International Journal of Reliability, Risk and Safety: Theory and Application

Online ISSN: 2676-3346

OPEN ACCESS

Vol. 8/ Issue 1/ Year 2025/ pp. 98-113
DOI: 10.22034/IJRRS.2025.8.1.9
Received: 24 April 2025, Revised: 27 July 2025, Accepted: 30 July 2025

**Available online at: https://www.ijrrs.com**

Industrial Case Study

# Fault Lines Due to Ignored Early Warnings: Lessons from the Cheshmeh-Khosh Oil Transmission System

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**Abstract**

Globally, oil pipeline failures can lead to catastrophic human casualties, environmental damage, and economic losses, emphasizing the need for robust risk management. This study addresses these challenges through a case analysis of the Cheshmeh-Khosh–Ahvaz oil pipeline in southwestern Iran, integrating multiple methodologies within a dynamic risk assessment framework. The approach combines Fault Tree Analysis (FTA) and Failure Modes and Effects Analysis (FMEA) to identify and evaluate operational risks systematically, employs fuzzy logic to quantify uncertain linguistic data, and incorporates a Bayesian Network (BN) for real-time probability updating. The model is informed by field observations, expert interviews, and historical data, and Bayesian inference enables continuous updating of failure likelihoods as new information emerges. This multi-method approach quantifies uncertainty and dynamically reprioritizes risk factors, identifying improper pipeline routing as a dominant failure cause in the case study. Notably, while prior studies applied fuzzy FTA to subsea pipeline systems, this work is the first to implement a fuzzy-FTA–FMEA–BN methodology for a terrestrial pipeline, capturing onshore-specific risk factors and enabling real-time risk updates. Practical implications include enhanced pipeline safety through real-time monitoring and targeted maintenance, as well as improving resource allocation to mitigate the highest risks. In sum, the integrated framework offers both a theoretical advancement in probabilistic risk modeling and an operational tool for safer pipeline decision-making.

**Keywords:** Oil pipeline risk management; Safety engineering; Fuzzy logic; Bayesian networks; Risk-informed decision making.

## 1. Introduction

Incidents in the oil and gas industry, though infrequent, can lead to catastrophic consequences, including significant loss of life, extensive property damage, and severe environmental degradation [1]. Such incidents are primarily attributed to hydrocarbon explosions and fires, which account for over 70% of accidents in oil and gas facilities [2]. Among the critical infrastructure components, oil trans- mission pipelines are particularly vulnerable, facing risks such as leaks, environmental damage, fires, and explosions. Factors including aging infrastructure, adverse environmental conditions, suboptimal design, inadequate maintenance practices, pressure management challenges, and flow assurance issues exacerbate these risks.

The conditions in this sector are especially tough—harsh environments combined with vast amounts of flammable materials and tightly packed equipment mean accidents are both more likely and more serious than in many other industries [3]. That's why it's so important to have strong systems in place for identifying, evaluating, and managing risks. Doing so helps prevent incidents in the first place and, if one does happen, limits damage to people and the bottom line.

**How to cite this article:**
A.R. Abtahi, F. Haghighi-Rad, M. Sohrabi Rad, and M. Soori, "Fault lines due to ignored early warnings: lessons from the Cheshmeh-Khosh oil transmission system," *International Journal of Reliability, Risk and Safety: Theory and Application*, vol. 8, no. 1, pp. 98-113, 2025, doi: 10.22034/IJRRS.2025.8.1.9.

### 1.1 The Cheshmeh-Khosh–Ahvaz Pipeline Case Study

Located in southwestern Iran, the Cheshmeh-Khosh–Ahvaz pipeline is a critical component of the country's oil transportation network. Spanning 151 kilometers, this terrestrial pipeline links the Cheshmeh-Khosh oil fields to key processing and distribution facilities. Its geographic position (see Table 1) in a region with extreme environmental conditions, such as high temperatures and frequent dust storms, presents unique operational challenges. Additionally, the pipeline's proximity to populated areas and critical infrastructure increases its exposure to third-party interference and environmental hazards.

The pipeline's operational characteristics highlight its importance as a case study. Handling 18,000 barrels per day, it plays a significant role in the region's oil production. However, historical records highlight recurring risks, including material corrosion, improper routing, and inadequate maintenance practices. These challenges necessitate the application of advanced risk assessment methodologies to ensure the pipeline's safety and reliability. Table 2 shows the technical specifications of the Cheshmeh-Khosh pipeline.

**Table 1.** Geographical position of the pipeline

| Status | Length (km) | Pipeline route |
|---|---|---|
| Ag* | 2.5 | Cheshmeh-Khosh – Abu Ghoveyr (1–2) |
| Ug* | 74 | Abu Ghoveyr – West of Karkheh (2–3) |
| Ag | 1.5 | West of Karkheh – East of Karkheh (3–4) |
| Ug | 73 | East of Karkheh – Shirgah (4–5) |

*Ag = Aboveground, *Ug = Underground

**Table 2.** Technical specifications of the Cheshmeh-Khosh pipeline

| | |
|---|---|
| Pipeline length | 151 km |
| Pipe material | API 5L X52 |
| Cover type | Polyethylene |
| Cathodic protection stations | 5 |
| Service | Crude oil |

### 1.2 Research Context and Methodological Framework

The pioneering work by Cheliyan and Bhattacharyya [4] introduced a fuzzy fault tree analysis (FFTA) methodology to assess the probabilistic failure of subsea production systems. Their research demonstrated the utility of FFTA in addressing uncertainties inherent in failure probability data, offering a significant advancement over conventional fault tree analysis (FTA). By applying fuzzy set theory to expert-elicited data, the study quantified the likelihood of critical events, identified key vulnerabilities, and provided actionable insights into risk mitigation strategies. While their work focused primarily on subsea systems, it laid a robust foundation for extending FFTA applications to other contexts.

Building upon this foundation, the present study addresses key gaps in the existing literature by applying the FFTA methodology to the Cheshmeh-Khosh–Ahvaz pipeline. Unlike subsea systems, terrestrial pipelines face distinct risk factors, including environmental conditions, third-party interventions, and maintenance challenges. This study enhances the methodological framework of Cheliyan and Bhattacharyya [4] by incorporating recent incident data into a Bayesian network model, enabling dynamic updates to failure probabilities. This adaptation significantly improves the model's responsiveness and predictive accuracy. Moreover, this research introduces a novel integration of fuzzy set theory with Failure Modes and Effects Analysis (FMEA) to evaluate the risk priority number (RPN) parameters—occurrence probability, severity, and detection likelihood—within the fuzzy domain. By quantifying these parameters, the study provides a more nuanced understanding of interrelated risks and their cascading effects.

### 1.3 Research Questions and Structure

This study seeks to advance risk management practices by addressing the following research questions:

1. What are the primary risks influencing oil leaks in transmission pipelines?
2. How are these risks interrelated, and what patterns emerge from their interactions?
3. How do recent incident data quantitatively affect these risks, and how can such data be leveraged to improve predictive accuracy?

The remainder of this paper is structured as follows. Section 2 outlines the research methodology, including the integration of FFTA and Bayesian networks. Section 3 details the case study, focusing on the Cheshmeh-Khosh–Ahvaz pipeline and elaborating on the procedural steps undertaken to address the research questions. Section 4 presents an in-depth analysis of the results, highlighting key risks and their implications. Finally, Section 5 concludes with a discussion of the study's contributions, limitations, and directions for future research.

By combining rigorous methodology with practical insights, this research contributes to the broader field of Operations Management by advancing risk assessment practices for critical infrastructure systems. The study's results offer valuable implications for both theoretical development and practical application, providing a robust framework for risk mitigation in the oil and gas sector.

