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INTEGRATED FUZZY AHP–SAM DECISION FRAMEWORK FOR OFFSHORE PIPELINE RISK MANAGEMENT INCORPORATING ECONOMIC RISK FACTORS

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A B S T R A C T

This study presents an enhanced decision-support framework for subsea pipeline risk management by integrating economic risk parameters into an existing hybrid model that combines Fuzzy Analytic Hierarchy Process (Fuzzy AHP), the Similarity Aggregation Method (SAM), Bayesian probability updating, and Monte Carlo-based uncertainty analysis. Alongside conventional environmental, design, structural, and operational factors, the revised methodology explicitly incorporates economic consequences such as repair costs, production interruptions, environmental penalties, and life-cycle cost variability. Environmental considerations include hydrostatic pressure, seabed characteristics, seawater temperature, currents, sediment transport, and corrosive exposure, while technical parameters align with established offshore pipeline standards. Bayesian updating and fuzzy logic support the evaluation of posterior risk probabilities, whereas Monte Carlo simulation enables the propagation of uncertainty related to economic loss estimations under multiple failure scenarios. As a result, the improved framework generates risk indices that reflect both operational vulnerabilities and financial exposure, thereby supporting more realistic, risk-informed decision-making for offshore pipeline systems. Although technical risk parameters are quantified through structured evaluation, the economic risk dimension is developed through a classification- and synthesis-based approach rather than project-specific financial data. Economic indicators are formulated as relative, decision-oriented constructs using normalization, comparative scaling, and prioritization of dominant contributors. This avoids dependence on absolute monetary values, enhances generalizability, and ensures consistent integration of economic considerations into the fuzzy AHP-SAM framework. By embedding economic consequences within the technical risk structure, the proposed methodology advances traditional risk assessment into a cost-aware decision-support system, enabling stakeholders to identify risks with moderate technical likelihood but disproportionately high economic impact.

Keywords: Bayes' theorem; fuzzy logic; similarity aggregation method; posterior probability; economic risk; life-cycle cost.

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1. Introduction

Risk is formally defined as exposure to the potential for injury, loss, or adverse consequences resulting from an event over a given period [1]. Traditionally, subsea pipeline risk assessments have focused primarily on technical failure probabilities and safety consequences. However, modern offshore developments increasingly necessitate the explicit integration of economic risk factors, including capital expenditures (CAPEX) associated with emergency repairs, operational expenditures (OPEX) due to extended maintenance cycles, deferred production losses, regulatory penalties, and environmental remediation costs. By explicitly accounting for these financial dimensions, risk assessment frameworks can capture the full spectrum of potential consequences, enabling more robust and cost-aware decision-making [2-5].

Mathematically, risk is expressed as the combination of the probability of occurrence and the severity of consequences - further refined through structured decision-making tools such as the Analytic Hierarchy Process (AHP), which enables simultaneous weighting of technical, environmental, and economic factors. The primary objective of risk analysis is to quantitatively evaluate the likelihood of specific accident scenarios and their multi-dimensional impacts. Methodological approaches to achieve this include Fault Tree Analysis (FTA), Event Tree Analysis (ETA), Bow-tie (BT) methodology, Safety Barrier Diagrams, and Bayesian Networks (BN), all of which can be adapted to incorporate economic consequence parameters [6-8].

Risk assessment encompasses a range of methodologies aimed at evaluating potential accident scenarios within the process industries. Among the most widely utilized techniques are Quantitative Risk Assessment (QRA), Probabilistic Safety Analysis (PSA), and Maximum Credible Accident Analysis [9, 10]. Although these approaches involve distinct procedures and phases, they universally incorporate two fundamental components: (1) the identification of accident scenarios and mechanisms, and (2) the quantification of likelihood and

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consequence severity, including monetary and operational impacts. Due to their reliability and effectiveness in analyzing and prioritizing accident scenarios, FTA, ETA, and BT models remain the most commonly adopted frameworks [11-14].

In offshore pipeline systems, failure events frequently propagate economic consequences exceeding direct repair costs, arising from extended shutdowns, deferred production, oil spill remediation, regulatory fines, and contractual penalties. Industry data indicate that such indirect economic losses can reach 3–5 times the direct repair costs in deepwater pipeline incidents, underscoring the necessity of embedding economic parameters into risk frameworks [15-17].

