Enhancing Risk Assessment in Natural Gas Pipelines Using A Fuzzy-Aggregation Approach Supported by Expert Elicitation

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ABSTRACT:

Although the natural gas pipeline network is the most efficient and secure transportation mode for natural gas, yet it is always susceptible to various external and internal risk factors. It is vital to address the associated risk factors such as corrosion, third-party interference, natural disasters, and equipment faults that may lead to pipeline leakage or failure. The conventional quantitative risk assessment techniques require massive historical failure data that is sometimes unavailable or vague. Experts or researchers in the same field can always provide insights into the latest failure assessment picture. In this paper, fuzzy set theory is employed by getting the expert elicitation through linguistic variables to obtain the failure probability of the Top Event (pipeline failure). By applying a combination of T- and S-Norms, the fuzzy-aggregation approach can enable the most conservative risk failure assessment. The findings from this study showed that internal factors, including material faults and operational errors, significantly impact the pipeline failure integrity. Future directions should include sensitivity analyses to address the uncertainty in data to ensure the reliability of assessment results.

Practical Applications

Natural gas pipelines are efficient and reliable transportation modes. The integrity of these valuable assets is threatened by various risks such as corrosion, environmental factors, human errors, and

mechanical faults. For newly developed or less monitored pipeline networks, historical data is either unavailable or faulty. To overcome this shortcoming, experts from pipeline networks can provide invaluable insight by providing their expert opinion. This study uses the expert's elicitation by applying a fuzzy aggregation approach to predict the pipeline failure probability. The finding of this study confirmed that material faults and operational errors are the most critical risk factors leading to pipeline failure. The results of this study can be used to develop effective mitigation strategies for pipeline networks to minimize future failures.

Keywords: Failure factors, Fuzzy set theory, Cause and effect, Pipeline failure, External and internal failure factors, Corrosion

Introduction

Natural gas is one of the significant components of the energy sector that meets the requirements of power plants, industries, and residential areas (Liu & Bao, 2022). Natural gas accounts for 24 percent of world energy consumption, and pipelines are necessary for transporting and distributing it over long distances (Ding & Yu, 2005). In the United States, natural gas is transported through a highly integrated pipeline network, which serves three purposes, including collection from the source, transmission to target areas, and distribution to end users (Gharabagh et al., 2009). About 4.8 million km (3 million miles) of pipeline networks connect consumers with natural gas production and storage areas. Approximately 77.7 million consumers received 781.6 billion cubic meter (27.6 trillion cubic feet) of natural gas during 2021 through the natural gas transportation network (Han & Weng, 2011). Being the most secure and cost-effective means of transportation for natural gas, pipeline networks have expanded exponentially to transport enormous quantities of natural gas from production sites to end users. However, these networks also may pose a significant threat to the safety of users and the environment being exposed to several internal and external risk factors (Ding & Yu, 2005). The most well-known risk factors are leakages, explosions, sabotage, environmental disasters, and health concerns (Gharabagh et al., 2009). Specifically, as the Pipeline and Hazardous Materials Safety Administration (PHMSA) reported, a pipeline rupture may result in catastrophic consequences, including injuries, deaths, revenue losses, and environmental damage. Since 2003, 660 pipeline incidents have been reported in the United States, resulting in 252 fatalities and 1,081 injuries (Pahlevan et al., 2019). For public safety and environmental protection, preventing these incidents and minimizing their consequences are crucial.

PHMSA's pipeline incident data indicates five significant causes contributing to pipeline incidents, including corrosion, equipment failures, third-party damage, incorrect operations, and material failures(@USDOT, 2023; Tan et al., 2021). While addressing the associated risks, it is imperative to consider all possible variables that threaten the pipeline network's integrity. Mainly, risks in pipeline applications can be categorized into two main types including external factors encompassing elements like corrosion, third-party interference, and natural disasters (earthquakes, floods, lightning, and temperature variations) and internal factors that involve construction, material, design faults, and incorrect operations (Yeganeh et al., 2022).Therefore, natural gas pipeline networks need risk assessments to identify potential hazards, evaluate their impacts, and take preventative measures.

Term risk assessment describes how different variables, basic events (BEs), or *causes* threaten the integrity of pipelines, leading to failures commonly known as *effects*. Pipeline risk management involves evaluating the likelihood and consequences of incidents or failures in pipeline networks (Sheng et al., 2021). Many techniques for risk assessment of pipeline networks, including qualitative, quantitative, and index modeling have been explored (Han & Weng, 2011). Traditional pipeline risk assessment methods use quantitative data and deterministic models by estimating the potential consequences of an event and calculating the associated risks. Event Tree Analysis (ETA), Fault Tree Analysis (FTA) (Pahlevan et al., 2019), Hazard and Operability (HAZOP) studies (Jabbari et al., 2021), and Failure Modes and Effects Analysis (FEMA) are commonly used traditional methods . Although these methods yield valuable models and provide an excellent tool for risk assessment, they have significant limitations since they cannot account for uncertainties, subjective judgments, and complex interactions between factors that impact risks (Hong et al., 2023).

Quantitative Risk Assessment (QRA) analyzes pipeline incidents using mathematical models and statistical data to determine their likelihood and potential consequences. QRA methods usually include Probabilistic Risk Assessment (PRA) and Monte Carlo simulation (Younesi Heravi et al., 2022). Although QRA has been widely used in pipeline safety assessments, it may not effectively account for emerging risks and uncertainties as it relies heavily on historical data. Index Modeling is yet another technique for risk assessment in which various risk factors are assigned numerical values, such as pipeline age, condition, proximity to population centers, and environmental sensitivity (Sheng et al., 2021). These factors are often combined into risk indices or scores to prioritize pipeline segments for further assessment or maintenance. Although Index Modeling can be quick and cost-effective, sometimes complex interactions may oversimplify risks (Tan et al., 2022). For instance, using soil pH and failure due to external coating as a risk indicator could underestimate risks.

Expert elicitation is a hybrid risk assessment technique involving gathering and integrating knowledge and expertise from subject matter experts (Zhang & Thai, 2016). This approach can be beneficial when dealing with complex systems, especially when no historical data is available, and uncertainties play a significant role in understanding and characterizing risks. It aims to assess and quantify risks associated with specific systems or processes (Salah & Moselhi, 2016). Risk assessment in pipelines often involves subjective judgments and uncertainties, such as the probability of rare events or human error. By eliciting expert opinion and insights, non-quantifiable knowledge, that cannot be quantified, is captured, and expert judgments can be represented and managed to handle inherent uncertainty (Sheng et al., 2021). Fuzzy Set Theory (FST) is a mathematical approach to evaluate and address risks based on uncertainty and imprecision. It is difficult to distinguish between low, medium, and high risks in many real-world situations, and risks can have varying degrees of severity or likelihood (Younesi Heravi et al., 2022). With fuzzy logic, uncertainties can be dealt with more nuancedly. Risks are classified into multiple categories simultaneously instead of rigid categories like true or false (Moein Younesi Heravi, 2023).