## 2. Literature Review

### 2.1 Risk Assessment in Oil and Gas Pipelines

Risk assessment in oil and gas pipelines is a critical endeavor due to the severe consequences of pipeline failures, including environmental pollution, safety hazards, and economic losses. Pipeline networks form the backbone of hydrocarbon transportation, and their failures (e.g., leaks or ruptures) can result in catastrophic outcomes. Consequently, a variety of risk assessment methodologies have been developed and applied in this domain. Traditional approaches often rely on quantitative risk analysis techniques that use historical failure data and probabilistic modeling. For instance, fault tree analysis (FTA) and event tree analysis are commonly employed to estimate the likelihood of failure scenarios and their consequences in pipeline systems [5]. Standard industry practice may also include semi-quantitative indices or codes that consider factors like corrosion rates, third-party interference, and design parameters to prioritize pipeline segments by risk. However, these

conventional methods face challenges when data are sparse or uncertain, as is frequently the case for rare but high-consequence pipeline failures [6]. Recent research has thus emphasized the incorporation of expert judgment and advanced computational techniques to improve pipeline risk assessments. Studies have shown that specialist elicitation combined with analytical models can enhance risk estimation for pipelines lacking extensive failure statistics. For example, Kalantarnia et al. [7] demonstrated a fuzzy multi-criteria approach to evaluate pipeline failure risks, reflecting a broader trend towards integrating traditional risk models with soft-computing methods to handle uncertainty. Overall, the literature emphasizes the need for robust risk assessment frameworks that can accommodate the complexity and uncertainty inherent in oil and gas pipeline operations.

## 2.2 Fault Tree Analysis (FTA) and Its Limitations

Fault Tree Analysis (FTA) is one of the most established techniques for quantitative risk analysis in engineering systems, including oil and gas pipelines. FTA uses a top-down, deductive logic structure to model how basic component failures (basic events) can combine (through logic gates) to cause a higher-level system failure (top event). In the context of pipeline risk, FTA has been utilized to identify critical failure combinations leading to events such as leakages or explosions, and to compute the probability of such top events [4]. Its popularity stems from the clear graphical representation and the ability to identify minimal cut sets, which reveal the combinations of basic events that can cause system failure. Despite its strengths, conventional FTA suffers from several well-documented limitations. First, FTA requires precise probabilities for all basic events as input. In practice, obtaining exact failure probabilities for pipeline components is often impractical due to insufficient or incomplete data [4]. Pipeline failures may involve rare events or novel conditions where historical data is scarce, forcing analysts to use rough estimates. Traditional FTA offers no mechanism to handle the uncertainty or vagueness in these probabilities explicitly. Second, FTA typically assumes independence of basic events and a static configuration, which means it cannot easily model the interdependencies or the temporal dynamics (e.g., degrading conditions, evolving external threats) that characterize real pipeline operations. As a result, once the fault tree is constructed and quantified, it provides a "snapshot" of the risk but cannot update its failure probability estimates when new information (such as an inspection report or sensor warning) becomes available. These limitations reduce the flexibility of FTA for dynamic risk management. Researchers have recognized these shortcomings and have proposed enhancements to the basic FTA approach. Notably, methods to incorporate uncertainty (through fuzzy logic or probability intervals) and to introduce dynamic updating (through conversion of fault trees to Bayesian networks [8]) have been explored to overcome the rigid data and independence assumptions of conventional FTA [6, 9]. Such improvements aim to retain FTA's logical clarity while extending its applicability to more complex and uncertain pipeline risk scenarios.

## 2.3 Integration of Fuzzy Logic in Risk Assessment

Fuzzy logic has emerged as a powerful tool to address uncertainty and subjectivity in risk assessments, particularly in domains like oil and gas pipelines, where empirical data may be limited but expert knowledge is available. The core idea of a fuzzy approach is to allow risk parameters (such as failure rates or consequence severity) to be expressed in linguistic terms (e.g., "high", "medium", "low") and represented as fuzzy numbers or fuzzy sets. This enables the modeling of imprecise or qualitative information in a mathematically tractable way. In pipeline risk analysis, fuzzy logic has been integrated with conventional techniques to create more robust assessment models. A prominent example is the fuzzy fault tree analysis (FFTA), wherein the precise failure probabilities of basic events in an FTA are replaced by fuzzy probability values to capture uncertainty. Cheliyan and Bhattacharyya's study [4] on subsea pipeline leakage is an illustrative case: by treating basic-event probabilities as fuzzy numbers and using expert elicitation, they transformed a traditional fault tree into an FFTA that could handle uncertain data and still estimate the top event (leakage) likelihood. Researchers have developed fuzzy Failure Modes and Effects Analysis (fuzzy FMEA) methods to improve the subjective scoring of failure modes' risk factors, thereby mitigating the known limitations of the conventional Risk Priority Number (RPN) approach [10]. These studies collectively indicate that incorporating fuzzy logic leads to a more resilient risk assessment, as it allows the inclusion of qualitative expert knowledge and deals with the ambiguity in failure data. The success of fuzzy-integrated models in pipeline risk management has paved the way for hybrid approaches that blend fuzzy logic with probabilistic methods for even greater effectiveness.

## 2.4 Bayesian Networks in Dynamic Risk Modeling

Bayesian Networks (BN) have gained traction in risk modeling as a means to represent complex dependency structures and to perform probabilistic inference in the presence of new evidence. A Bayesian network is a directed acyclic graph where nodes represent variables (e.g., events, component states) and edges represent causal or influential relationships; each node is associated with a conditional prob- ability table that quantifies the probability of the node's states given the states of its parent nodes. In the context of dynamic risk assessment, BNs offer two key advantages over static methods like FTA: they can naturally encode the interdependence between different risk factors, and they support Bayesian updating, which is the revision of prob- abilities when new data or evidence emerges. These features make BNs well-suited for modeling the operational risk of pipelines, where conditions can change over time and events are often interrelated (for example, a corrosion defect increasing the likelihood of a leak, which in turn might depend on maintenance quality or environmental factors). Early applications of Bayesian networks in process safety and reliability demonstrated their ability to overcome FTA's limitations by mapping fault tree structures into BNs models [9]. In such mappings, the logic gates of an FTA (AND, OR) are translated into conditional probability relationships in a BN, enabling the model to capture the same failure logic but with the added benefit of allowing real-time probability updates. For instance, if an inspection report indicates a worsening corrosion rate in a pipeline segment (new evidence), a Bayesian network model can update the probability of a leak in that segment immediately, which a static fault tree could not do without a complete re-analysis. Recent research in pipeline risk has adopted Bayesian network approaches to create more adaptive risk models. Maghiar et al. [11] introduced a hybrid fuzzy Bayesian network for pipeline failure risk modeling, wherein expert-elicited knowledge and fuzzy probabilities were embedded into a BN framework. This integration allowed them to simulate various failure scenarios and update failure likelihoods dynamically under uncertain information. Their work exemplifies how BNs facilitate dynamic risk modeling – the risk picture can evolve as input conditions change, which is essential for pipeline operators making time-sensitive decisions. Moreover, Bayesian networks have been extended to dynamic Bayesian networks (DBNs) or employed in conjunction with time-sequence data to model how risks progress with time explicitly. However, such approaches are more complex and computationally intensive. In summary, Bayesian network techniques significantly enhance pipeline risk assessment by introducing adaptability and a rigorous handling of conditional dependencies, thereby addressing some critical gaps left by conventional methods.

## 2.5 Hybrid Approaches: Combining FTA, FMEA, Fuzzy Logic, and Bayesian Networks

Given the complementary strengths of FTA, FMEA, fuzzy logic, and Bayesian networks, an emerging theme in the literature is the development of hybrid risk assessment frameworks that combine two or more of these techniques. The motivation for hybridization is to create a more comprehensive modeling approach that compensates for the weaknesses of any single method. In the pipeline risk domain, such hybrid approaches have shown promise. A typical hybrid framework might use FMEA as a preliminary step to identify failure modes systematically and the causes of failure in a pipeline system. The outcomes of FMEA (critical failure modes) can then inform the construction of a fault tree, ensuring that the fault tree's basic events cover a broad and systematically derived range of failure scenarios. Fuzzy logic can be integrated at this stage to handle the uncertainty in the failure data or expert estimates for those basic events, resulting in a fuzzy fault tree. Cheliyan and Bhattacharyya's work [4] can be seen as an early contribution in this direction: they effectively combined FTA with fuzzy set theory (FFTA) to assess pipeline leakage risk under uncertainty. However, their approach remained a static analysis and did not incorporate dynamic updating or a formal FMEA step. Subsequent research has pushed further towards fully integrated models. One line of advancement involves converting or mapping the fuzzy fault tree into a Bayesian network, thereby creating a fuzzy Bayesian network model.

This step enables continuous risk updating and probabilistic inference that accounts for new evidence. Wang et al. [12], for example, developed a hybrid model that merges fuzzy logic with a Bayesian network for pipeline failures. In their model, expert judgments provide fuzzy probabilities for basic events, and these are fed into a Bayesian network structure reflecting the fault logic. The result is a risk assessment tool that can both incorporate imprecise data and update risk estimates dynamically – a significant improvement over standalone FFTA or standalone BN models. Other studies have explored integrating FMEA results directly into Bayesian networks or fault trees. In such approaches, the traditional Risk Priority Number from FMEA might be replaced or supplemented by probabilistic reasoning: researchers have proposed using Bayesian belief network models to improve FMEA by accounting for dependency between failure modes and updating risk rankings as conditions change [10].