Recent scholarship emphasizes the alignment of risk assessment frameworks with sustainable development imperatives, particularly the United Nations Sustainable Development Goals (SDGs). Specifically, SDG 9 ("Industry, Innovation, and Infrastructure") and SDG 14 ("Life Below Water") are directly relevant to offshore pipeline risk management. SDG 9 advocates for resilient infrastructure and sustainable industrialization, which aligns with risk-informed design principles that integrate both technical integrity and economic resilience. For instance, pipelines managed under risk-based inspection regimes exhibit 20–30 % lower failure rates due to optimized maintenance intervals and early corrosion detection [18-21], thereby reducing both operational risks and associated financial liabilities.

Similarly, SDG 14 emphasizes the reduction of marine pollution. Historical events, such as the 2010 Deepwater Horizon spill, which released approximately 4.9 million barrels of oil, demonstrate the dual environmental and economic impacts of subsea pipeline failures [22-26]. Advanced risk assessment techniques, particularly Bow-tie analysis integrated with Bayesian Networks, facilitate the identification of causal chains and multi-layered safety barriers, while also incorporating economic consequence indicators. Comparative analyses suggest that pipelines evaluated using such integrated frameworks can achieve up to a 40% reduction in spill frequency, while simultaneously mitigating indirect financial losses [27].

By incorporating economic risk indicators into a probabilistic-fuzzy decision structure, this study extends conventional risk frameworks to enable simultaneous evaluation of safety performance and financial resilience, supporting sustainable offshore asset management and aligning with both SDG 9 and SDG 14 objectives.

2. New approach to risk forecasting incorporating economic risks

The result of risk forecasting fora certain event is the estimation of when, where and under what conditions the event is likely to occur. In general, non-parametric methods are often used in risk forecasting, for example, the least squares method, which evaluates the accuracy of the forecast.

Steps of the similarity aggregation method

The Similarity Aggregation Method (SAM) is a systematic approach to aggregate expert judgments into a single fuzzy number. It ensures consensus among multiple experts when fuzzy numbers are employed to represent uncertain parameters. This method has been widely applied in fault tree analysis, risk assessments, and decision-making under uncertainty [18, 28].

Summary of Steps:

- Agreement degree (Spq) - Measures similarity between experts.
- Average agreement (Ap) - Calculates individual expert's agreement with others.
- Relative agreement (Rp) - Normalizes agreement values.
- Consensus coefficient (Cp) - Balances weights and agreement.
- Aggregated judgment (EAG) - Combines expert opinions.
- Defuzzification (X*) - Converts fuzzy numbers into crisp values.
- Failure probability (PR) - Estimates the probability of failure.

Step 1: Degree of similarity

Given two sets of tuples $\tilde{A}$ and $\tilde{B}$, each containing sub-tuples with numerical components (a_1, b_1, c_1), (e_1, b_1, h_1) and (a_2, b_2, c_2), (e_2, b_2, h_2), the similarity $S(\tilde{A},\tilde{B})$ between these sets is defined using a formula that combines the sub-tuple comparisons.

$$S\left(\tilde{A},\tilde{B}\right)=\sqrt{S\left(\left(a_1,b_1,c_1\right),\left(a_2,b_2,c_2\right)\right)\times S\left(\left(e_1,b_1,h_1\right),\left(e_2,b_2,h_2\right)\right)}\quad(1)$$

The formula (1) involves computing sub-similarities for each group of triplets and then multiplying and taking the square root.

Step 2: Average agreement degree AA(Eu)

For a group of n experts $E_1, E_2,\ldots,E_n$, the average agreement degree AA(Eu) for an expert E_u is the mean similarity between Eu's opinion and those of all other experts:

$$AA\left(E_u\right)=\frac{1}{1-n}\sum_{\substack{v=1\\ v\neq u}}^{n}S(\tilde{R}u\tilde{E}v)\quad(2)$$

$$A=\frac{1}{M-1}\sum_{n=1}^{M}Spq\quad(3)$$

where $\tilde{E}v$ and $\tilde{R}u$ are the opinions of experts E_u and E_v, respectively.

Step 3: Relative agreement degree RA(Eu)

The Relative Agreement degree RA(Eu) for an expert Eu is a normalized version of the average agreement:

$$RA\left(E_u\right)=\frac{AAE_u}{\sum_{u=1}^{n}AAE_u}\quad(4)$$

This quantifies how Eu's agreement compares to the total agreement of all experts.

