Public Quarterly Report

Date of Report: 2nd Quarterly Report – March 28, 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: March 31, 2025

1: Items Completed During this Quarterly Period:

Item #	Task #	Activity/Deliverable	Title
4	4	Perform literature review activities to identify the state of the art.	Document existing PIR prediction methods, limitations, and industry experience using PIR.
5	2	Submit monthly updates on PRIMIS.	Monthly Updates
6	3	1st Quarterly Status Report	Submit the 2nd 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:

<u>Item #4, Task #4: Perform literature review activities to identify state of the art</u>
The first subtask for the project was to perform literature review activities to identify the state of the art. Specifically, the expectation was to begin documenting existing PIR prediction methods and industry experience using the PIR. Next, the thermodynamic foundation for the calculation was investigated. This task spans two quarters, where the activities commenced during this quarter and are expected to continue into the next quarter. Next quarter's task differs in that all the findings will be documented in the final report, which the team has started.

Existing PIR Calculation Methods and Industry Applications:
The calculation of the PIR is required by 49 CFR 192 Subpart O - Gas Transmission Pipeline Integrity Management. The regulation focuses specifically on transmission pipelines, which tend to travel long distances, contain gas at elevated pressure (~1,000 psig), and pass through densely populated areas. Conversely, pipelines that service the local distribution network and the natural gas gathering network do not share these three critical characteristics. Distribution pipelines, which provide gas service to homes and businesses, operate at relatively low pressures (<100 psig) and are regulated by a separate integrity management program. Finally, while gathering pipelines can operate at elevated pressures, they typically pass through unpopulated areas. Therefore, the impact from a potential loss of containment in gathering lines is minimal. The PIR is intended to be used for transmission pipelines.

PIR calculations for natural gas and hydrogen pipelines are outlined in 49 CFR 192 Subpart O, which defines the specific formula for the PIR of natural gas as:

$$r = 0.69\sqrt{p \cdot d^2}$$

where r is the PIR in feet, p is the maximum allowable operating pressure (MAOP) in the pipeline segment in pounds per square inch, and d is the nominal diameter of the pipeline in inches.

For the transporting gases other than natural gas, the operator should apply the different factors to calculate the corresponding PIR (Baker Jr, 2005):

$$r = \sqrt{\frac{14490 \cdot \mu \cdot \chi_g \cdot \lambda \cdot C_d \cdot H_C \cdot Q \cdot p \cdot d^2}{a_0 \cdot I_{th}}}$$

where, r is the PIR in feet, μ is the combustion efficiency factor, χ_g is the emissivity factor, λ is the release rate decay factor, C_d is the discharge coefficient, H_C is the heat of combustion in BTU per pound, Q is the flow factor, p is the maximum allowable operating pressure (MAOP) in the pipeline segment in pounds per square inch, d is the nominal diameter of the pipeline in inches, a_0 is the sonic velocity of gas in feet per second, and I_{th} is the threshold heat flux in BTU per hour per square feet.

The team's industrial partners commented on their use of the PIR. The feedback received by the team indicates that industry applies the following constants for the PIR calculation: 0.47 for hydrogen, 0.69 for lean natural gas, and 0.73 for rich natural gas. Using the equation listed above, a hydrogen pipeline would have a smaller potential impact radius than a rich natural gas line. For mixed hydrogen and natural gas pipeline systems, the industrial partners polled for this project indicate that they use the more conservative constant for that pipeline's PIR calculation. This leads to applying standoff distances that may be unnecessarily conservative. Industry is very interested in obtaining a valid constant for hydrogen-natural gas pipeline systems that would provide a more accurate PIR.

Thermodynamic Foundation for the PIR Calculation:
The objective of this project is to improve the PIR calculation for hydrogen and blended gas applications. Therefore, one of the first steps in the project is to understand the thermodynamic foundation for the existing PIR calculation so that it can be expanded and improved if needed. Specifically, the team investigated the basis for the PIR applied to natural gas applications. Data were gathered from the original team that developed the PIR formula in 2005, dissecting the published PIR calculation, and by taking a fresh look at the hazards created by a flammable gas pipeline failure.

Hazards on flammable gas pipeline systems begin with a loss of containment. In other words, when the flammable gas escapes the confines of the pressurized pipe and enters the atmosphere in large quantities, it becomes very dangerous. This process is called "release and dispersion." Figure 1 shows a flow chart of the consequences of the escaped gases (Crowl & Louvar, 2019). Since hydrogen and natural gas are not toxic chemicals, the relevant concern follows the right branch on the flow chart, which pertains to the hazard of flammable gases. Flammability limits, including the lower (LFL) and upper flammable limits (UFL), along with the concentration distribution profile, are critical factors to consider when modeling the consequence from a loss of containment. Additionally, the time to ignition determines the type of hazardous event. Immediate ignition results in a sustained jet fire, while delayed ignition has the potential to lead to an explosion.