A formal comparison with the pipeline risk model of Cheliyan and Bhattacharyya (2018) helps illustrate the progress in hybrid methodologies. Their FFTA study

[4] demonstrated the value of combining expert judgment with fault tree analysis via fuzzy mathematics, but it was essentially limited to a static snapshot of risk. In contrast, newer hybrid approaches (including the one presented in this paper) extend this concept by adding Bayesian network-based updating and FMEA-driven comprehensiveness. Unlike Cheliyan and Bhattacharyya's model, which required precise expert input for one-time calculation of fuzzy failure probabilities, a fuzzy–Bayesian hybrid model can iteratively update those probabilities when new operational data (inspections, sensors, etc.) become available. Moreover, our approach's inclusion of FMEA means that the fault tree (and subsequent BN) is built on a foundation of systematically identified failure modes, reducing the chance of overlooking a hazard. Cheliyan and Bhattacharyya did not explicitly use FMEA to generate their fault tree; they focused on four primary leakage sources based on expert knowledge. By integrating FMEA, the present approach ensures a more exhaustive hazard identification process before quantitative analysis.

In summary, hybrid frameworks that unite FTA, FMEA, fuzzy logic, and BNs represent a significant evolution in risk assessment methodology. They seek to offer the best of all worlds: the deductive clarity of fault trees, the thoroughness of FMEA, the uncertainty handling of fuzzy logic, and the adaptability of Bayesian networks. The literature in this area, while still growing, indicates that such multi-faceted models can yield more realistic and actionable risk assessments for complex systems like oil and gas pipelines [13, 14, 15]. This paper builds on and extends these hybridization efforts, aiming to demonstrate an improved risk analysis platform through the synergistic use of all four techniques.

### 2.6 Research Gap and Contribution

Despite the advancements in risk assessment techniques outlined above, significant gaps remain that the current research aims to fill. Prior studies have typically focused on partial integrations – for example, using fuzzy logic with FTA [4], or developing fuzzy Bayesian networks for specific cases [16, 3, 12, 15], or improving FMEA with either fuzzy or probabilistic methods. However, to the best of our knowledge, no study has yet presented a unified framework that holistically combines FTA, FMEA, fuzzy logic, and Bayesian networks for oil and gas pipeline risk assessment. This gap is significant because only a fully integrated approach can simultaneously address all of the key challenges: incomplete data, complex failure interdependencies, dynamic operational conditions, and the need for systematic hazard identification. The contribution of the authors' work lies in proposing and demonstrating such an integrated risk assessment model. In our framework, the traditional pipeline risk analysis is enhanced at multiple levels:

1. Comprehensive hazard identification – by incorporating FMEA, we ensure that a broad spectrum of failure modes is considered before deeper analysis, thereby improving the coverage of the risk model.
2. Structured causal modeling – by using FTA, we maintain a logical cause-consequence structure that is transparent and aids in identifying critical combinations of events (cut sets).
3. Uncertainty handling – through fuzzy logic, we convert expert opinions and sparse data into fuzzy probabilities, enabling the model to function even when precise data are lacking.
4. Dynamic updating and inference – via Bayesian network conversion, we empower the risk model to update failure probabilities as new evidence comes in and to capture dependencies between events that FTA alone would miss. The novelty of this approach is that it brings all these elements together in one coherent model for pipeline risk assessment. This not only bridges the gap left by earlier works that dealt with only subsets of these methods, but also provides a practical tool for decision-makers. The integrated model is expected to yield more reliable and up-to-date risk estimates, which are important for timely maintenance, mitigation, and emergency response in pipeline operations. In summary, our literature review highlights the progression from traditional risk assessment methods to sophisticated hybrid techniques, and it pinpoints that a fully unified FTA–FMEA–Fuzzy–BN approach is the logical next step. The remainder of this paper will detail the development of such a methodology and demonstrate its application, thereby underlining the contribution of this research to advancing the state-of-the-art in pipeline risk management.

## 3. Methodology

This research develops a dynamic, quantitative risk assessment framework for the Cheshmeh-Khosh–Ahvaz oil pipeline by integrating Fault Tree Analysis (FTA), Failure Modes and Effects Analysis (FMEA), Bayesian Networks (BNs), and fuzzy logic into a single cohesive approach. The integration of these methodologies leverages the strengths of each: FTA provides a hierarchical breakdown of failure causes, FMEA prioritizes risks via structured scoring, fuzzy logic captures uncertainty in expert judgments, and BNs enable probabilistic inference with real-time data updates. To clarify the process, Figure 1 illustrates the conceptual flowchart of the methodology, showing how FMEA results feed into the FTA, which is then converted to a BN for dynamic updating, culminating in an integrated risk mitigation strategy. Each step is executed in sequence and informed by the previous steps, ensuring a synergistic analysis.

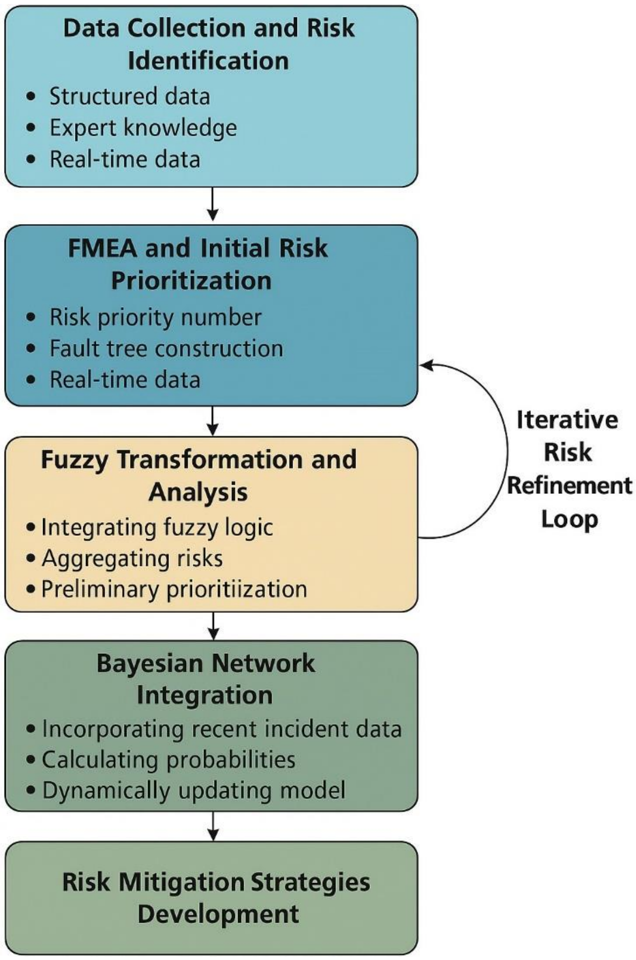


**Figure 1.** Conceptual flowchart of the integrated methodology, combining FMEA, FTA, fuzzy logic, and Bayesian Network

In contrast to earlier fuzzy fault-tree applications in subsea systems, our framework extends FFTA to a terrestrial pipeline context with significant adaptations for the pipeline's operational environment. Terrestrial pipelines like Cheshmeh-Khosh–Ahvaz face unique failure patterns and external risk factors not present in subsea: for example, extreme temperatures and soil conditions, possible third-party interference (e.g., accidental damage from nearby human activities), and more accessible but sometimes inconsistent maintenance regimes. These factors lead to different probabilistic behaviors and uncertainties compared to subsea pipelines (which primarily contend with underwater pressure, corrosion from seawater, and marine interventions). By incorporating region-specific data and expert insight, the methodology is tailored to capture these onshore risk dynamics, thereby demonstrating the generalizability of fuzzy-FTA beyond its original subsea formulation. The following five interrelated steps define the methodological procedure:

1. Data Collection and Risk Identification
2. FMEA and Initial Risk Prioritization
3. Fault Tree Construction and Analysis
4. Bayesian Network Integration
5. Integration and Mitigation

Each step is detailed in the subsections below. This structured approach ensures that each phase builds on the previous one, resulting in a robust framework capable of adapting to new data and evolving risks in real time.