Step 4: Consensus coefficient degree CC(Eu)

This step calculates the Consensus coefficient degree CC(Eu) for expert Eu:

$$CC\left(E_u\right)=\beta\omega\left(E_u\right)+(1-\beta)RA\left(E_u\right)\quad(6)$$

Where $\omega(E_u)$ is the expert's assigned importance, β is a relaxation factor (with $0 \le \beta \le 1$) that controls the balance between $\omega(E_u)$ and RA(E_u). A higher value of β emphasizes expert opinion more, while a lower value favors system-derived output (SAM outputs).

Step 5: Aggregation of experts' opinions, $\tilde{R}_{AG}$

The final step aggregates the opinions of all experts:

$$\tilde{R}_{AG}=\prod_{u=1}^{n}CC\left(E_u\right)\times\tilde{R}_{AG}\quad(6)$$

This formula uses a product of each expert's consensus coefficient and their respective opinion.

Step 6: Defuzzification of the aggregated fuzzy number

The aggregated fuzzy number $\tilde{R}_{AG}$ is converted into a crisp value R_d for decision-making.

For a triangular fuzzy number (a, b, c), the defuzzified value R_d is calculated as:

$$R_d = \frac{a+b+c}{3} \tag{7}$$

where a, b, and c are the lower bound, peak, and upper bound of the fuzzy number.

For trapezoidal fuzzy numbers, Using the center area method for trapezoidal fuzzy sets (n_1, n_2, n_3, n_4):

$$X^* = \frac{\int_{n_1}^{n_2}\left(\frac{x-n_1}{n_2-n_1}\right)xdx + \int_{n_2}^{n_3} xdx + \int_{n_3}^{n_4}\left(\frac{n_4-x}{n_4-n_3}\right)xdx}{\int_{n_1}^{n_2}\left(\frac{x-n_1}{n_2-n_1}\right)dx + \int_{n_2}^{n_3} dx + \int_{n_3}^{n_4}\left(\frac{n_4-x}{n_4-n_3}\right)dx} \tag{8}$$

Simplified, the crips value is:

$$X^* = \frac{\left(n_4+n_3\right)^2 - n_4 n_3 - \left(n_1+n_2\right)^2 + n_1 n_2}{3\left(n_4+n_3-n_1-n_2\right)} \tag{9}$$

Step 7: Estimation of probability

The defuzzified value R_d is further converted into a probability $P(R_d)$, providing a normalized confidence measure. The failure probability P_r is calculated as:

$$P_r = \begin{cases} \frac{1}{10^K} \times X^*, & X^* \neq 0, \\ 0 & X^* = 0, \end{cases} \tag{10}$$

where,

$$K = 2.301 \times \left[\frac{1-X}{X^*}\right]^{\frac{1}{3}} \tag{11}$$

Alternatively, for normalized crips values:

$$P\left(R_d\right) = \frac{R_d - R_{min}}{R_{max} - R_{min}} \tag{12}$$

In addition to technical risk forecasting, the proposed framework introduces an economic risk layer (ERL) defined as:

$$ERL = P_f \times C_e$$

P_f - posterior probability of failure

C_e - fuzzy-estimated economic consequence

Economic consequences are modeled using fuzzy numbers to reflect uncertainty in market conditions and operational response. The economic risk sub-factors presented in table 1 are selected to quantify the financial consequences associated with key subsea pipeline failure mechanisms. These sub-factors provide a structured approach to incorporate economic considerations alongside technical risk parameters, enabling cost-aware risk prioritization.

To quantify economic uncertainty, Monte Carlo simulation ($N = 10\,000$ iterations) is integrated with posterior failure probabilities. Input parameters including repair duration, vessel day rates, oil price variability, and penalty ranges are modeled as fuzzy–probabilistic distributions.

The simulation outputs an economic risk index (ERI), enabling ranking of failure modes based on expected monetary loss (EML):

$$EML = \sum\left(P_i \times L_i\right) \tag{13}$$

where L_i represents simulated loss scenarios.

The final decision index is reformulated as:

Total Risk Index (TRI) = α·Technical Risk + β·Economic Risk with weighting coefficients ($\alpha + \beta = 1$) defined via Fuzzy AHP.

This enables cost-effective inspection prioritization, optimization of corrosion protection investment and economic justification for redundancy and safety barriers.

3. Methodology

The primary objective of this study is to enhance conventional offshore pipeline risk assessment methodologies by explicitly grounding technically evaluated parameters within an economically justified decision framework. To achieve this, the proposed approach introduces a structured methodological enhancement in which technical risk indicators are systematically mapped to quantified economic consequences, thereby enabling an integrated and cost-aware risk evaluation paradigm. Some similar questions have been considered by several authors [29-34].