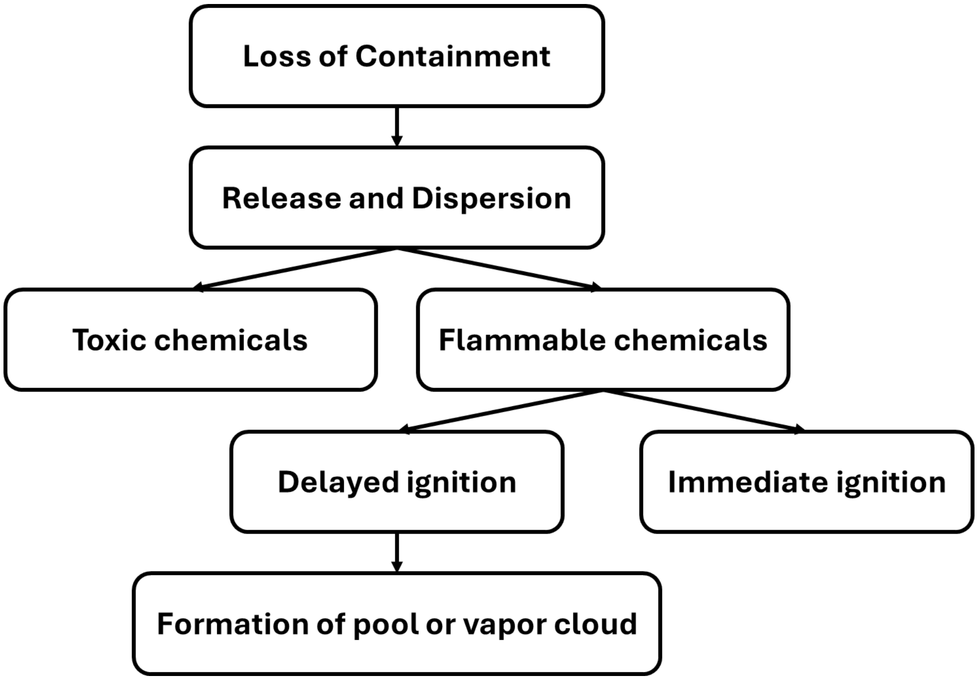


Figure 1. The Trend of Gas Transmission and Gathering Incidents for Hydrogen and Natural Gas
This diagram differentiates between toxic and flammable gas hazards and illustrates how ignition timing determines the nature of the resulting hazardous event, either sustained jet fire or potential explosion.

Since the hazards from pipeline loss of containment include dispersion, fire, and explosion, a simple equation cannot solve all of these hazards. The original PIR calculation made a critical simplification based on the most prominent hazard. Currently, PIR calculations are based upon the possibility of a sustained jet fire scenario and not on a possible explosion. The premise is that thermal radiation from a sustained jet or trench fire poses the dominant hazard in the event of pipeline rupture. The PIR formula was derived from a fire model that considers the threat to human life from thermal radiation (Baker Jr., 2005; Stephens et al., 2002).

Publicly available data indicate that the exclusion of explosion hazard analysis from the PIR calculation could underpredict the impact radius of a transmission pipeline loss of containment, leading to unnecessary injuries and fatalities. Table 1 shows the types of natural gas transportation incidents, based on a survey of 131 incidents in 1995 (Montiel et al., 1996). The data show that explosions account for most incidents across the study.

Table 1. Type of Incident of Transportation of Natural Gas (Adapted from Montiel et al., 1996)
Explosion incidents accounted for the highest percentage (65.6%) of events, indicating the importance of considering explosion risks in PIR calculations, even though current models primarily address fire hazards.

Type	Number of Entries	Percentage of Total
Explosion	86	65.6
Fire	56	48.1
Gas Cloud	3	2.3

Furthermore, the Pipeline and Hazardous Materials Safety Administration (PHMSA) regulates hydrogen and natural gas pipelines, enforces safety standards, and investigates incidents. PHMSA also publishes statistical reports on pipeline accidents, fatalities, injuries, and damages to enhance safety. According to data from PHMSA (2025), the trend of gas transmission and gathering incidents for hydrogen and natural gas, comprising 1,505 incidents related to natural gas and five related to hydrogen, is shown in Figure 2. Except for the San Bruno pipeline explosion, which claimed eight lives and caused 51 injuries in 2010, the trend of safety impacts for natural gas pipelines has remained relatively constant. In other words, the pipelines could benefit from improved safety standards to reduce the number of incidents, injuries, and fatalities.