## 3.1 Data Collection and Risk Identification

A multi-pronged data collection strategy was employed to capture the full spectrum of risks pertinent to the Cheshmeh-Khosh–Ahvaz pipeline. Direct field observations were conducted on-site to identify physical vulnerabilities (e.g., points of corrosion, inadequate supports) and operational inefficiencies along the 151km pipeline. Concurrently, semi-structured expert interviews were carried out with a panel of 15 pipeline specialists (senior engineers, operators, and safety managers) selected via purposive sampling. Each interview lasted approximately one hour and followed a standardized protocol covering recent incidents, perceived weaknesses, and existing safeguards. This ensured depth and consistency in expert input, capitalizing on an average of over 10 years of experience per expert.

Additionally, extensive document analysis was performed: historical maintenance logs, incident reports, and technical design documents were reviewed to uncover recurring failure modes and contextual factors. By integrating insights from on-site inspections, expert elicitation, and archival records, a comprehensive risk register was established. This triangulation of data sources provides a high-confidence foundation for subsequent analysis, ensuring that the identified risks reflect real-world operating conditions and expert domain knowledge rather than theoretical conjecture.

## 3.2 FMEA and Initial Risk Prioritization

Failure Modes and Effects Analysis (FMEA) was utilized to prioritize the identified risks systematically. Each risk mode was evaluated on three scales: occurrence likelihood, severity of impact, and detectability of the issue before it manifests. The evaluation employed predefined scoring tables (cf. Table 3, Table 4, and Table 5) that translate qualitative judgments (e.g., "Rare" frequency, "High" severity) into numerical scores on a 1–10 scale for each criterion. This structured scoring approach – adapted from company standards and industry best practices – minimizes subjectivity and ensures consistency across experts. For example, a risk event that experts described as having a "long" expo- sure duration and occurring "sometimes" might be assigned an Occurrence score of 6, while an event causing a major oil spill with lasting environmental damage could receive a Severity score of 8 or 9 (on a scale where 10 denotes catastrophic impact). Detectability scoring similarly gauges how likely it is that each risk can be identified and intercepted with existing controls (with 10 meaning essentially undetectable in advance, and one meaning easily detected well before escalation).

**Table 3.** Scoring Guide for Likelihood

| Frequency | Exposure Duration | Score Range |
|---|---|---|
| Several times per day | More than 6 hours | 10 |
| Every two days | 4 to 6 hours | 8–9 |
| Once a week | 2 to 4 hours | 6–7 |
| Every 15 days | 1 to 2 hours | 4–5 |
| Once a month or more | Less than 1 hour | 1–3 |

**Table 4.** Scoring Guide for Severity

| Score | Safety and Health Impact | Environmental Impact |
|---|---|---|
| 1 | Minor discomfort or negligible injury | No environmental impact |
| 2 | Outpatient treatment; minor injuries | Slight local environmental effect |
| 3 | Minor fractures or burns; recovery < 1 month | Minor environmental impact within the facility |
| 4 | Major injury or disability; 1–3 months recovery | Moderate impact beyond the facility |
| 5 | Permanent disability of one or more | Regional environmental damage |
| 6 | Death or severe multiple disabilities | National environmental consequences |

**Table 5.** Scoring Guide for Detectability

| Score | Description of Detection Likelihood |
|---|---|
| 10 | Consequence is impossible to detect with current controls |
| 7–9 | Very low chance of detection before occurrence |
| 4–6 | Moderate chance of detection; not consistently reliable |
| 2–3 | High likelihood of detection with current measures |
| 1 | Consequences can be reliably and clearly detected early |

To convert linguistic probability terms into fuzzy numbers, deterministic probability ranges were mapped to triangular fuzzy equivalents as shown in Table 6.

**Table 6.** Upper and lower bounds for converting deterministic probability to fuzzy probability

| Deterministic Probability Range | Fuzzy Equivalent (Triangular a, b, c) |
|---|---|
| 0–0.1 | (0.00, 0.05, 0.10) |
| 0.1–0.3 | (0.10, 0.20, 0.30) |
| 0.3–0.5 | (0.30, 0.40, 0.50) |
| 0.5–0.7 | (0.50, 0.60, 0.70) |
| 0.7–0.9 | (0.70, 0.80, 0.90) |
| 0.9–1.0 | (0.90, 0.95, 1.00) |

These expert assessments were consolidated and formatted into success/failure probabilities as shown in Table 7, which were used as inputs for the Bayesian network.

**Table 7.** Success and failure probabilities of preventive systems

| System | Success Probability | Failure Probability |
|---|---|---|
| Automatic Valve Halt | 0.85 | 0.15 |
| Containment Barriers | 0.65 | 0.35 |
| Fire Suppression | 0.74 | 0.26 |

To evaluate the impact of oil leakage events, consequence probabilities were estimated based on expert judgment and incident history, as summarized in Table 8.

Table 8: Probability of oil leakage consequences

| Consequence Type | Estimated Probability |
|---|---|
| Minor Leak (quick recovery, no injuries) | 0.22 |
| Moderate Leak (local impact, minor injuries) | 0.35 |
| Severe Leak (widespread impact, major damage) | 0.28 |
| Catastrophic Leak (multiple fatalities, major fire/explosion) | 0.15 |

Once all risks were scored, the occurrence (Oi), severity (Si), and detectability (Di) ratings for each risk i were combined to compute its Risk Priority Number. The RPN calculation is given by Equation 1, which in this case is simply the product of the three component scores for risk i:

$$RPNi = Oi \times Si \times Di \quad (1)$$

Higher RPNi indicates a more critical risk requiring attention. After computing RPN values for all identified failure modes, a threshold criterion was applied in line with the pipeline operator's risk management standards: any risk with RPN < 75 was deemed low-priority and excluded from further analysis. This thresholding (75 out of a maximum 1000) focuses the subsequent analysis on the most serious risk factors, effectively filtering out minor issues so that resources can be concentrated on the top risks.

## 3.3 Fault Tree Construction and Analysis

Fault Tree Analysis (FTA) was then employed to investigate how the high-priority basic events (risk causes) interact to trigger an oil leakage incident (the top event). Following the methodology of Cheliyan and Bhattacharyya (2018), a fault tree diagram was constructed with the top event defined as a significant oil leak in the Cheshmeh-Khosh–Ahvaz pipeline. This top event (TE) was logically linked to intermediate events and ultimately to the basic events (BEs) identified by FMEA. Figure 2 shows the fault tree architecture.