Within this enhanced framework, technical risk outcomes are synthesized through five economically representative parameters (table 1): (E1) repair and replacement costs, capturing direct asset restoration expenditures; (E2) production downtime losses, reflecting revenue losses due to operational interruptions; (E3) environmental penalties and remediation costs, accounting for regulatory, ecological, and reputational liabilities; (E4) inspection and intervention costs, representing preventive and corrective operational expenditures; and (E5) life-cycle cost escalation, addressing long-term financial amplification driven by degradation, aging, and repeated interventions over the asset's operational lifetime.

By embedding these economic dimensions into the risk assessment process, the proposed methodology establishes a causal and quantitative linkage between technical failure mechanisms and their downstream financial impacts. This

Table 1

Economic risk sub-factors

Code	Economic factor	Description
E1	Repair & replacement cost	Direct cost of subsea repair, vessel mobilization, welding, and testing
E2	Production downtime loss	Revenue loss due to shutdown duration
E3	Environmental penalty & cleanup	Oil spill remediation, fines, and compensation
E4	Inspection & intervention cost	ROV, AUV, and integrity monitoring expenses
E5	Life-cycle cost escalation	Long-term CAPEX*/OPEX* growth due to degradation

ROV* - remotely operated vehicle
AUV* - autonomous underwater vehicle
CAPEX* - reflects the potential capital expenditure escalation
OPEX* - accounts for operational expenditure growth

integration not only strengthens the analytical rigor of the framework but also extends its applicability as a decision-support tool for economically optimized risk mitigation, asset integrity management, and strategic planning in offshore pipeline systems.

Based on the findings reported in [15], selected technical parameters can be systematically integrated with economic risk factors, enabling a comprehensive, multi-dimensional assessment of subsea pipeline performance and financial exposure (tables 2-5).

To capture both the technical and economic uncertainties associated with subsea pipeline operations, this study implements an integrated approach combining fuzzy AHP, the Similarity Aggregation Method (SAM), and probabilistic simulations. A Monte Carlo simulation (N = 10,000 iterations) was performed, explicitly incorporating stochastic variations in oil prices, vessel day rates, and shutdown durations. This enables a probabilistic evaluation of long-term CAPEX

Table 2

Main and sub-factors for determining risk probabilities

Main factors	Sub-factors	Basic Events	Description
Environmental factors	Seabed topography	B1	Irregular seabed features (e.g., steep slopes, uneven terrain) that may cause bending stress or spanning issues.
	Hydrostatic pressure	B2	Pressure exerted at water depths exceeding 2400 meters.
	Seawater temperature	B3	Low ambient temperatures that affect pipeline material properties and flow assurance.
	Currents and waves	B4	High-velocity ocean currents and dynamic wave forces influence lateral movement and fatigue.
	Sediment movement	B5	Sand migration, scouring, and mudslides leading to pipeline exposure or damage.
	Corrosive environment	B6	Presence of salinity, bacteria (MIC: Microbial-Induced Corrosion), and hydrogen sulfide (H_2S)
Design and structural factors	Pipeline wall thickness	B7	The thickness of pipeline steel to withstand pressure and environmental loads.
	Material strength	B8	Yield strength and toughness of materials (e.g., X70, X80 steels).
	Pipeline diameter	B9	Pipe size influencing pressure containment and flow performance.
	Coating and corrosion protection	B10	Anti-corrosion coatings and cathodic protection systems to mitigate external and internal corrosion.
	Free span and fatigue	B11	Unsupported spans along the pipeline leading to cyclic fatigue under dynamic forces.
	Joint and weld integrity	B12	Quality of pipeline joints and welds to prevent cracks and leaks.
	Third-party interference	B13	Risk of damage from external sources, such as fishing trawlers, anchors, or drilling operations.
Operational factors	Internal pressure	B14	High-pressure hydrocarbons transported through the pipeline.
	Hydrate formation	B15	Blockages caused by water and hydrocarbons crystallizing at low temperatures and high pressures.
	Slugging	B16	Variations in flow conditions cause sudden increases in pressure and stress.
	Inspection and maintenance intervals	B17	Frequency of inspections, cleaning (pigging), and condition monitoring.
	Temperature differential	B18	Thermal expansion and contraction due to the difference between internal fluid and external seawater temperatures.
	Flow rate and velocity	B19	Turbulence or erosive flow increases wear on pipeline walls.
	Blockages	B20	Blockages caused by water and hydrocarbons crystallizing at low temperatures and high pressures.