Using the FST, risks can be represented and analyzed flexibly because the boundaries between risk levels are unclear and overlapping. Risks are multifaceted, and it is difficult to quantify or categorize them in a traditional binary fashion when associated with complex systems and decision-making processes (Salah & Moselhi, 2016). This approach facilitates a more holistic assessment of risks by considering the broader context and interdependencies of risk factors. Pipeline experts can provide detailed insights into challenges and vulnerabilities (Ren et al., 2009). Emerging risks and unique circumstances are particularly beneficial when using this approach, and input from domain experts and regular updates make expert elicitation adaptable to these changes. In addition, this can bridge the gap by combining qualitative and quantitative approaches as experts can provide qualitative insights while quantifying their judgments (Yeganeh et al., 2022).

Researchers have used FST for risk assessments to assess the risks associated with different variables. Using the Fuzzy Inference System, Raeihagh et al. developed a model to quantify the risks associated with sour gas pipelines, ensuring improved safety measures with applicability limited to sour gas pipelines (Raeihagh et al., 2020). Babaeian et al. proposed a semi-quantitative Risk-based inspection (RBI) by concluding that corrosion and erosion are the critical risk factors leading to the failure of gas pressure reduction station equipment for gas pipeline networks (Babaeian et al., 2023). Wen et al. proposed a hybrid machine learning model to assess the risks due to landslides by combining traditional assessment methods with machine learning. Although risks related to sour gas can be assessed using this method but risk assessment due to landslide comes in different domain and may not be applicable to most common natural gas pipeline risks (Wen et al., 2023). By combining the fuzzy technique for Order Preference by Similarities to Ideal Solution (TOPSIS) and cloud inference, Liang et al. proposed a methodology for integrated risk assessment, and findings indicate polyethylene gas pipelines work effectively in urban settings. One possible limitation is that this methodology is primarily suitable for urban areas, potentially excluding consideration for pipelines made of other material types (Liang et al., 2022). Chen et al. introduced a method for classifying pipelines in high-risk regions based on failure scenarios and subjective data. They found that risk assessment in such areas is applicable when enough data is available (Chen et al., 2022). Using subtractive clustering fuzzy logic for risk assessment, Osman and Shehadeh investigated interstate pipelines. The study used hypothetical data to assess the risks associated with interstate pipelines, demonstrating its potential in pipeline risk assessment. However, it is important to note that since the modeling relied on hypothetical data, its accuracy may be limited in real life (Osman & Shehadeh, 2022). Using fuzzy Analytical Hierarchy Processes (AHP), Jabbari et al. (2021) assessed the risks of fire, explosion, and toxic gas release. Through this model, safety managers received valuable data for decision-making (Jabbari et al., 2021). Based on fuzzy AHP, Ba et al. developed a corrosion risk assessment model by validating its effectiveness using a case study. The developed model used expert data only, which may introduce subjectivity (Ba et al., 2022). Zhang et al. introduced Fuzzy Bayesian networks (FBN) to assess the safety of heavy oil pipelines. The lack of data was addressed using FBN, which provided a valid model for risk assessment (Zhang et al., 2019). Pahlevan et al. analyzed the consequences of offshore pipeline failure using a fuzzy approach. Risk assessment of offshore pipelines was streamlined with a systematic approach (Pahlevan et al., 2019). Using Pythagorean fuzzy sets, Oz et al. assessed the risk of clearing and grading processes in natural gas pipeline projects by facilitating risk assessment in pipeline construction through a decision support system, but its relevance was mainly in pipeline construction (Oz et al., 2019). Yu et al. developed a fuzzy fault tree approach for assessing leakage risk in submarine pipelines but the applicability of the approach to pipelines in other setting is not known (Yu et al., 2019).

Due to several key benefits, FST can also be used to assess the risk of pipelines through expert elicitation. Subjective expertise can be incorporated, which is helpful when historical data is faulty or unreliable, thus enhancing the accuracy of assessments (Hawari et al., 2018). Due to the complex and evolving nature of pipeline risk assessments, FST is ideally suited to coping with uncertainty and vagueness, allowing experts to define membership functions for input variables simplifies complexity and facilitates adaptability (Guo et al., 2021). Additionally, due to the interdisciplinary nature of this method, practical evaluation is ensured by bringing together experts from diverse backgrounds. Despite a lack of historical data, it provides transparent decision-making, facilitates risk communication, and can be applied even when no historical data is available. Expert elicitation with FST enables informed decision-making and proactive risk management during pipeline operations, making it a valuable tool for risk assessment (Ba et al., 2022).

As traditional risk assessment methods like QRA and FEMA heavily rely on quantitative data, historical records, and precise numerical values to evaluate the likelihood and consequences of different risk factors, there is a need for an alternative risk assessment methodology to bridge these gaps due to the dynamic risk factors, inherent uncertainties, and data limitations associated with natural gas pipeline networks. This paper introduces a fuzzy-aggregation-based expert elicitation approach to address this challenge by leveraging FST and expert opinions. The presented method provides a comprehensive risk assessment framework that thrives in data-scarce or data-uncertain environments. The methodology incorporates linguistic variables using membership functions and fuzzy-aggregation techniques to accommodate inherent uncertainties that quantitative data may not capture. Natural gas infrastructure will benefit from this innovative approach by improving safety, optimizing resource allocation, and guiding informed decisions. Specifically, this paper will meet the above-mentioned goal through creating a probabilistic questionnaire for expert elicitation, collecting expert opinions using the questionnaire, and applying a fuzzy-aggregation approach to quantify failure probabilities. This fuzzy-aggregation-based expert elicitation methodology is applied to assess the cause-and-effect relation leading to pipeline failure as a Top Event (TE).

This paper adopts the following structure. A fuzzy-aggregation approach is described in Step 2 to elicit expert opinions about the occurrence probabilities of BEs. After applying the proposed approach to Midwest region pipeline networks of the United States, next section reports the application methodology. Considering the findings, later proposed approach's applicability and results is discussed, while last section provides the conclusions.