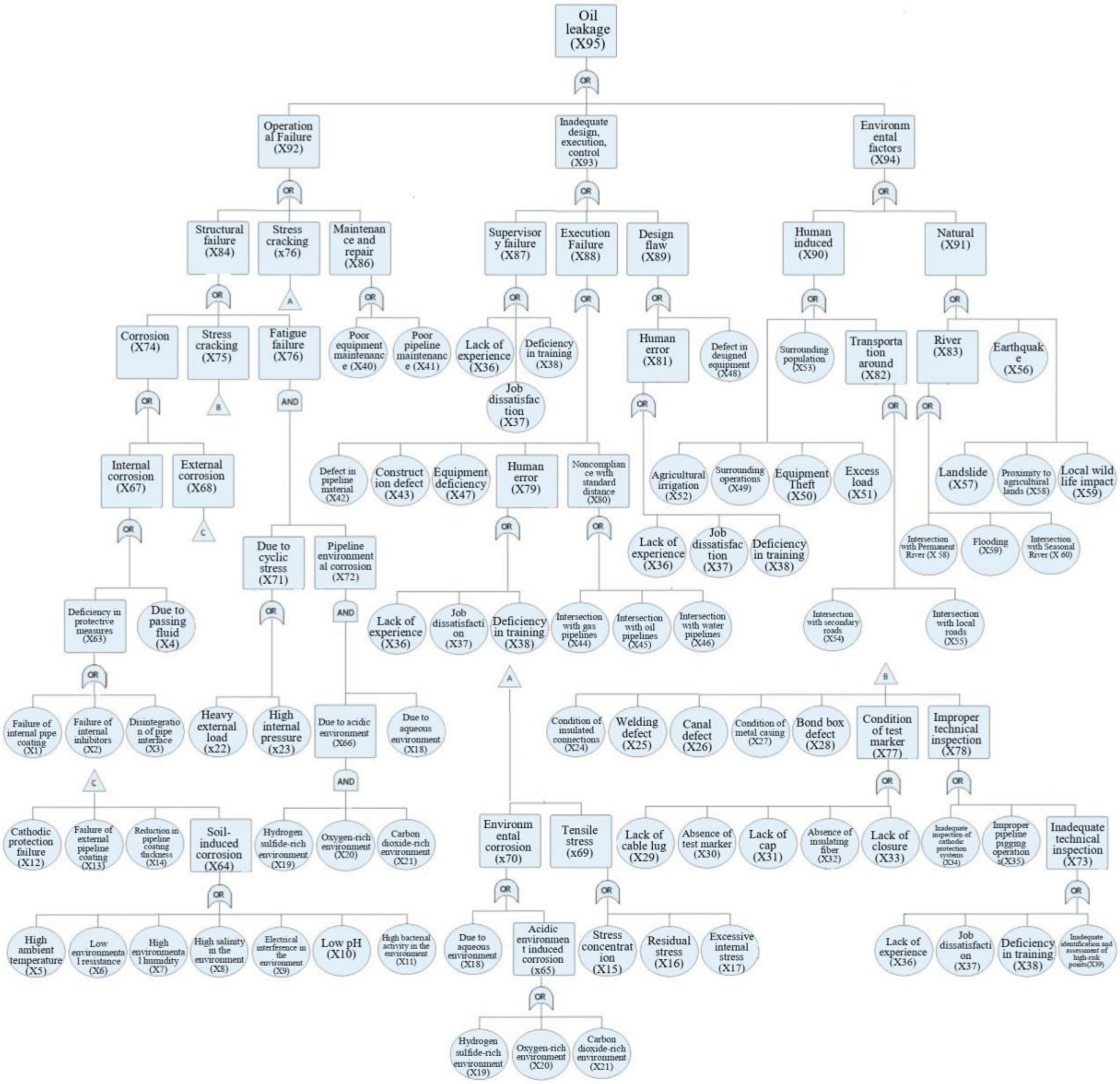


**Figure 2.** Fault tree constructed for the top event of oil leakage (TE = Top Event; BE = Basic Event)

Quantitative analysis of the fault tree was conducted by assigning failure probabilities to each basic event and propagating these through the logic structure to estimate the likelihood of the top event. Because complex data on rare failure events were limited, expert elicitation under uncertainty was used to obtain the base probabilities. Domain experts provided subjective probability estimates for each basic event in linguistic terms (e.g., "very low", "medium", "high" likelihood of occurrence). To rigorously incorporate this uncertainty, fuzzy set theory was applied to these inputs. Each linguistic probability term was mapped to a fuzzy number—typically a triangular fuzzy distribution defined by a triplet $(a, b, c) $ representing its minimum, most likely, and maximum plausible values. Figure 3 illustrates the fuzzy membership functions for the qualitative probability scale used.

For each basic event, multiple experts' fuzzy probability inputs were aggregated (via fuzzy averaging) to produce a combined fuzzy probability. This aggregated fuzzy value was then defuzzified using the centroid method to yield a crisp probability estimate P (BEj) for each basic event j.

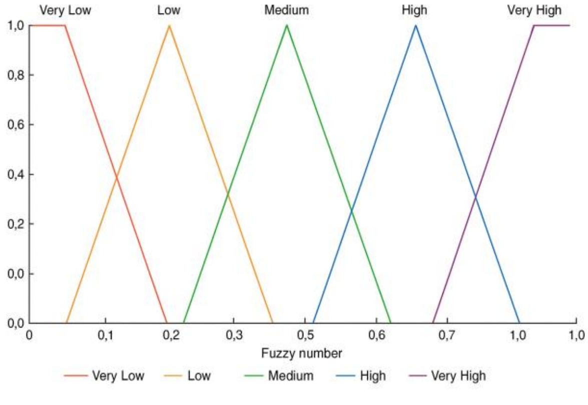


**Figure 3.** Fuzzy membership functions

The defuzzified probabilities retain the influence of all expert opinions while providing a single value that can be used in numerical calculations. With these basic event probabilities in hand, the fault tree was evaluated to compute the likelihood of the top event (oil leakage). Standard probabilistic propagation rules for fault trees were applied: for an OR-gate linking *n* independent input events, the output probability is:

$$P_{out} = 1 - \prod_{i=1}^{n}(1 - P_i) \quad (2)$$

which gives the chance that at least one of the n input events occurs. Conversely, for an AND-gate with m input events, the joint probability of all inputs is:

$$P_{out} = 1 - \prod_{k=1}^{m} P_k \quad (3)$$

Assuming the input events are independent. Using these relations (as appropriate for each gate in the fault tree), we computed the probability of the top event by propagating the basic event probabilities up through the tree (Equation 2 and Equation 3). The resulting estimated leak probability for the pipeline provides a baseline risk level before considering any new data updates.

Beyond the top event probability, the FTA was used to derive measures of importance for each contributing factor. Adopting Cheliyan and Bhattacharyya's approach, we calculated: (i) probabilistic importance, which measures the increase in top event probability caused by a slight increase in a basic event's probability; (ii) critical importance, which highlights basic events that, if fixed or prevented, would cause the most significant reduction in overall risk; and (iii) minimal cut sets, which are combinations of basic events that could jointly cause the top event. These analyses, extended into the fuzzy domain (using fuzzy-weighted indices to account for uncertainty in the probabilities), confirmed that the highest-priority basic events identified earlier (such as improper routing and maintenance failures) indeed dominate the risk of pipeline leakage. The fault tree results thus not only quantify the leak probability but also pinpoint the most critical failure paths requiring management attention.

## 3.4 Bayesian Network Integration

To incorporate dynamic updating and conditional analysis capabilities, the static fault tree was transformed into a Bayesian Network (BN). The BN retains the same causal structure as the fault tree (with nodes corresponding to the top event, intermediate events, and basic events) but represents these relationships in a directed acyclic graph suitable for probabilistic inference. Figure 4 depicts the Bayesian network derived from the fault tree of Figure 2. Each node in the BN corresponds to an event (risk factor or outcome), and each directed edge reflects a causal dependency identical to the logical relationships in the FTA. The primary advantage of the BN formulation is that it enables probabilistic inference: given evidence about specific events, the probabilities of other connected events can be updated in real time. This is particularly worthy for the pipeline case, where new information, such as a detected failure in a pump station or a leak alarm, may drastically alter the risk landscape. Quantitatively, the Bayesian network encodes the joint probability distribution of all events in the system. If we denote the set of all N events by $X_1, X_2, ..., X_N$ (including basic and intermediate events and the top event), the BN factorizes its joint probability as shown in Equation 4:

$$P(X_1, X_2, \dots, X_N) = \prod_{i=1}^{N} P(X_i | Parents(X_i)) \quad (4)$$

where Parents (Xi) refers to the direct predecessor nodes of event Xi in the network (the events that have direct causal links into $X_i$). For basic events (which have no parent causes in the BN), $P(X_i \mid \text{Parents}(X_i))$ reduces to the prior probability of that event (obtained from the FTA/fuzzy analysis). For the top event and other dependent nodes, each term in the product is a conditional probability that can be read from a conditional probability table (CPT). All CPTs in the network were populated using the probabilities derived from the fault tree analysis. In cases where historical incident data were available for certain links (e.g., the conditional probability that an oil leak occurs given a valve failure), those data were used to refine the CPT entries, ensuring the BN parameters reflect the pipeline's operational history and regional context.

The BN enables *Bayesian updating* of probabilities whenever new evidence $E$ is introduced. For instance, if a sensor detects a pressure drop (evidence of a possible leak in a segment), the network can update the posterior prob- ability of the top event (and related causes) given that evidence. This update follows Bayes' theorem. In general, for any event $A$ and new evidence $B$, the posterior probability $P(A \mid B)$ is calculated as:

$$\mathrm{P(A \mid B)} = \frac{\mathrm{P(B \mid A) \cdot P(A)}}{\mathrm{P(B)}} \quad (5)$$

which is Equation 5 in the context of the BN. In the pipeline application, Equation 5 allows us to refine risk estimates continuously. As an illustrative example, if an "External Interference" event (e.g. unauthorized excavation near the pipeline) has occurred ($B$), we can update the probability of the top event $A$ (oil leak) using the known likelihood $P(B \mid A)$ that interference accompanies a leak, combined with the prior probabilities from the FTA. Conversely, observing no incidents in a time can also be treated as evidence that updates the belief in specific failure modes (essentially lowering their probabilities if time passes without occurrence). In this manner, the BN integration makes the risk assessment *dynamic*: it is continually calibrated with incoming data, whether from routine monitoring or actual incident occurrences.