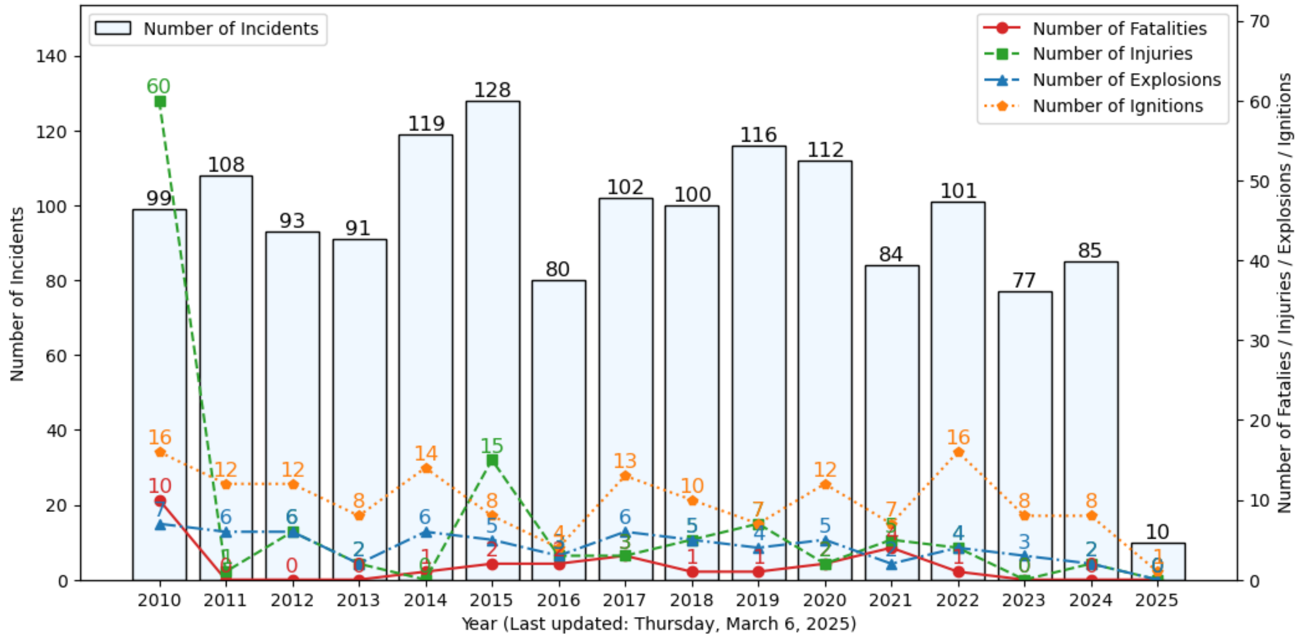


Figure 2. Trends of Gas Transmission Incidents for Hydrogen and Natural Gas
With the exception of the San Bruno fire, the trend of incidents, injuries, and fatalities has not improved over the 15 years of data presented in the chart, underscoring the need for risk-informed PIR modeling.

Interestingly, only 66 out of the 1,505 incidents shown in Figure 2 resulted from explosions, which is significantly less than the 1996 Monteil study. The remainder resulted from a sustained fire. Even though the percentage of explosions among the incidents was only around 4%, these explosions led to 17 fatalities and 95 injuries. Further, Figure 3 shows that explosions made up most of the fatalities and injuries from the incidents recorded by PHMSA.

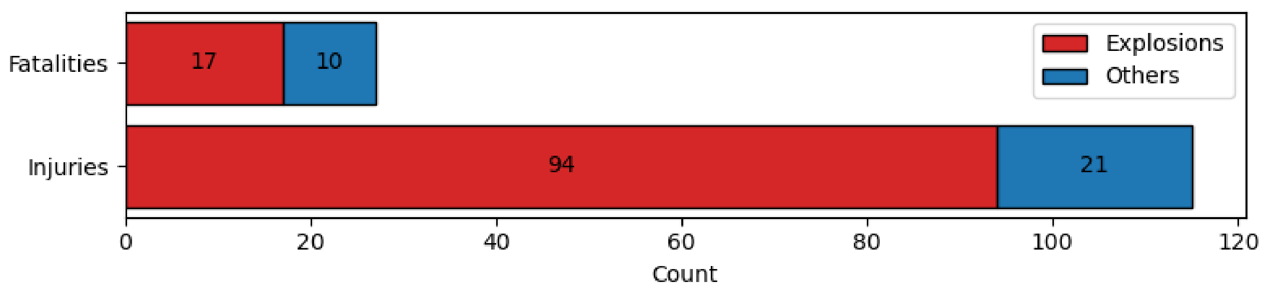


Figure 3. Comparison of Injuries Caused by Explosions and by Other Causes
Despite making up only 4% of total incidents, explosions were responsible for most fatalities and injuries, reinforcing their disproportionate impact relative to frequency.