Fuzzy aggregation approach

The proposed fuzzy aggregation procedure for expert elicitation is illustrated in Figure 1 to determine the likelihood of failure probabilities. It consists of three steps including the meticulous formulation of questionnaire, the systematic gathering of expert opinions, and the robust fuzzy aggregation process. The following subsections explain these steps, detailing the effectiveness of this proposed methodology.

Meticulous Questionnaire Formulation

Determination of BEs

The first step of a risk assessment methodology is to identify and characterize the fundamental components of risk or BEs. Based on the literature review and discussion with experts from the pipeline industry, sixteen BEs have been determined that potentially contribute to pipeline failure (Bertuccio & Moraleda, 2012; Hassan et al., 2022; Kabir et al., 2016). These BEs include transmitted material, soil pH, cathodic protection, external coating, earthquake, flood, thunder/lightning, temperature variation, third-party interference, material type, construction fault, material fault, design fault, and incorrect operation (Liu et al., 2020). Figure 2 represents the cause-and-effect relationship between the BEs and their relation to intermediate events (IEs), finally leading to pipeline failure, denoted as TE. Tier 2 and Tier 3 are the IEs getting influenced by BEs situated in Tier 3. The cumulative failure probabilities of IEs lead to pipeline failure (TE) in the risk assessment model.

Development of the cause-and-effect relation

After finalizing the determination of BEs, a cause-and-effect relationship needs to be established. For establishing the interactions and their influence on TE, BEs are examined, and causal relation is affirmed either directly or indirectly (Yu et al., 2023). For instance, as a direct representation of cause-and-effect relation, pipeline failure could occur due to external factors such as internal coatings, resulting in internal corrosion. It is crucial to distinguish stress corrosion cracking from typical external and internal corrosion processes. Unlike traditional forms of corrosion, stress corrosion cracking is a distinct phenomenon caused by a combination of tensile stress, susceptible material, and a corrosive environment. It often occurs in materials under mechanical stress, such as pipelines, and can lead to catastrophic failures without visible corrosion signs. Therefore, stress corrosion cracking is not categorized as external or internal corrosion. However, stress corrosion cracking can compromise the structural integrity of the pipeline, potentially creating pathways for external corrosion to occur over time due to exposure to environmental factors. So, while stress corrosion itself does not cause external corrosion, it can indirectly contribute to conditions conducive to external corrosion. To establish this indirect cause-and-effect relation, stress corrosion and cracking are not directly linked to external corrosion; rather, they are associated with external factors that ultimately result in pipeline failure.

Pressure reduction stations, an integral component of natural gas pipeline networks, are susceptible to failure when expansion valves, regulators, or relief devices malfunction. As part of failure analysis, equipment failure accounts for the malfunctioning of these components (Howard et al., 2011; Nasser et al., 2021; Xu et al., 2022). Corrosion and erosion are indirect factors contributing to the failure of equipment in pressure reduction stations (Babaeian et al., 2023). Degradation and failure of materials are accelerated by environmental factors such as extreme weather events, earthquakes, or soil erosion. Weather conditions such as heavy rainfall or flooding can cause pipeline components to corrode, making them more susceptible to failure. Additionally, seismic events can damage pressure reduction equipment, compromising its integrity and reliability. Pressure reduction stations fail due to indirect causes such as environmental factors and equipment malfunctions (Xu et al., 2022). The indirect causal relationship between corrosion, mechanical faults, and environmental factors contributing to and leading to pressure reduction station equipment failure is shown in Figure 3.

Questionnaire formulation

In this step, expert opinions are gathered and a quantitative analysis is conducted on various risk factors. Unlike previous steps of risk assessment, this involves the use of a survey questionnaire designed to capture insights from domain experts in the pipeline industry. Within this questionnaire, experts employ linguistic variables, spanning from "Very Low" to "Very High," to provide nuanced responses (Jamshidi et al., 2013). For instance, external corrosion is an outcome of external failure coating due to surface exposure. In this particular question, experts are asked to provide their input based on their experience and knowledge. Another example is third-party interference, experts are asked to provide their opinion using their background knowledge to predict the pipeline failure due to external interference. To quantify fuzzy possibilities and probabilities through defuzzification, FST is applied. FST serves to systematically capture and process expert knowledge and opinions as expressed in the survey questionnaire. Ultimately, this step allows for the quantitative evaluation of the risk profile of the pipeline system.

Systematic Experts' Opinions Gathering

Experts' knowledge and experience are invaluable to assess the associated pipeline risks. Expert opinions are gathered and analyzed in this phase to develop a systematic analysis method. A comprehensive risk assessment of pipeline infrastructure can only be possible through analyzing these expert opinions, which are vital in quantitatively evaluating the BEs and their interconnectedness.

Selection of experts

The process of opinion-gathering hinges upon selecting experts who possess a deep understanding of pipeline failure, risk assessment methodologies, and related fields of natural gas pipeline operations. For this study, individuals are chosen based on their practical experience and industry knowledge. A thorough selection process is employed to select a panel of experts based on their professional positions, experience, education, and age, as outlined in Table 1 (Leonardo Leoni, 2023). Although experience accounts for professional involvement with duration, age still is considered as one influencing factor as it may provide additional insight into how industry practices and technologies have changed over time and age may influence cognitive abilities, including adaptability, learning capacity, and decision-making, which affect expert judgment quality and reliability. Within the expert pool, these criteria ensure the inclusion of diverse perspectives and experiences so that accurate and credible experts influence the risk assessment decisions.

Expert opinion elicitation

Risk assessment techniques by obtaining expert opinions and judgments provide valuable insight, especially if historical data is limited or unavailable. Informed decisions are based on domain experts' knowledge, reducing risk by leveraging their expertise and experience. To extract valuable insights from the panel of experts, a thorough process of eliciting expert opinions was conducted. These experts were consulted and surveyed systematically, each tailored to specific aspects of the risk assessment process. Using linguistic variables such as "Very Low," "Low," "Fairly Low," "Medium," "Fairly High," "High," and "Very High," experts assess the likelihood and severity of each BE. Experts communicated risk assessments nuancedly by utilizing these linguistic variables to consider the inherent uncertainties and complexity associated with pipeline risk.

Iterative and collaborative approaches were used to elicit expert opinions. Using their extensive knowledge and experience, experts provided detailed explanations for their assessments. Experts differ in the depth of their knowledge, so weighing factors should be considered when determining their primary status. When evaluating an expert's status, professional characteristics, qualifications, and experience are considered. This study assessed four types of weights: professional position, education, experience, and age to weigh the BEs (Shan et al., 2017). Weighing factors and scores assigned are shown in Table 1.