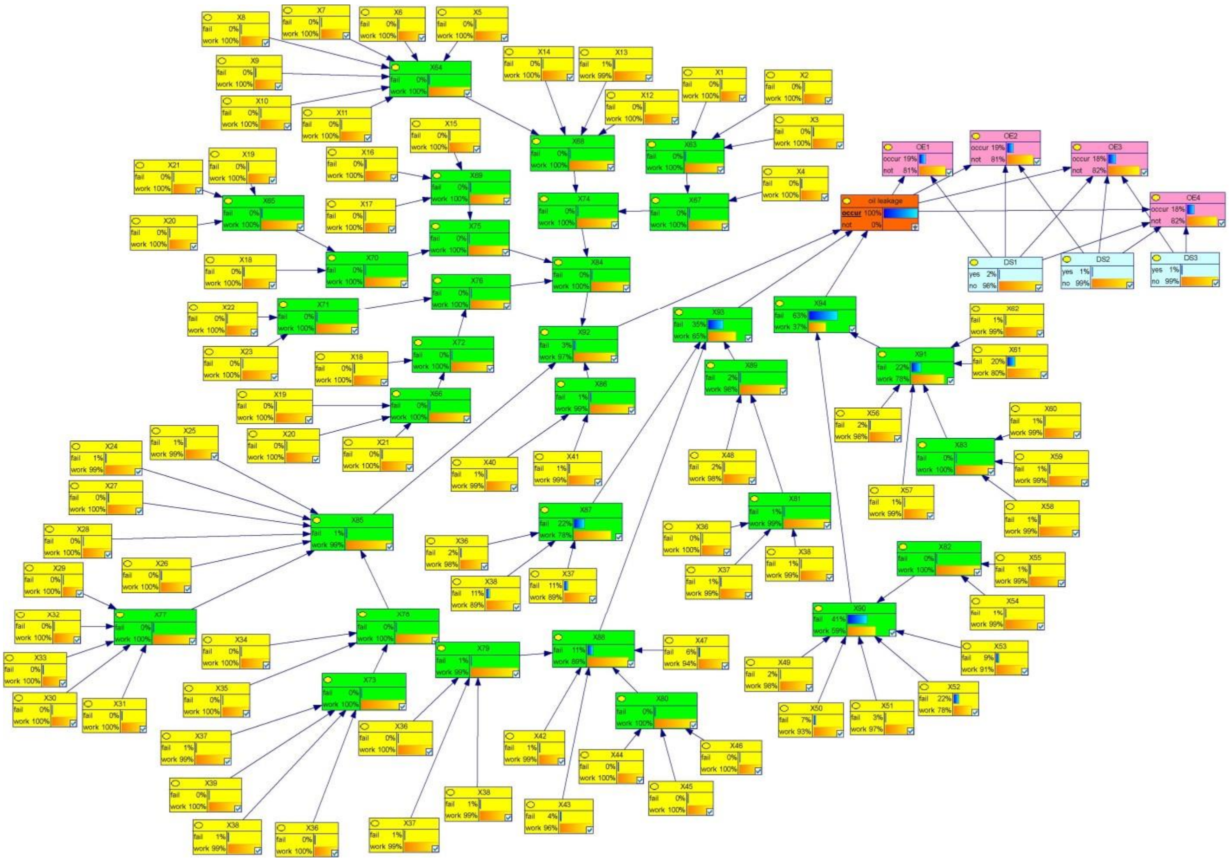

**Figure 4.** Bayesian Network representation of the pipeline risk model

### 3.5 Integration of Results and Mitigation Strategy Development

The final methodological step synthesizes the insights from the FMEA screening, FTA, and BN to develop actionable risk mitigation strategies specifically for the Cheshmeh- Khosh–Ahvaz pipeline. In this step, the high-priority risks and failure pathways identified earlier are each addressed with targeted controls or interventions, and the effectiveness of existing preventive measures is evaluated. The integration of results involved reviewing the ranked list of critical basic events (from the FMEA/FTA analysis) alongside the BN's indication of which factors most strongly drive the top event probability.

Overall, this integrated methodology not only identifies and quantifies the most critical risks to the pipeline but also directly informs a localized risk mitigation plan. Each recommendation is tied to a specific outcome from the analysis. Furthermore, the Bayesian network can be used as a living tool to continuously evaluate the effectiveness of these strategies. As improvements are implemented, the model's parameters (e.g., updated probabilities of basic events) can be adjusted and the overall leak risk recalculated. This feedback loop allows pipeline managers to quantitatively track risk reduction over time and make informed decisions about where to allocate resources for maximum safety gain.

## 4. Results and Discussion

### 4.1 Incident Context

On July 6, 2021, a gas leak triggered a devastating explosion along the Cheshmeh-Khosh–Ahvaz pipeline, killing three technicians and injuring four others [17]. This real incident starkly illustrates the stakes of pipeline risk management and frames the importance of our analysis. The following sections present key results, emphasizing critical risks, dynamic Bayesian updates, localized mitigation strategies, comparisons with prior literature, and practical implications for managers and policymakers.

### 4.2 Overview of Critical Risks

The risk assessment revealed a clear hierarchy of threats. **Improper pipeline routing** emerged as the single most critical risk factor, contributing disproportionately to overall failure likelihood. This Evidence indicates that decisions made during the pipeline's design and route selection (e.g., running the line through high-consequence areas like crowded villages, agricultural fields, and river crossings) have had lasting impacts on its risk profile. Close behind, **inadequate maintenance practices** (e.g., deferred inspections, poor cathodic protection upkeep) and **human error** (operational mistakes, training gaps) were identified as major contributors to leak probability (Fig. 5).

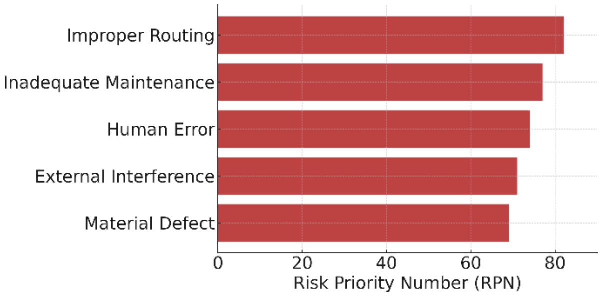


**Figure 5.** Top five risk factors identified for the Cheshmeh-Khosh pipeline

These top three factors significantly exacerbate vulnerabilities in the pipeline system. Notably, they highlight that beyond mechanical issues, organizational and environmental factors play a pivotal role in this terrestrial pipeline's safety. Lesser but still significant risks included **external interference** (third-party damage such as construction near the pipeline or deliberate vandalism) and material defects (e.g., welding flaws, aging-related deterioration). Using the FMEA process, we applied a screening threshold (Risk Priority Number, RPN = 75) to filter out lower-priority hazards, ensuring focus on the high-impact issues. As a result, dozens of minor risks (with RPN < 75) were set aside so that resources and attention could be concentrated on the critical few. This targeted approach aligns with best practices in pipeline risk management, where Pareto analyses often show a small number of causes driving the majority of the risk [18].

The dominance of improper routing as a risk factor emphasizes how the pipeline's local context amplifies certain dangers (Table 9). Routing the line through areas with high environmental stressors and human activity (such as corrosive soils, flood-prone riverine zones, dense agricultural irrigation networks, and populated settlements) has made it inherently more vulnerable. These conditions differ markedly from, say, an offshore pipeline or a remote uninhabited route, and they elevate both the probability of incidents and the severity of consequences.

**Table 9.** Success and failure probability assessment of current preventive systems VH=Very High, H=High, M=Medium, L=Low, VL=Very Low

| Preventive System | Estimated Success Probability | Estimated Failure Probability |
|---|---|---|
| Automatic Valve Halt | 0.85 | 0.15 |
| Rapid Oil Containment Barriers | 0.65 | 0.35 |
| Fire Suppression & Rescue | 0.74 | 0.26 |

## 4.3 Dynamic Probability Updates (Bayesian Analysis)

A key advance of this study is the integration of a Bayesian Network (BN) to update risk probabilities dynamically in light of new evidence. While the Fault Tree Analysis (FTA) provided a static picture of how basic events lead to oil leakages, the BN allowed those probabilities to be revised in real-time as incident data or field observations became available.