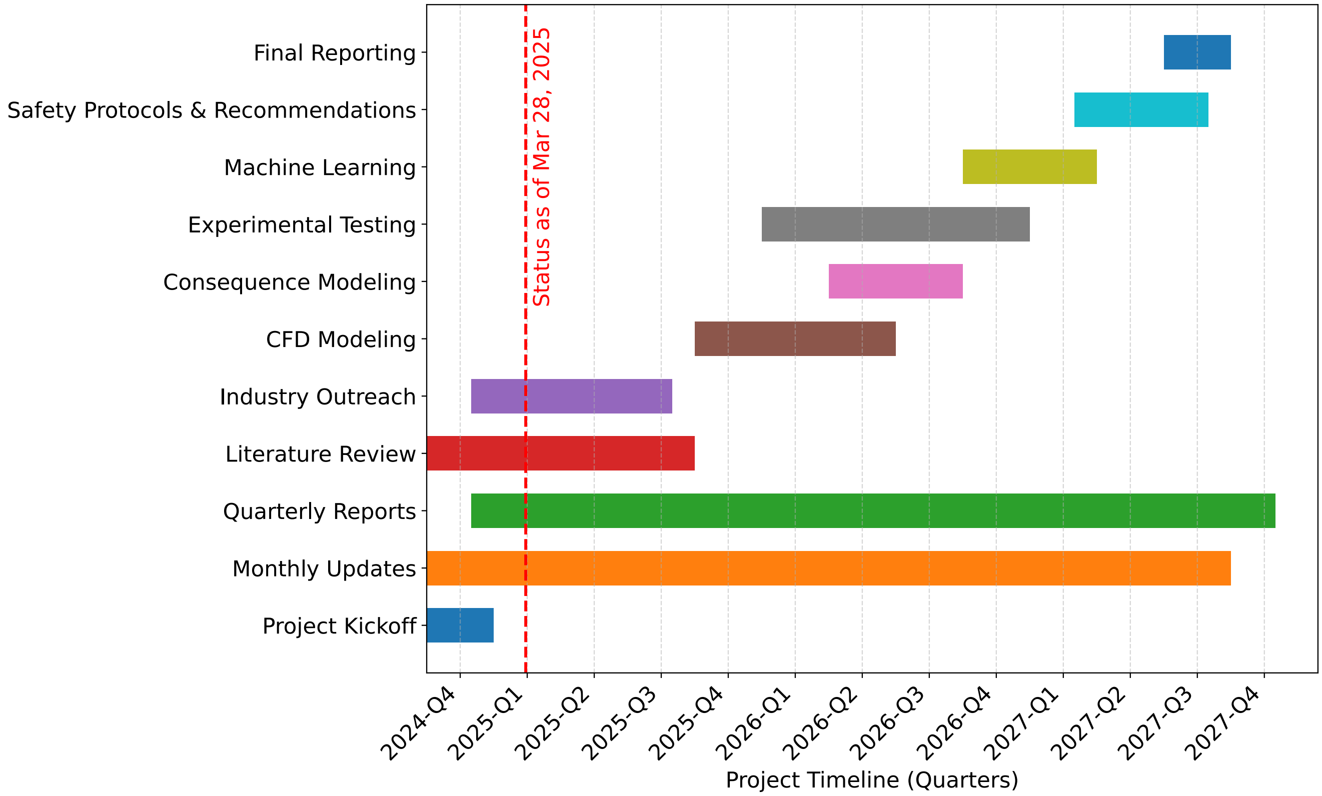
Further investigation into the likelihood and severity of explosions versus jet fire will take place in the next quarter. However, pivoting this study to investigate explosions, as well as jet fire consequences from pipeline loss of containment, is not within the budget or schedule available for this project. Therefore, the team will investigate ways to incorporate the investigation of explosions on a limited scale during the next quarter.

The team identified one additional limitation on the scope proposed for this project. Specifically, the validation testing proposed for this project was designed to mirror aboveground pipe installations and subsequent leaks. However, most transmission gas pipelines are buried. The team will review the literature to determine if the resulting plume from a buried pipeline failure varies from an aboveground pipeline. If so, adjustments to the experimental program may be suggested.

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

Item #6, Task #3: 2nd Quarterly Status Report – Submit 2nd Quarterly Status Report
This report is the second quarterly status report.

5: Project Schedule –
The project is on schedule.



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