Outlier treatment and weighing

Expert opinions play a significant role in the credibility and quality of risk assessment methodologies. For accurate risk assessment, it is crucial to identify outliers before deciding whether to include or exclude them from the dataset (Nooghabi, 2019). An outlier is a data point that deviates significantly from the rest of the dataset. Outliers occur by measurement or data collection errors, unknown underlying patterns, or incorrect assumptions about data distribution (Tang et al., 2015). In risk assessment, outliers are always an issue that needs to be addressed before proceeding with data analysis. There are two main reasons for the occurrence of outliers. First, expert opinions differ significantly, especially when determining the likelihood of rare and severe events. It is imperative to recognize that one expert's assessment may be accurate while another may be completely different from the first. Secondly, being an outlier means that the questionnaire can be complex for some experts to comprehend, which can be considered an unknown factor affecting an expert's decision. Those errors can also appear as outliers if they are introduced inadvertently (Bhargavi & Sireesha, 2022). Analyzing data with outliers is always problematic because skewness always causes the data to be imbalanced resulting in unrealistic results (Zijlstra et al., 2011).

This study uses interquartile range (IQR) criteria to derive the most comprehensive aggregated probability by incorporating a range of viewpoints and excluding extreme values. IQR is calculated by subtracting the first quartiles from the third quartiles, and outliers are detected by adding 1.5 times the IQR to the third quartile and deducting 1.5 times the IQR from the first quartile. Any data point outside this range is considered an outlier (Jeong et al., 2017). Outliers are more likely to be excluded if using this method of outlier detection instead of only using absolute criteria, which leads to a more comprehensive and accurate analysis of the data. Aside from being more straightforward to implement, IQR criteria are also more reliable since they do not rely on a fixed threshold and consider the entire data set. Since IQR criteria can be used to explain outliers and provide meaningful insights, they are also easier to interpret (Greco et al., 2023).

Fuzzy aggregation approach

Fuzzy Set Theory (FST)

Zadeh (1965) presented the FST as a tool for subjective judgment related to vagueness, ambiguity, and multi-criteria decision-making (MCDM) (Zadeh, 1965). The FST allows for a more nuanced and flexible representation of uncertainty in decision-making. The fuzzy numbers introduced in this approach are used to quantify and describe the uncertainty associated with imprecise values within the framework of traditional set theory. In this way, uncertain information can be represented more flexibly (Zhang et al., 2016). Fuzzy logic-based approaches handle uncertainty and imprecision in data and reasoning. This technique is helpful when there is uncertainty with traditional binary or Boolean logic, which describes only true or false states (Liang et al., 2022).

As part of the FST, imprecise data, subjective assessments, and linguistic terms are considered to represent and account for uncertainties and vague information. To capture uncertainties associated with pipeline risk factors, fuzzy sets can be used instead of crisp values to model membership degrees of belief. Pipeline risks can be assessed qualitatively or subjectively utilizing this method, such as corrosion rates, natural disasters and equipment faults (Yu et al., 2021). Using fuzzy sets, we can represent various levels of risk, including very low, low, medium, high, and very high. In a more advanced decision-making approach, it is possible to consider multiple pipeline risk factors (Kabir et al., 2016).

A fuzzy set consists of objects without well-defined boundaries that separate them. Among the members of a fuzzy set, there may be a degree of partial membership or uncertainty. A range of relevance or connection may exist between objects within a set (Kabir et al., 2016). A fuzzy number is used in the FST to represent inherent subjectivity and imprecision in expert judgment. A membership function establishes a relationship between an ambiguous quantity, such as the probability of an event or a root node. Membership functions quantify a fuzzy set's relevance or membership to that set, ranging between 0 and 1 with 0 being the very low and 1 very high. A fuzzy number, either regular, bound, or convex, can express the vagueness of natural language using linguistic variables. Linguistic variables are usually represented by trapezoidal fuzzy numbers (TFZs) or triangular fuzzy numbers (TpFNs) (Zarei et al., 2019). Since TpFNs and TFZs are characterized by linear membership functions, this study utilizes TpFNs since they are versatile and easy to operate, providing advantages over other membership functions.

Conversion of linguistic terms to fuzzy numbers

A failure probability estimate is based on expert elicitation and FST for basic root events (causes). The likelihood of the top event "pipeline failure" can be determined by analyzing the root events and determining their prior probabilities (Eleye-Datubo et al., 2008). Effective risk management strategies are expected to be developed and implemented based on this information to identify the most critical root events and their effects. Besides reducing the risk associated with the studied system, FST ensures accurate and reliable estimates. Table 2 explains the seven scale linguistic variables, their fuzzy membership values, and possible descriptions of each term.

As illustrated in Figure 4, TpFNs represent linguistic terms and their corresponding membership functions. These membership functions address the vagueness associated with linguistic terms by graphically representing the values associated with each set. This graphical transition between the value of zero and one helps determine a term's membership in a set by indicating whether it is a member.

Fuzzy Possibilities (FPs) calculations

Although there are many techniques to calculate FPs, fuzzy linear opinion pool is a simple yet effective method and is therefore used for this study. This method combines multiple experts' opinions to determine if the probability of an event or outcome can be determined by agreement or an aggregate estimate. Expert opinions are categorized using weights assigned to each source, which are aggregated to calculate the final results. It integrates opinions to arrive at an assessment and indicates the degree to which an expert believes a particular outcome or event will occur (Thakur et al., 2022). Equation (1) can be used to calculate FPs:

$$FPs = \sum_{i=1}^{n} W_j A_{ij}\,, \qquad j = 1,2,3, \ldots, m. \qquad (1)$$

In Equation 1, A_{ij} is the linguistic value derived from expert j about event i, FPs is the fuzzy possibility representing the aggregated fuzzy value of event i, and W_j is the weighing score of expert j about event I if there are n total events and m total experts. Table 1 describes the different criteria for experts and their relevant scores based on their position, education, experience, and age.

Defuzzification

Defuzzification is the process of transforming fuzzy sets into crisp values, creating a more efficient and effective decision-making process. This method involves converting fuzzy sets, which represent uncertain information, into crisp values that are more suitable for decision-making. Defuzzification methods include the maximum or mean-maximum method, the weighted average method, and the center of area (CoA). A standard defuzzification method is the CoA, which calculates the crisp value from a fuzzy set. Trapezoidal fuzzy numbers (TpFNs) or triangular fuzzy numbers (TFZs), Gaussian, and sigmoid membership functions can be used to represent linguistic terms (S, 2023; Zarei et al., 2019).