For example, after incorporating data from a recent leak incident (such as the 2021 explosion), the model's posterior probabilities for specific root causes shifted significantly. In our analysis, the likelihood of **external interference** increased when evidence suggested third-party activity in the vicinity of the failure, whereas the probability of **material defect** as a cause was adjusted downward after inspections ruled out construction flaws in the failed segment.

This Bayesian updating mechanism captures the intuition that risk levels are not static—they respond to the latest information. By applying Bayes' theorem, the prior failure probabilities (initial estimates based on expert opinion and historical data) were converted to posterior probabilities conditioned on the occurrence of new events. The result is a *dynamic risk profile* that evolves with time.

The ability to observe such changes is practically worthwhile. It produces a "risk alignment sheet" along the pipeline— conceptually similar to those used in industry to visualize how risk varies by location—thereby suggesting where additional preventive measures should be focused [18].

From a methodological standpoint, the Bayesian network's Conditional Probability Tables (CPTs) were customized with regional data to ensure realistic dynamic updates. For instance, the CPT for "Third-party Interference" was weighted to reflect a higher prior probability in agricultural and populated zones (consistent with local history of unauthorized digging and equipment theft). When an incident occurred in such a zone, the BN inferred an even greater posterior probability for future interference events.

This aligns with recent research demonstrating the power of Bayesian methods in pipeline risk assessment. Pang et al. [15] showed that mapping an FTA into a Bayesian Network enables real-time risk analysis of pipeline corrosion as new observations come in. Our evidences echo these studies—the dynamic BN approach proved to be a game-changer for risk monitoring, allowing us to continually refine the risk levels of basic events and the top event.

In quantitative terms, the BN reduced the uncertainty range around the top event probability by incorporating evidence—a behavior also observed by Cheliyan and Bhattacharyya [4] when comparing fuzzy vs. conventional FTA. In short, the dynamic updates provide a more responsive risk model, one that can alert pipeline operators to emerging threats much sooner than a traditional one-and-done analysis.

## 4.4 Localized Mitigation Strategies

Given the insights above, especially the locally elevated risks, we devised mitigation strategies tailored to the specific conditions of the Cheshmeh-Khosh pipeline. Rather than generic recommendations, these strategies focus on the high-priority risks and the contexts in which they manifest.

**Route Adjustments and Hardening.** Addressing improper routing is challenging once a pipeline is built, but targeted interventions are possible. For segments identified as high-risk due to routing (e.g., where the pipeline runs above ground near villages or crosses unstable soil by the river), we recommend engineering reinforcements. This could include adding protective concrete sleeves or deeper burial for exposed stretches, constructing barriers or fences in populated areas to prevent third-party damage, and rerouting small portions if feasible (e.g., around sensitive ecosystems or densely populated pockets). In the case of the Cheshmeh-Khosh line, an above-ground span near the Karkheh River might be retrofitted with flood protection and anti-corrosion coatings, or even diverted via a safer crossing point in future maintenance shutdowns. While major rerouting is costly, micro-adjustments in hazardous spots can substantially lower risk by removing the hazard at its source.

**Enhanced Maintenance Protocols.** The results highlight inadequate maintenance as a critical risk driver, so a localized strategy is to institute a predictive and preventive maintenance regime that reflects the pipeline's environmental stresses. For example, in areas with known corrosive soil (high salinity or low pH, as identified in root causes X8, X10 in Figure 2), the operator should increase the frequency of inline inspections (smart pigging [20]) and ensure cathodic protection stations (there are five along the route) are functioning optimally. Records show that specific stretches had "poor pipeline and equipment maintenance" (risk factors X40/X41). For those stretches, maintenance crews should prioritize repairing coating defects, replacing aged gaskets, and tightening any loose connections before they fail. A schedule of targeted maintenance rounds, especially before high-risk seasons (e.g., summer heat or spring floods), would be appropriate. This risk-based maintenance approach aligns with industry guidance that encourages focused risk reduction on high-threat segments [18].

**Human Error Reduction and Training.** Several basic events pointed to human factors—such as "operator inexperience" (X36), "poor training" (X38), and "inadequate hazard recognition" (X39). A tailored mitigation strategy is to improve human reliability through context-specific training programs for operators and technicians. These programs should address observed failures: emergency response drills for leak containment (especially in light of the 2021 incident), refresher sessions on maintenance procedures, and scenario-based exercises that emphasize regional risks (e.g., recognizing signs of external interference or soil corrosion). We also recommend implementing safety incentives and regular competency evaluations to combat complacency and skill decay. This human-centered approach reflects broader industry best practices in risk mitigation [14].

**Safety Barriers and Systems Optimization.** Our bowtie analysis (FTA and event tree) revealed three critical safety barriers: (1) emergency shutdown valves, (2) rapid oil containment measures, and (3) fire suppression and rescue systems. A practical strategy is to reinforce these systems: test and maintain shut-off valves regularly (especially at pumping stations like the one affected in the 2021 explosion), install remote-control capabilities, and pre-position spill kits for immediate use. Local teams—including community volunteers—can be trained for first response. Similarly, coordination with Khuzestan emergency services and conducting joint response drills can drastically improve reaction time. While these measures do not reduce the *prob- ability* of a leak, they significantly mitigate *consequences*.

**Community and Environmental Safeguards.** Given that the pipeline passes through populated and agricultural areas, mitigation must go beyond technical interventions. We recommend launching a *community awareness program* to inform farmers and residents about the pipeline's location, excavation hazards, and how to report suspicious signs. Local stakeholders can act as early detectors, enhancing leak discoverability. Environmentally, soil and groundwater monitoring should be carried out routinely to detect early contamination, especially in farming zones. To mitigate consequences post-leak, operators can enforce buffer zones (no digging/farming within set distances) and establish protocols with irrigation authorities to isolate affected channels quickly.

Each of these localized strategies maps directly to the high-impact risks identified in our analysis. By tailoring interventions to the Cheshmeh-Khosh pipeline's specific vulnerabilities, the operator can achieve greater impact than with generic, one-size-fits-all measures. For instance, IoT deployment is recommended primarily at high-risk locations (e.g., pump stations and river crossings). At the same time, "enhanced maintenance" is concretely operationalized as increased pigging and corrosion control in known hotspots. This grounded approach ensures that recommendations are both technically sound and practically relevant to decision-makers within Iran's oil pipeline sector.

## 4.5 Comparison with Base Literature

This study builds on and significantly extends the framework of Cheliyan and Bhattacharyya [4], which was a foundational work using fuzzy fault tree analysis (FFTA) for oil and gas leakage risk in subsea production systems. In the base paper, the authors addressed uncertainty in failure data by employing fuzzy set theory within an FTA, allowing them to calculate failure probabilities of a top event (leakage) despite sparse data. They identified critical basic events through importance measures, with *third-party damage* emerging as the top-ranked cause of subsea leaks in their analysis.

We adapted this methodology to a **terrestrial pipeline context** and introduced several novel elements to account for differences in environment and available data.

First, whereas Cheliyan & Bhattacharyya focused on a subsea system—subject to high-pressure, low-temperature conditions and typically mechanical failure modes—our case involves an onshore pipeline exposed to a broader range of risk factors, including human and environmental conditions not prevalent offshore. We expanded the fault tree to include 67 basic events spanning human error, ecological stress, operational failures, and design issues (many of which, like inadequate training or soil corrosivity, were beyond the scope of the base paper's scenario).

This contextual broadening demonstrates the adaptability of the fuzzy FTA approach to different operational settings. One key insight is that the highest-priority cause in our onshore pipeline (improper routing choices) would be irrelevant to a fixed subsea installation, showing how risk profiles shift with context. At the same time, some similar works exist: for example, Cheliyan et al. found that a basic event representing leak control failure (an operational issue) was highly ranked, and we similarly found that operational failings (e.g., maintenance lapses) are critical.This points to the robustness of the FFTA method across settings.

Second, we enhanced the methodological framework by integrating a **Bayesian update mechanism** on top of the fuzzy FTA. The base paper did not use Bayesian networks for dynamic updating and instead produced static probability estimates for the leak event. By mapping our fault tree into a Bayesian Network, we were able to update probabilities when new evidence (like incident data) became available. This adds a temporal dimension to Cheliyan & Bhattacharyya's approach and transforms the risk assessment from a one-time analysis into a living model that ingests continuous data.

Our study thus contributes a fuzzy FTA + dynamic BN hybrid model, which, to our knowledge, has not previously been applied to Iranian pipeline infrastructure. Notably, our work applies this multi-method integration philosophy directly to pipeline systems, confirming its broader practical value.