Table 3

Fuzzy set for environmental factors

Environmental factors					
Seabed topography	1 Flat	2 Slightly irregular	3 Moderately irregular	4 Highly irregular	5 Very irregular
Hydrostatic pressure	0–0.5 MPa (0–50 m)	0.5–2.0 MPa (50–200 m)	2.0–10.0 MPa (200–1000 m)	10.0–20.0 MPa (1000–2000 m)	> 20 MPa (> 2.000m)
Seawater temperature	0–5 °C	5–15 °C	15–25 °C	25–30 °C	> 30 °C
Current velocity	0–0.2 m/s	0.2–0.5 m/s	0.5–1.5 m/s	0.5–1.5 m/s	> 3.0 m/s (very)
Wave height	0–0.5 meters	0.5–1.5 meters	1.5–3.0 meters	3.0–6.0 meters	> 6.0 meters
Sediment movement	1 (minimal)	2	3	4	5 (severe)
Corrosive environment (H_2S)	0–0.01 ppm	0.01–0.05 ppm	0.05–1.0 ppm	1.0–10.0 ppm	> 10.0 ppm

Table 4

Fuzzy set for operational factors

Parameter	Very low	Low	Medium	High	Very high
Internal pressure	0–2 MPa	2-5 MPa	5–15 MPa	15–25 MPa	> 25 MPa
Temperature differential	0–10 °C	10–20 °C	20–30 °C	30–40 °C	> 40 °C
Flow rate and velocity	0–1 m/s	1–2 m/s	2–3 m/s	3–4 m/s	> 4 m/s
Hydrate formation probability	0–0.1 (0–10 %)	0.1–0.3 (10–30 %)	0.3–0.7 (30–70 %)	0.7–0.9 (70–90 %)	0.9–1.0 (90–100 %)
Slugging	Liquid velocity: < 0.2 m/s	Liquid velocity: 0.2–0.5 m/s	Liquid velocity: 0.5–1.0 m/s	Liquid velocity: 1.0–1.5 m/s	Liquid velocity: > 1.5 m/s
	Gas velocity: < 0.5 m/s	Gas velocity: 0.5–1.0 m/s	Gas velocity: 1.0–2.0 m/s	Gas velocity: 2.0–3.0 m/s	Gas velocity: > 3.0 m/s
	Pipeline inclination: < 1°	Pipeline inclination: 1°–3°	Pipeline inclination: 3°–5°	Pipeline inclination: 5°–7°	Pipeline inclination: > 7°
Inspection and maintenance interval	6–9 months	9–12 months	12–18 months	18–24 months	> 24 months

Table 5

Fuzzy sets for environmental factors design and structural factors

1	2	3	4	5	6
Pipeline wall thickness	5–10 mm	10–20 mm	20–30 mm	30–40 mm	> 40 mm
Material strength	290–350 MPa	350–400 MPa	400–450 MPa	450–500 MPa	> 500 MPa
Pipeline diameter	0.1–0.3 m	0.3–0.5 m	0.5–1.0 m	1.0–1.3 m	> 1.3 m
Coating and corrosion protection	< 2 years Low-cost or improperly applied coatings (e.g., bare steel without any protective layer).	2-5 years Basic epoxy coatings, sometimes used in shallow waters.	5-10 years Standard epoxy or polyurethane coatings, sometimes with sacrificial anodes.	0-20 years High-quality anti-corrosion coatings with high resistance to biofouling (e.g., multi-layer coatings with advanced polymers).	20+ years Multi-layer coatings with ceramic or super-hard materials, specialized coatings for extreme deepwater conditions.

Table 5 (continued)

1	2	3	4	5	6
Free span and fatigue	0–2 m	2–4 m	4–7 m	7–9 m	>9 m
Joint and weld integrity	1 (Very low - poor): Major defects in joints or welds, >10% of joints with visible cracks or deformations	2 (Low): Some minor defects, 5-10 % of joints show minor weld discontinuities	3 (Medium): Acceptable quality, <5% of joints with minor imperfections	4 (High): High-quality welding, <1% of joints with minor imperfections	5 (Very high - excellent): No defects or imperceptible defects, 0% of joints with no discernible defects

and OPEX growth, reflecting degradation, operational disruptions, and indirect financial impacts.