TpFZs are employed in this study to de-fuzzify and convert trapezoidal shapes into crisp values describing fuzzy set membership functions. Figure 5 illustrates the CoA method using TpZFs, which have four dimensions: the left shoulder, the rising edge, the falling edge, and the right shoulder, represented by a_1, a_2, a_3, and a_4. The following equation represents the CoA defuzzification method (Sugeno & Kang, 1986):

$$X = \frac{\int \mu(x) x dx}{\int \mu(x)}. \qquad (2)$$

In Equation 2, $\mu(x)$ represents the aggregated membership function, x is the output variable, and X represents the de-fuzzified output. For a given input variable x, the TpZFs (x) can be defined as follows (Natarajan, 2011).

$$
\begin{aligned}
\mu(x) &= 0, && For\ x < a_1\ or\ x > a_4; \\
\mu(x) &= \frac{(x - a_1)}{(a_2 - a_1)}, && For\ a_1 \leq x \leq a_2; \\
\mu(x) &= 1, && For\ a_2 < x \leq a_3; \\
\mu(x) &= \frac{(a_4 - x)}{(a_4 - a_3)}, && For\ a_3 x \leq a_4.
\end{aligned}
\tag{3}
$$

where the membership of fuzzy input variable x is represented by μ(x) in the fuzzy set. Depending on how strongly an input variable has been included in the fuzzy set, the degree of membership can range from 0 to 1. A value of 0 indicates impossibility, and 1 shows certainty.

Calculating FPr

An FPr is a way of representing probabilities that capture the uncertainty associated with the likelihood of an event in the context of fuzzy sets or fuzzy logic. A fuzzy arithmetic operation and a fuzzy inference technique can be used to calculate FPr (S, 2023). FPr distributions, or fuzzy numbers, are derived by incorporating input uncertainty and propagating it to estimate the FPr distributions. In this study, Onisawa's function was used to convert FPs into FPr (Onisawa, 1988):

$$
\mathrm{FPr} = \begin{cases} \frac{1}{10^K}\ if\ FPs\ \neq 0 \\ 0\ if\ FPs\ = 0 \end{cases}, \tag{4}
$$

$$
\text{where, } K = \left[\left(\frac{1-\mathrm{FPs}}{\mathrm{FPs}}\right)\right]^{\frac{1}{3}} \times 2.301.
$$

Equation (4) calculates *K* using the FPs value obtained from Equation (1). To introduce non-linearity, which is desirable for certain applications, and show direct one-to-one mappings between possibility and probability, Onisawa's function used the exponent of 1/3. Based on empirical rules for specific scaling or normalization, a constant of 2.301 is used (ONISAWA, 1988).

Fuzzy “AND” (T-Norm) and “OR” (S-Norm) operators

Fuzzy “AND” (T-Norm) operators assess all conditions collectively to determine their degree of fulfillment, calculated as the minimum of their fuzzy probabilities by considering all conditions together.

This approach quantifies the contribution of each condition or factor to risk assessment. For instance, applying the fuzzy "AND" operator, the minimum (MIN) of these fuzzy probabilities for BEs corrosion, maintenance quality, and environmental conditions is considered. The risk associated with this minimum operation reflects the contribution of all three BEs' conditions. Conversely, the fuzzy "OR" (S-Norm) operators determine the extent to which at least one condition has been met by calculating the maximum of the BEs' fuzzy probabilities. Unlike the fuzzy "AND" operator, the maximum of the fuzzy probabilities is taken as a result of each condition when applying the fuzzy "OR" operator. These two operators enable handling complex, uncertain, data and reasoning by accommodating degrees of truth and membership (Shi et al., 2014).

"AND" operators promote conservative decision-making by requiring both conditions to be true for the overall condition to be considered, and the result becomes more confident, decreasing the likelihood of making risky choices. However, when a more lenient approach is permitted, the "AND" operator may lead to excessively pessimistic decisions, reducing the possibility of positive outcomes or missing out on opportunities. The "OR" operator allows for inclusiveness and adaptability in decision-making by allowing either condition to be true and providing additional decision-making flexibility. It is suitable where strict criteria are not necessary, and adopting a more accommodating approach can be advantageous. Although the use of these operators is at the discretion of the decision-makers, however, using these operators requires a thorough understanding of the problem because "AND" is more conservative and cautious, while "OR" is more flexible and tolerant (Gupta & Qi, 1991).

Application of Fuzzy-aggregation approach using PHMSA data and domain expert elicitation in the Midwest USA

To validate the developed fuzzy-aggregation approach for assessing the risk involved in pipeline networks, this study analyzed the natural gas pipeline risk in Midwest USA using PHMSA historical database from 2010 to 2022. The historical data was employed to calculate CPr. While, to calculate the

FPr, domain experts from the Midwest region were also elicited in the data analysis process to supplement the factors for which historical data is scarce (Database, 2023). A sole focus of this study is the elicitation of expert data to evaluate the proposed model and description of CPr is to compare the effectiveness of the approach.

Calculation of expert's weighing score

Each variable received in linguistic terms was added to the total weight using Equation (2), and weighing values were calculated using Equation (3). Expert elicitation received from experts showing their professional position, experience, education, age, and weighing score and value are shown in Table 3.

Calculation of CPr and FPr

A CPr reflects the likelihood of an event or outcome based on historical data. Each risk factor is considered individually and its corresponding CPr is calculated. Dataset from PHMSA contains information about pipeline incidents, failure modes, and contributing factors (Database, 2023). The dataset was carefully reviewed and preprocessed before analysis to ensure data quality and integrity. In this process, the data was cleaned, missing values were addressed, and the consistency of variables was verified. Table 4 shows the CPr calculated from the historical data for the Midwest region and based on the pre-processed dataset, CPr is calculated for pipeline network risk factors and failure modes.

To calculate the FPr through expert elicitation, a survey questionnaire was formulated using Qualtrics based on variables explained in Section 2.3.1. and submitted for formal approval by the Institutional Review Board (IRB). After the IRB approval, the survey questionnaire was sent to fifty experts in the field and academia with expertise and experience in pipeline networks. The experts were selected based on their cutting edge research reports submitted to the PHMSA for the last five years, 2018-2023 (Database, 2023).

A few reminders later, fifteen responses were received, but after reviewing, it was realized that they needed to be sorted according to their completeness. Outliers were identified using the IQR technique to make the responses fit for analysis. Five responses were declared outliers due to inconsistent points outside the σ ± 1. Therefore, only ten complete responses from the Midwest region have been considered for conducting for calculation of FPr. As these responses come from experts from industry and academia with different backgrounds and areas of specialization, they cover various aspects of the problem.

