermore, the publications were also sorted based on gas medium and incident scenario, as illustrated in Figure 4. The left panel (4a) shows that the majority of the studies focus on natural gas, with comparatively fewer addressing hydrogen and blended gases, highlighting a research gap that reinforces the importance of this project's focus on hydrogen and hydrogen-natural gas mixtures. Figure 4(b) summarizes the types of scenarios studied, including dispersion, fire, and explosion, with dispersion being investigated most. Additionally, a significant number of studies, 24 in total, specifically consider buried pipeline configurations, which underscores the importance of accounting for buried conditions in real-world failure scenarios. Recognizing this, the project team is exploring how to incorporate buried pipeline considerations into the experimental testing phase. A more concrete and detailed approach for this aspect is expected to be developed and presented in the next quarterly report or in future project stages.

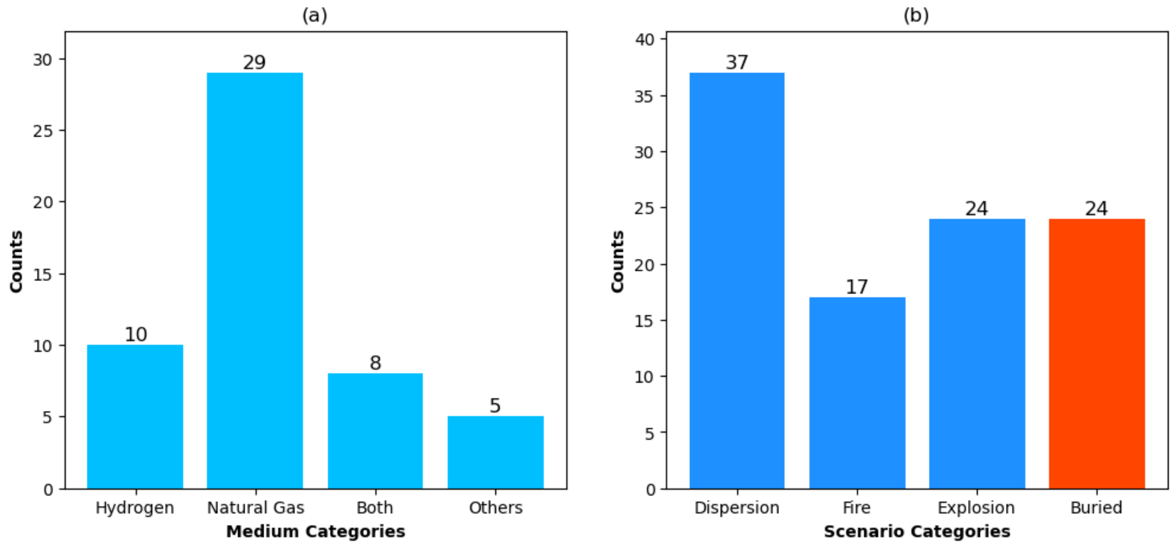

Figure 4. Categories for Collected Publication of Experiment and Incident Analysis: (a) Medium Categories; (b) Scenario Categories

The figure summarizes the distribution of studies based on gas type and scenario. The left panel shows counts across experimental studies and incident analyses for natural gas, hydrogen, blended gas, and others, dominated by natural gas. The right panel highlights that dispersion is the most studied phenomenon, followed by explosion and fire. Of these 78 studies, 24 focused on buried pipelines.

In the next quarter, the team will continue and complete the literature review, with a focus on finalizing the assessment of numerical and machine learning approaches. Upon completion, all findings will be compiled into the final report for this phase. This effort will support the transition into the next phase of the project, which will focus on developing computational fluid dynamics (CFD) models and planning the corresponding experimental work to support model validation and further development of the PIR prediction framework.

Item #5, Task #2: Submit Monthly Reports on PRIMIS – Monthly updates
This quarter, three monthly updates were composed and uploaded to PRIMIS.

Item #6, Task #3: 3rd Quarterly Status Report – Submit 3rd Quarterly Status Report
This report is the third quarterly status report.

5. Project Schedule:

The project is on schedule (Figure 5).

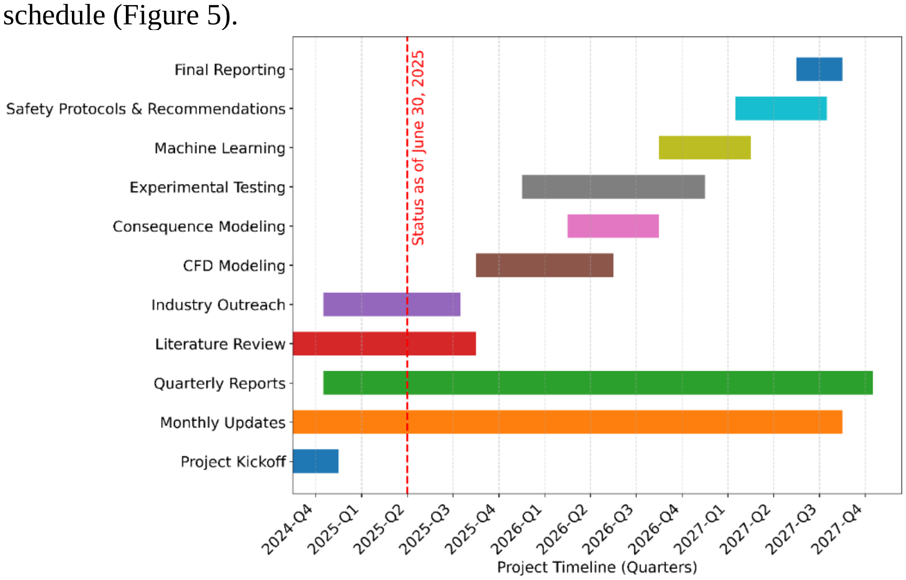

Figure 5. Project Schedule

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