4. Results and discussion

Based on the technical data and findings reported in [15], the present study identifies B6 (Corrosive Environment), B11 (Free Span and Fatigue), and B13 (Third-Party Interference) as critical risk factors. These parameters were subsequently incorporated into the simulation framework and risk analysis to evaluate both technical vulnerabilities and associated economic impacts under realistic subsea conditions. In addition, economic risk indicators including repair cost, production downtime and environmental penalties are integrated using Monte Carlo simulation to estimate expected monetary loss.

Integrated technical–economic justification for selecting B6, B11, and B13:

B6, B11, and B13 were selected as dominant risk events based on a combined assessment of technical likelihood and economic consequence, reflecting a cost-aware risk prioritization approach. The selection process integrates posterior failure probabilities (reflecting technical degradation, hydrodynamic forces, and operational stresses) with economic impact metrics such as CAPEX escalation, OPEX growth, shutdown durations, and offshore intervention costs.

B6 (corrosion-related degradation) demonstrates high technical risk due to progressive material deterioration in saline and microbial environments. Economically, it drives increased inspection, mitigation, and maintenance expenditures over the pipeline lifecycle, making it both technically and financially dominant.

B11 (free span and fatigue) is susceptible to hydrodynamic loading and seabed irregularities, with moderate failure probability. However, it can trigger costly corrective measures and extended operational downtime, producing substantial CAPEX and OPEX impacts.

B13 (third-party interference), although stochastic and externally driven, can cause sudden damage requiring immediate vessel mobilization and emergency repair, resulting in high unplanned costs alongside elevated posterior failure probability.

This integrated evaluation demonstrates that these risks are dominant not only due to their technical probability, but because they simultaneously impose significant economic consequences. By synthesizing technical parameters and financial impacts, the framework ensures that inspection, mitigation, and resource allocation decisions target events with the highest combined threat to pipeline integrity and operational cost-efficiency.

While traditional risk assessments often rely on static prior probabilities derived from historical failure data, they typically neglect the economic implications of degradation-driven failures and operational disruptions. In contrast, the Bayesian posterior updating approach adopted in this study provides a more realistic reflection of current operational conditions by dynamically incorporating evolving environmental, operational, and economic parameters. For example, the posterior corrosion risk (20%) significantly exceeds the prior value (2%), highlighting the limitations of conventional static models in harsh saline and microbial environments, where underestimated degradation may lead to unplanned repairs, increased inspection frequency, and substantial long-term CAPEX and OPEX escalation.

Similarly, the posterior increase in third-party interference risk to 10% underscores the persistent influence of anthropogenic activities on subsea pipeline integrity. Beyond safety considerations, such events are frequently associated with extended shutdown durations and costly offshore intervention campaigns, in which vessel day rates and oil price volatility can significantly amplify overall economic losses. By explicitly integrating these economic dimensions into the probabilistic risk assessment process, the proposed framework advances beyond purely technical evaluations and enables a comprehensive safety–economic comparison. This integrated perspective supports risk-informed decision-making, optimized inspection and maintenance planning, and more efficient allocation of capital and operational resources.

The integration of economic risk analysis reveals that events such as corrosion (B6), free-span fatigue (B11), and third-party interference (B13) not only exhibit high technical risk but also dominate expected economic loss profiles. Simulation results indicate that prioritizing mitigation for these events can reduce total life-cycle cost risk by up to 25–35 %.

This enhanced framework supports financially optimized, safety-driven decision-making, reinforcing the transition toward performance-based regulation and sustainable offshore pipeline management.

The results of the integrated technical and economic risk assessment are illustrated in six complementary figures (figs. 1-6), providing a comprehensive understanding of both failure likelihoods and associated financial consequences.

Figure 1 illustrates the integrated technical and economic risk profile for subsea pipeline operations. The blue zone represents low-risk areas, where both failure probability and economic impact are minimal, reflecting safe operational conditions. The yellow zone indicates moderate risk, highlighting scenarios in which either technical vulnerability