A significant difference exists between crisp failure probabilities derived from PHMSA data and corresponding FPr derived from expert elicitation, as shown in Table 5. Uncertainty introduces considerable ambiguity in risk analysis, and lack of failure probability data, inherent ambiguity, and imprecise information lead to underestimating or overestimating risks. (Zarei et al., 2019). Secondly, enhanced safety measures at gas facilities play a crucial role, and due to technological advances, preventive measures, and other factors, recent years have seen substantial improvement in safety levels. (Ramzali et al., 2015). As a result, databases such as PHMSA often present failure data that remains static over time and fails to adequately represent recent advancements in component reliability. Consequently, fuzzy failure probabilities are anticipated to yield results more reflective of the nuanced and evolving safety environment, in contrast to the reliance on rigidly crisp probabilities. Figure 6 explains the comparison of FPr calculated through expert elicitation for sixteen BEs.

Employment of Fuzzy-logic Operators

Before employing T-Norms (fuzzy “AND” operators) or S-Norms (fuzzy “OR” operators), logical relationships are considered to decide the use of sixteen BEs. The T-Norm is used in strict conjunction when all conditions must be met simultaneously for an event to occur. For instance, failure due to transmitted material will cause failure of internal coating and eventually lead to internal corrosion. On the contrary, S-Norm is used as a permissive conjunction when at least one associated condition is satisfied e.g., soil pH, failure due to cathodic protection, and failure of external coating, if any of the conditions is met, it will lead to external corrosion. (Singh et al., 2022). Based on the same rules, Table 6 shows the application of both operators for the fuzzy-aggregation approach. When the T-Norm is used, it will ensure the conservative approach by taking the minimum value out of two failure probabilities.

Figure 7 describes the graphical representation of the fuzzy logic operator for risk assessment probability for TE. For BE1 and 2, T-Norm is used by assuming that transmitted material and failure of internal coating are expected to happen simultaneously or that transmitted material is the root cause for the occurrence of internal corrosion. External corrosion may occur due to poor soil conditions or external coating failure, suggesting employing S-Norm. For natural disasters, T-Norm is used because typically inclement weather, lightning/ thunder, and flood happen simultaneously, leading to natural disasters. Different faults are independent, suggesting using S-Norm leading to IE faults. To ensure risk is represented conservatively and realistically, the T-Norm is used for external factors probability determination. For IEs, internal corrosion, external corrosion, soil pH, stress corrosion cracking, natural disasters, and third-party interference, all critical conditions must be met simultaneously for the event to be deemed probable. S-Norm allows for a more realistic representation of "Internal Factors" probabilities by aligning with the logic that any critical condition can independently lead to the top event. Finally, as part of the risk assessment process, T-Norm calculates the probability of pipeline failure since it captures the logic that for the TE to occur, a combination of external and internal factors must occur simultaneously.

Results and discussion

In this study, the pipeline risk assessment model, a fuzzy-aggregation approach, is employed to calculate the risk probability of pipeline failure as TE. The model integrates sixteen BEs into four IEs, i.e., internal corrosion, external corrosion, natural disaster, and faults in the first step. BE 1 and 2 yielded a failure probability of 0.005 for internal corrosion using T-Norm. BE 3,4 and 5 resulted in a failure score of 0.0132 for external corrosion using S-Norm. The output for IE 3 (Natural disaster), using BE 6,7,8 and 9, is 0.0011 using T-Norm. For IE 4, we used S-Norm for BE 12, 13, and 14, which yielded a failure probability of 0.0098. IEs calculation depicts the membership values for "External Factors" and "Internal Factors," which encompass events related to external risks such as corrosion, third-party interference, and natural disasters. The calculated membership value for "External Factors" is 0.0011, indicating a low but non-negligible likelihood of external factors collectively leading to pipeline failure. Internal factors represent internal risks like material faults and operational errors. The calculated membership value for "Internal Factors" is 0.0098, signifying a higher likelihood of internal risk factors contributing to pipeline failure. Higher probability explains that risks contributing to human error or design faults are more significant than external factors and require deliberate attention to reduce the risk of TE occurrence. Table 7 describes the calculation for TE occurrence. TE results explain the final risk probability for Pipeline Failure. Applying the AND operator to the membership values of "External Factors" and "Internal Factors," a failure probability value of 0.0011 is calculated. This value represents the likelihood of external and internal risk factors coinciding with a pipeline failure event.

Interpreting these results is crucial in understanding the overall risk assessment and its implications. The nearly identical membership values for "External Factors" and "Internal Factors" (0.0011 and 0.0098, respectively) indicate that both external and internal factors play a crucial role in pipeline failure. This balanced contribution suggests that risk mitigation efforts should consider internal and external factors. T-Norm or “AND” tends to be more conservative because it takes the minimum value, assuming the smallest possibility or the most pessimistic estimate. It focuses on the lower bounds of confidence and is associated with a safer, more cautious approach. On the contrary, S-Norm or “OR” tends to be less conservative because it takes the maximum value, assuming the largest possibility or the most optimistic estimate. It's risk-acceptant and may be perceived as less cautious or safe. The higher membership value for "Internal Factors" implies that internal risks, such as material faults and operational errors, may significantly impact pipeline failure. This sensitivity underscores the importance of rigorous quality control, maintenance, and operating procedures. The lower membership value for "External Factors" suggests that while external risks like corrosion and natural disasters are significant, the pipeline may have some resilience against them. Protective measures such as coatings and monitoring systems effectively reduce the likelihood of external factors leading to failure. Based on these results, risk mitigation strategies should focus on maintaining the integrity of internal factors, reducing the impact of external factors, and ensuring a comprehensive risk management plan that addresses both types of risks.

A fuzzy-aggregation approach using fuzzy logic operators offers several advantages over traditional binary methods for assessing natural gas pipeline risk. Fuzzy logic captures the interaction between risk factors and models their dependencies, which is ideal for assessing pipeline failure risks. This approach avoids the potential pitfalls of overestimation and underestimation that binary methods can face due to their balanced consideration of internal and external risk factors. The conservative estimation approach ensures a realistic and cautious risk assessment by combining T-Norms (AND operators) with S-Norms (OR operators). Consequently, the method avoids risk exaggeration while accommodating subtle shifts in risk conditions, thereby offering a balanced assessment that is both reliable and accurate.