Third, we introduced **fuzzy-FMEA** into the framework to prioritize risks before fault tree construction. Cheliyan & Bhattacharyya relied solely on expert judgment for assigning probabilities in FTA; we went a step further by conducting a full FMEA (scoring occurrence, severity, and detectability) on all identified risks, and then fuzzified these scores to manage linguistic uncertainty. This allowed us to screen and rank risks even without precise numerical data, ensuring that our FTA focused on the most relevant hazards. This risk prioritization method enhances the practicality of the approach for industrial users—many of whom already implement FMEA—by providing a bridge between familiar tools and more advanced fuzzy probabilistic models.

In summary, our study demonstrates how a probabilistic fuzzy risk analysis can be **adapted and enriched** for a new domain (onshore pipelines) and made more responsive through dynamic updating. We validate the effectiveness of fuzzy logic in handling uncertainty, as pioneered by Cheliyan & Bhattacharyya, and extend it by integrating Bayesian updating and fuzzy-FMEA. Furthermore, we add region-specific insights: while the base paper analyzed an Indian offshore case, our work addresses a Middle Eastern onshore pipeline—filling a literature gap and encouraging cross-domain learning in pipeline risk management research.

## 4.6 Managerial and Practical Implications

The outcomes of this study carry significant implications for industry practitioners, pipeline operators, and policymakers aiming to improve pipeline safety and reliability. By translating the analytical results into actionable guidance, we highlight how managers can proactively manage risks using our insights:

**Risk-Based Inspection and Maintenance.** For pipeline operators, a clear message is to adopt a *risk-based approach* in operational decisions. Our results identified specific segments and failure modes as high-risk; these areas deserve disproportionate attention and resources. Instead of applying equal inspection intervals across all 151 km, operators should *increase inspection frequency* in critical segments (e.g., above-ground stretches, river crossings). Non-destructive testing techniques (e.g., ultrasonic, smart pigging) should be deployed more often in sections flagged by the Bayesian network as high-risk. Maintenance budgets should prioritize the refurbishment of components associated with these risks—for example, investing in rerouting or reinforcement where improper routing is a dominant threat, or upgrading valves where valve failure is a concern. This targeted allocation of effort is consistent with PHMSA's recommendation to focus on dominant risk drivers and critical segments [18].

**Implementation of IoT and Real-Time Monitoring.** Embracing digital technologies provides a practical way to enhance both detectability and dynamic risk management. Managers should consider deploying *IoT-enabled sensors* and real-time monitoring systems along the pipeline. These can include vibration sensors, acoustic leak detectors, pressure/flow variance indicators, and even aerial drone surveillance. Our Bayesian model supports ingesting such continuous data streams to update risk estimates in real time, effectively functioning as a *decision support system*. For example, if vibration anomalies appear at an aging pump station (like the one near Shush), the model can update the probability of failure and trigger pre-emptive maintenance. Given the catastrophic impact of pipeline failures, this investment is cost-effective and justifiable. In the Cheshmeh-Khosh case, sensors should be prioritized at high-consequence locations (river crossings, urban fringes, and pump stations). The Iranian Oil Minister's response to the 2021 explosion specifically called for improved HSE practices [17], which this infrastructure would directly support.

**Emergency Preparedness and Response Planning.** Despite all prevention efforts, incidents can still occur; hence, preparedness is essential. Emergency response plans must be *tailored to local realities*. Pipeline operators should coordinate with local emergency services (fire departments, environmental agencies) and conduct joint drills. Readiness measures include positioning firefighting foam, oil booms, and first aid supplies near the pipeline. Establishing direct communication links (e.g., hotlines or SMS alerts) with nearby communities allows for faster detection and response. Managers should institutionalize community reporting mechanisms as an auxiliary safety net.

**Continuous Learning and Data Updating.** The dynamic nature of our model supports a management culture of continuous learning. Every incident or near-miss should be used as new input to refine the risk model. This means implementing a structured post-incident review process that feeds data into the BN and adjusts failure probabilities based on real-world performance. Over time, such data aggregation will yield a robust, localized database of pipeline behavior. Regulators can mandate this by requiring operators to maintain probabilistic risk models that are regularly updated, an approach long used in the aviation industry.

**Regulatory and Investment Implications.** At the policy level, our results suggest updates to safety regulations. Since improper routing was identified as a systemic issue, safety requirements must be considered from the design stage onward. This might include mandates for route reviews that avoid dense populations or ecologically sensitive areas, as well as enforceable limits on proximity to critical infrastructure. For existing pipelines like Cheshmeh-Khosh, risk-triggered retrofits may be necessary: e.g., mandated valve upgrades or monitoring systems for segments exceeding acceptable risk thresholds. Economically, preventive investment is more cost-effective than post-accident remediation. Our quantified risk assessment provides a basis for calculating return on prevention, supporting operator requests for funding safety measures or enabling insurers to offer incentives for risk-reduction initiatives.

In conclusion, the managerial takeaway is that an **integrated, dynamic risk assessment framework** is not just a technical tool—it is a strategic asset. By adopting predictive maintenance, prioritizing critical segments, improving workforce readiness, and modernizing safety systems, pipeline operators can significantly reduce incident likelihood and consequence severity. For the Cheshmeh Khosh pipeline, such actions are particularly urgent due to increased environmental and societal exposure. Ultimately, this roadmap balances solid analysis with real-world practicality, giving decision-makers the tools they need to safeguard both people and infrastructure. The 2021 gas leak explosion in Iran—where three technicians lost their lives—really brings the stakes into focus. Our recommendations are designed to make sure nothing like that happens again, whether in Iran or in other systems that face similar risks.

# 5. Conclusion

In this study, we introduced a novel risk assessment framework that integrates Fault Tree Analysis (FTA), Failure Modes and Effects Analysis (FMEA), Bayesian Networks (BNs), and fuzzy logic. This combined methodology leverages fuzzy logic to capture the uncertainty inherent in expert judgments and applies Bayesian inference to update failure probabilities as new operational data become available dynamically. The result is a more accurate, flexible, and responsive evaluation of risk compared to traditional static models [4, 9, 19].

Applying this framework to the Cheshmeh-Khosh–Ahvaz oil pipeline revealed how localized environmental and operational conditions exacerbate risk exposure. The pipeline's route through agricultural lands, water bodies, and densely populated regions collectively heightens the likelihood of failure events and amplifies the severity of their consequences. However, the identification of these high-risk segments also enables targeted inspections, thereby improving the detectability of emerging issues. Improper pipeline routing, inadequate maintenance practices, and human error were identified as dominant risk factors, corroborating findings from historical incidents in similar contexts [19, 16].

From a managerial perspective, these insights support the implementation of several actionable strategies. First, the deployment of Internet of Things (IoT)-enabled sensors in vulnerable areas facilitates real-time surveillance and early warning of anomalies, allowing operators to mitigate risks proactively. Second, the Bayesian Network component of the framework enables dynamic updates to risk prob- abilities following incidents, thereby optimizing resource allocation for maintenance and emergency response activities. Third, this integrated approach supports the evaluation of long-term cost-benefit trade-offs between preventive infrastructure investments and reactive maintenance expenditures. Together, these measures enhance operational safety, improve decision-making, and ensure more efficient use of resources across the pipeline system.

Despite its contributions, this study has certain limitations. It relies on expert-elicited estimates for several risk parameters, which may introduce subjectivity, although structured scoring methods were employed to minimize bias [10]. Furthermore, the analysis is confined to a single case study—the Cheshmeh-Khosh–Ahvaz oil pipeline—which may limit the generalizability of the findings to other contexts. Addressing these limitations in future research could enhance the applicability and robustness of the proposed framework. For example, the incorporation of diverse data sources, such as automated sensor streams and multi-region datasets, as well as the examination of additional case studies, would strengthen external validity.

Building on this foundation, future research could extend the framework across various high-risk industries, such as chemical processing, power generation, and urban gas distribution, to evaluate its adaptability and domain-specific performance. Another promising direction involves the integration of artificial intelligence (AI) and machine learning (ML) techniques for automated data preprocessing, event prediction, and probabilistic reasoning. Such integration can reduce reliance on subjective inputs while enhancing predictive precision. Additionally, incorporating real-time IoT data into the Bayesian Network would allow for more responsive and continuous risk monitoring under dynamic operating conditions. By exploring these avenues, researchers can develop an even more robust, scalable, and data-driven risk management system that supports real-time decision-making in pipeline operations and beyond.

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