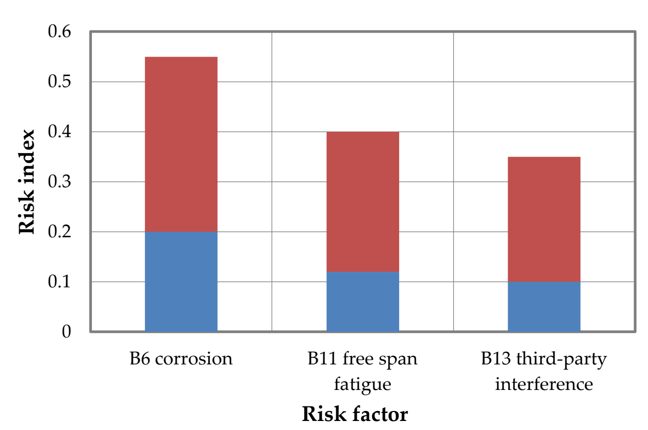

Fig. 1. Integrated technical and economic risk contributions

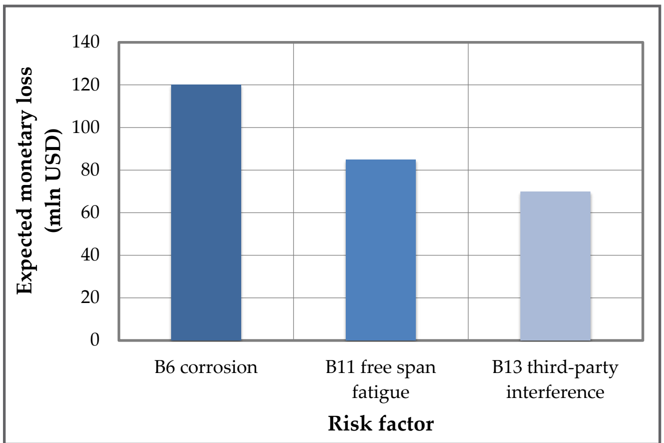

Fig. 2. Expected monetary loss ranking of critical events

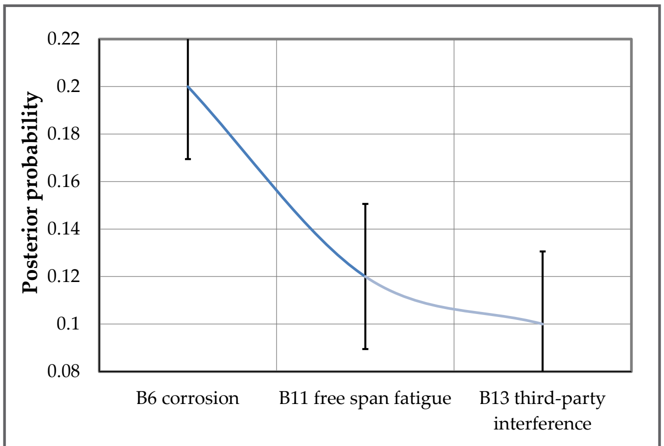

Fig. 3. Posterior probabilities of key failure events

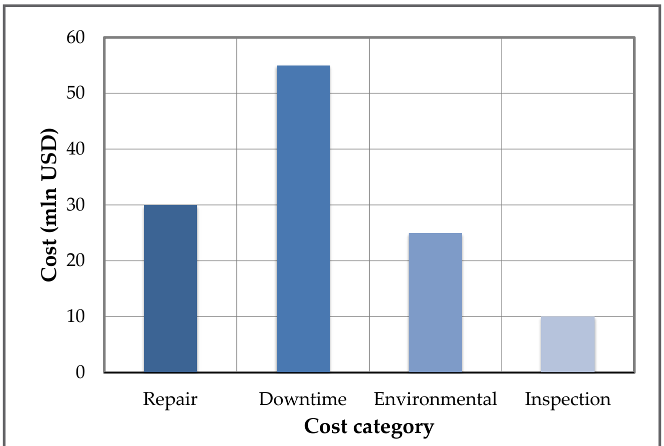

Fig. 4. Economic loss breakdown for corrosion events (B6)