This balanced assessment informs practical maintenance and design decisions for pipeline networks. The calculated probabilities derived from this approach offer valuable insights into maintenance prioritization and design enhancements. Prioritizing maintenance activities based on calculated probabilities allows for optimal resource allocation, reducing the likelihood of unplanned downtime or incidents. Moreover, insights from these probabilities inform the design and construction of new pipeline infrastructure or the retrofitting of existing systems. Design enhancements may include redundant safety features, optimized material selection, or advanced monitoring systems, all aimed at mitigating identified risks. By leveraging the calculated probabilities from the fuzzy-aggregation approach, pipeline operators can proactively manage risks, allocate resources efficiently, and enhance the overall safety and reliability of pipeline networks.

The results of this fuzzy-aggregation approach analysis provided valuable insight into data refinement efforts and can be used to identify the key factors contributing to uncertainty. Acknowledging the variability of calculated probabilities over time and as the pipeline degrades, it is recognized that these probabilities are not fixed values and can dynamically change based on evolving pipeline conditions. Pressure reduction stations are a crucial part of the natural gas pipeline system and are vulnerable to failure due to faulty expansion valves, regulators, and relief devices. The analysis incorporates equipment failure and environmental factors to assess malfunction risk. Environmental factors can exacerbate equipment degradation, increasing its susceptibility to failure. Corrosion of pipeline components, particularly in severe weather conditions, further heightens the risk. Additionally, seismic events threaten pressure reduction equipment's integrity and reliability. The failure probability of 0.6% arising from third-party interference endorsed the implementation of ASME B31.8 by designing a higher-class location which will reduce the risk of leakage or rupture by minimizing the corrosion or overpressure to a considerable limit. Observation of ASME B31.8 helps to reduce the risk of leaks, ruptures, and other failures by enhancing public safety and environmental protection. Adherence to these standards is also crucial for the safe and reliable operation of natural gas pipeline networks by promoting industry best practices and regulatory compliance.

Cost-benefit analysis is crucial for pipeline risk assessment models as it helps quantify the economic implications of safety measures versus potential risks. This also helps decision-makers identify optimal strategies to mitigate risks while maximizing cost-effectiveness and ensuring resource allocation aligns with safety priorities. There is a notable absence of a cost-and-benefit analysis within the research which is attributed to the lack of data from the PHMSA database, which hindered the authors' ability to conduct such an analysis.

Conclusions and Future Work

In this paper, a practical approach to modeling pipeline risk assessment complexity and uncertainty has been developed by combining fuzzy aggregation with expert elicitation. Using qualitative methods, such as probability factors, pipeline risks are assessed more nuancedly than binary methods, which only determine success or failure. Further contributions from this study are summarized as follows:

- The results indicate that both internal and external risk factors influence pipeline failures. Internal factors, such as material faults and operational errors, cause more pipeline failures due to human errors and manufacturing faults.
- By analyzing internal factors, it is evident that material faults and operational errors are the most critical factors leading to pipeline failures. The findings of this study show that it is imperative to address the risks associated with external risk factors such as corrosion, third-party interference, and natural disasters.
- This study shows that qualitative methods provide a better understanding of pipeline risks and facilitate decision-making. With crucial insights into natural gas pipeline risk profiles, the investigation will significantly improve pipeline safety and reliability.
- In addition to promoting the development and maintenance of natural gas pipelines, the model can provide a base for research on mitigating pipeline risks and informing policymakers about potential risks.
- The proposed framework can assess potential risks associated with soil characteristics, environmental factors, and material faults. Further, it can evaluate the effectiveness of various mitigation measures, such as leak detection and corrosion control, by highlighting the corrosion risks by pipeline operators in the form of expert elicitation.

There is potential for improvements in several areas in this field, such as conducting sensitivity analyses to address the concerns about uncertainty in data to ensure the reliability of assessment results, and including more diverse expert views considering gender and ethnic diversity, etc. Efforts can be made to minimize the inaccuracies in the input data by enhancing the data collection and monitoring process. Developing novel methods to account for dependencies is possible, providing a more precise representation of complex systems. Further validation with empirical data is necessary to ensure the model's practical applicability. Furthermore, refinement techniques can make the quantification process more robust and consistent. Conducting targeted studies and risk assessments by including pressure reduction stations can help fill the knowledge gaps and inform decision-making processes aimed at enhancing safety and reliability. To ensure public safety and promote environmental sustainability and efficiency in natural gas transportation, future studies should incorporate the guidelines and requirements outlined in ASME B31.8. Future works may also include the cost-benefit analysis for these invaluable assets to facilitate the decision-makers for the best implementation of these risk assessment models.

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Data Availability Statement

The data, models, or code that support the findings of this study are available from the corresponding author upon reasonable request.

The following symbols are used in this paper: $\sum$: summation; $\int$: Integral; $<$: Less than; $>$: greater than.

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Tables

Table 1. Weighing scores are given to experts based on their characteristics.

Criterion	Description	Score	Criterion	Description	Score
Professional Position	Sr./Jr. academic	5	Experience	<5	2
	Engineer	4		5-9	2
	Technician	3		10-19	3
	Operator	3		20-30	4
	Other	2		>30	5
Education	Ph.D.	5	Age	<30	2
	Masters	4		30-39	3
	Bachelor	3		40-50	4
	Social degree	3		>50	5
	High school	2			
	Other	2			

Table 2. Explanation of linguistic variables and membership function with possible description (Guo et al., 2021).

Linguistic variables	Fuzzy membership function				Description
Very Low (VL)	0	0	0.1	0.2	Indicates an extremely low level of risk that the likelihood of an adverse event or the severity of its consequences is extremely unlikely or negligible.
Low (L)	0.1	0.2	0.2	0.3	Signifies a relatively low level of risk that the likelihood of an adverse event or the severity of its consequences is low but not as negligible as in the case of "very low."
Fairly Low (FL)	0.2	0.3	0.4	0.5	A moderately low level of risk means that the likelihood of an adverse event or the severity of its consequences is somewhat higher than "low" but remains at a reasonably manageable level.
Medium (M)	0.4	0.5	0.5	0.6	A moderate level of risk means that the likelihood of an adverse event or the severity of its consequences is neither too high nor too low, falling within an average range.
Fairly High (FH)	0.5	0.6	0.7	0.8	A moderately high level of risk means that the likelihood of an adverse event or the severity of its consequences is somewhat higher than "medium" but still manageable.
High (H)	0.7	0.8	0.8	0.9	A significant level of risk means that the likelihood of an adverse event or the severity of its consequences is considerably higher, demanding increased attention and comprehensive risk management strategies.
Very High (VH)	0.8	0.9	1	1	An extremely high level of risk means that the likelihood of an adverse event or the severity of its consequences is significantly elevated, requiring immediate action and extensive risk mitigation efforts.