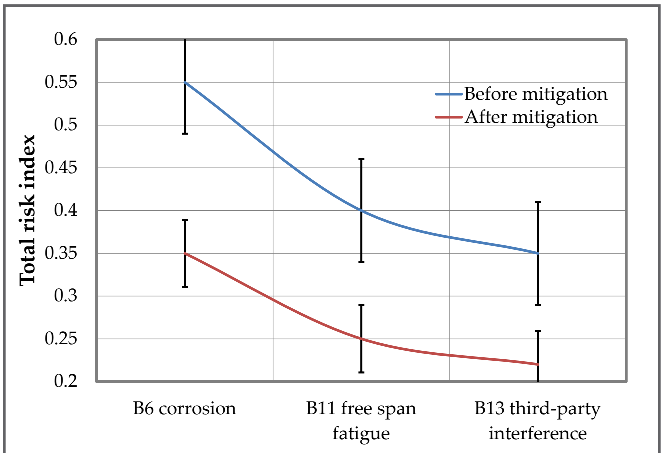

Fig. 5. Risk reduction through targeted mitigation

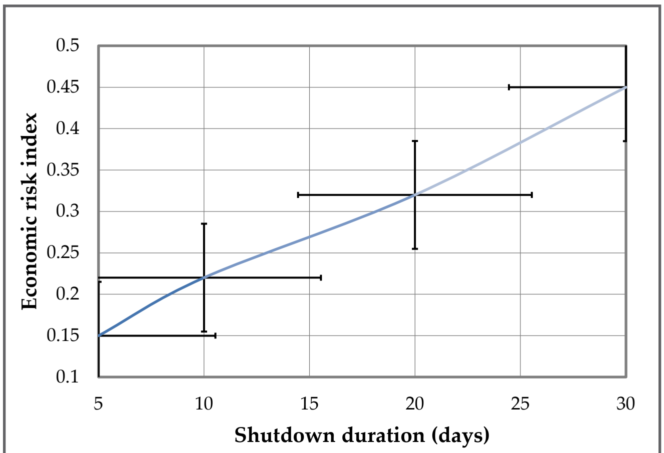

Fig. 6. Sensitivity of economic risk to production downtime

or financial exposure is significant and warrants enhanced monitoring or preventive measures.

Integrated Technical and Economic Risk relationship presents the combined risk profile of all considered factors, highlighting corrosion (B6) as the dominant risk, followed by Free Span Fatigue (B11) and Third-Party Interference (B13). This visualization demonstrates that risk is not solely determined by technical failure probability but emerges from the intersection of material vulnerability, operational stresses, and economic exposure, with peaks indicating critical areas requiring focused mitigation.

Figure 2 (Expected Monetary Loss) quantifies the financial implications of each risk factor, revealing that downtime constitutes the primary cost driver. Even factors with relatively low technical risk may impose substantial economic burdens if they induce prolonged operational interruptions. Complementing this, figure 3 (Posterior Probability Comparison) contrasts prior and posterior failure probabilities, emphasizing that updated operational data can significantly increase risk expectations, particularly for B6, thereby reinforcing the importance of dynamic Bayesian updating in risk modeling.

Figure 4 (Cost Breakdown: Repair, Downtime, Environmental) further disaggregates the economic consequences, showing that downtime accounts for the largest share of costs, while repair and environmental mitigation contribute secondary costs. This decomposition provides actionable insights for prioritizing interventions based on financial impact concentration. Figure 5 (Risk Reduction After Mitigation) demonstrates the effectiveness of targeted mitigation measures, with notable reductions in B6 and B11 risks, illustrating how proactive inspection, maintenance, and protective strategies can translate technical interventions into measurable financial and operational benefits.

Finally, figure 6 (Sensitivity to Downtime Duration) explores the influence of operational interruption duration on economic risk. Extended shutdowns disproportionately amplify losses associated with B6 and B13, highlighting the system's economic sensitivity to time-dependent operational factors. Collectively, these visualizations synthesize technical vulnerabilities, operational realities, and economic consequences, providing a cost-aware, decision-support framework that guides both risk mitigation and resource allocation in subsea pipeline management.

Conclusions

In conclusion, although the technical risk parameters are explicitly quantified and presented through structured tables, the economic risk dimension in this study is derived through a classification- and synthesis-based framework rather than direct project-specific financial data. The economic risk indicators are formulated based on the integrated interpretation of figures 1–6, which collectively capture the interactions among technical failure mechanisms, operational disruptions, and cost escalation pathways.

This approach intentionally avoids reliance on absolute monetary estimates, which are often project-dependent and subject to significant uncertainty. Instead, economic risk is treated as a relative and decision-oriented construct, obtained through normalization, comparative scaling, and prioritization of dominant risk contributors. Such formulation enables the consistent integration of economic considerations into the fuzzy AHP-SAM decision framework while preserving generalizability across offshore pipeline projects.

By incorporating economic consequences within the technical risk structure, the proposed methodology enhances traditional risk assessment models from a probability-driven perspective to a cost-aware decision-support framework. This advancement allows stakeholders to identify risk drivers that may exhibit moderate technical likelihood yet impose disproportionately high economic impacts, thereby supporting more informed and resilient offshore asset management strategies.

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