Table 3. Expert's details and corresponding weight for the Midwest region.

Expert	Professional Position	Education Level	Experience	Age (Years)	Weighing Score	Weighing value
E1	5	5	2	3	15	0.0904
E2	5	5	2	5	17	0.1024
E3	4	5	4	4	17	0.1024
E4	4	5	5	5	19	0.1145
E5	5	5	3	3	16	0.0964
E6	5	5	2	3	15	0.0904
E7	5	5	3	4	17	0.1024
E8	5	5	3	4	17	0.1024
E9	5	5	3	3	16	0.0964
E10	4	3	5	5	17	0.1024

Table 4. CPr based on PHMSA historical data for the Midwest region.

Attribute	Basic Event	Frequency	CPr (%)
Internal corrosion	Failure due to transmitted material (**BE 1**)	1	0.3
	Failure of internal coating (**BE 2**)		
External corrosion	Soil pH (**BE 3**)	17	4.8
	Failure of cathodic protection (**BE 4**)		
	Failure of external coating (**BE 5**)		
Natural Disaster	Failure due to earthquake (**BE 6**)	No data	
	Flood (**BE 7**)	10	2.8
	Thunder/ lightning (**BE 8**)	14	4
	Temperature variation (**BE 9**)	9	2.6
Third-party interference	third-party interference (**BE 10**)	117	33.3
Stress corrosion cracking	Stress corrosion cracking (**BE 11**)	No data	
Faults	Construction fault (**BE 12**)	21	6
	Material fault (**BE 13**)	20	5.7
	Design fault (**BE 14**)	No data	
Material defect	Incorrect operation (**BE 15**)	No data	
Design fault	Material type (**BE 16**)	No data	

Table 5. Calculations of FPs and FPr for BEs.

BEs	Fuzzy aggregation number				*K*- Value	FPs	FPr (%)
BE1	0.37	0.46	0.565	0.68	2.24	0.5188	0.57
BE2	0.28	0.42	0.585	0.71	2.30	0.4988	0.5
BE3	0.36	0.505	0.685	0.82	2.03	0.5925	0.93
BE4	0.44	0.545	0.66	0.77	2.00	0.6038	1
BE5	0.42	0.57	0.74	0.86	1.88	0.6475	1.32
BE6	0.12	0.2	0.31	0.44	3.22	0.2675	0.14
BE7	0.22	0.33	0.45	0.56	2.67	0.3900	0.14
BE8	0.12	0.18	0.28	0.42	3.32	0.2500	0.11
BE9	0.28	0.4	0.535	0.65	2.41	0.4663	0.24
BE10	0.44	0.565	0.69	0.79	1.95	0.6213	0.6
BE11	0.28	0.4	0.555	0.69	2.36	0.4813	0.53
BE12	0.37	0.54	0.725	0.84	1.96	0.6188	0.32
BE13	0.31	0.43	0.55	0.65	2.35	0.4850	0.28
BE14	0.33	0.515	0.705	0.81	2.04	0.5900	0.65
BE15	0.42	0.57	0.735	0.85	1.89	0.6438	0.98
BE16	0.19	0.355	0.53	0.64	2.53	0.4288	0.45

Table 6. Application of fuzzy-logic operators.

Level	T-Norms (fuzzy "AND" operator)	S-Norms (fuzzy "OR" operator)
Third tier (BEs)	• Failure due to transmitted material • Failure of internal coating	• Soil pH • Failure of cathodic protection • Failure of external coating
	• Failure due to earthquake • Flood • Thunder/ lightning • Temperature variation	• Construction fault • Material fault • Design fault
Second tier (IEs)	• Internal corrosion • External corrosion • Soil pH • Stress corrosion cracking • Natural disaster • Third-party interference	• Material type • Faults • Incorrect operation
Top Event (Pipeline failure)	• External factors • Internal factors	

Table 7. Calculation of failure probability for TE.

<table>
<tr><th>BEs</th><th>IEs</th><th>IEs</th><th>TE</th></tr>
<tr><td>BE1</td><td rowspan="2">IE 1=
BE1∩BE2 = MIN [μ (0.0057), μ (0.0050)] = 0.0050</td><td rowspan="11">IE 5=
IE1∩IE2 ∩ BE10∩IE 3 ∩BE11 = MIN [μ (0.0050), μ (0.0060), μ (0.0132), μ (0.0053), μ (0.0011)] = 0.0011</td><td rowspan="16">TE=
IE5∩IE6 = MIN (0.0098, 0.0011) = 0.0011</td></tr>
<tr><td>BE2</td></tr>
<tr><td>BE3</td><td rowspan="3">IE 2=
BE3∪BE4∪BE5 = MAX [μ (0.0093), μ (0.0100), μ (0.0132)] = 0.0132</td></tr>
<tr><td>BE4</td></tr>
<tr><td>BE5</td></tr>
<tr><td>BE6</td><td>BE6</td></tr>
<tr><td>BE7</td><td rowspan="4">IE 3=
BE6∩BE7∩BE8∩BE9 = MIN [μ (0.0014), μ (0.0014), μ (0.0011), μ (0.0024)] = 0.0011</td></tr>
<tr><td>BE8</td></tr>
<tr><td>BE9</td></tr>
<tr><td>BE10</td></tr>
<tr><td>BE11</td><td>BE11</td></tr>
<tr><td>BE12</td><td>BE12</td><td rowspan="5">IE 6=
BE15∪IE4∪BE16 = MAX [μ (0.0098), μ (0.0065), μ (0.0045)] = 0.0098</td></tr>
<tr><td>BE13</td><td rowspan="3">IE 4=
BE12∪BE13∪BE14 = MAX [μ (0.0032), μ (0.0028), μ (0.0065)] = 0.0065</td></tr>
<tr><td>BE14</td></tr>
<tr><td>BE15</td></tr>
<tr><td>BE16</td><td>BE16</td></tr>
</table>

List of figure captions

Figure 1. Fuzzy aggregation technique to determine the probability of failure incidents.

Figure 2. Cause-and-effect variables leading to natural gas pipeline failure are represented in three tiers.

Figure 3. Indirect causal relation of risk factor responsible for pressure reduction station failure.

Figure 4. Linguistic terms with corresponding fuzzy membership functions.

Figure 5. Trapezoidal fuzzy number $\tilde{A}$.

Figure 6. Comparison of FPr using expert elicitation.

Figure 7. Graphical representation of fuzzy logic operator.