Safety Science 201 (2026) 107272

Contents lists available at ScienceDirect

Safety Science

journal homepage: www.elsevier.com/locate/safety

Bayesian network-based evaluation of a novel fault detection system for preventing catastrophic condenser failures in offshore facilities☆

Furkan Ertan [a], Özkan Uğurlu [a,*], Fatih Tonoğlu [a], Fırat Sivri [a], Serdar Yıldız [b], Jin Wang [c]

[a] Maritime Transportation and Management Engineering Department, Ordu University, Ordu, Turkiye
[b] Maritime Transport Department, Sharjah Maritime Academy, Sharjah, United Arab Emirates
[c] Liverpool Logistics, Offshore and Marine (LOOM) Research Institute, Liverpool John Moores University, Liverpool, UK

ARTICLE INFO

Keywords:
Condenser failure
Combined cycle systems
Bayesian Network (BN)
Fuzzy logic
System reliability

ABSTRACT

This study investigates the causes and consequences of condenser failures in seawater-cooled combined cycle systems on offshore platforms, using a real-life accident scenario as a case study. A Bayesian Network (BN) integrated with fuzzy logic was employed to model the failure pathways and assess the impact of contributing factors, such as operator errors and alarm deficiencies. The resulting network enabled the development and evaluation of targeted system improvements, including the integration of additional analyzers and a shutdown command mechanism. These enhancements demonstrated a significant reduction in the probability of catastrophic failure. Expert evaluations supported the effectiveness of the proposed measures in enhancing operational safety and reducing human error. The study emphasizes the critical role of timely intervention, robust control systems, and preventive maintenance in mitigating failure risks. The study results also highlight the need for continuous risk analysis, improved component/system or part selection, and training programs to support resilient operations in high-risk offshore environments. The findings offer practical recommendations for industry stakeholders and contribute to the development of safer and more reliable offshore energy systems.

1. Introduction

Offshore energy platforms are high-risk socio-technical systems operating under harsh environmental conditions, where even a minor failure can rapidly escalate into operational disruptions affecting the entire facility (Eneh, 2011; Zhang et al., 2017; Itiki et al., 2019). In such environments, the continuity of the power generation processes is critical not only for operational efficiency but also for the sustainable and safe operation of the platform. However, the dynamic and uncertainty-driven nature of these systems exposes the limitations of traditional risk analysis and highlights the need for resilience-oriented approaches (Itiki et al., 2019; Karlilar Pata and Balcilar, 2024). Due to their socio-technical structure, critical infrastructures operating in harsh environments can quickly be driven into cascading failure dynamics through interrelated failure pathways, and the lack of early detection is known to create conditions for emergency situations (Sarwar et al., 2018; Adumene et al., 2021). Therefore, sustainability of safety in offshore facilities depends not only on equipment reliability, but also on the capacity to anticipate disruptive events, limit their impacts, and maintain system functionality and integrity (Deyab et al., 2018).

In complex systems, tight interactions between technical and organizational components can cause failures to spread rapidly from their point of origin to the entire operational structure (Nord et al., 2014; Haglind, 2008). For this reason, resilience requires the analysis of both technical and organizational vulnerabilities within the anticipate-absorb-adapt-recover cycle (Berkeley et al., 2010; Sarwar et al., 2018). The emphasis on multidisciplinary and scenario-based risk assessment approaches in offshore operations further indicates that these knowledge gaps require a holistic or the comprehensive most evaluation (Nguyen et al., 2016; Mazzetti et al., 2021; Guikema et al., 2015). In this context, condenser systems play an important role as critical subcomponents within the complex operational structure of offshore terminals (Islam et al., 2020). Problems such as fouling, corrosion, tube cracking, or reduced heat transfer efficiency can increase turbine back

☆ This article is part of a special issue entitled: 'Crisis and Emergency Management' published in Safety Science.

* Corresponding author.
E-mail address: ougurlu@odu.edu.tr (Ö. Uğurlu).

https://doi.org/10.1016/j.ssci.2026.107272
Received 18 August 2025; Received in revised form 6 April 2026; Accepted 29 April 2026
Available online 8 May 2026

pressure, leading to load losses, emergency shutdowns, or large-scale operational disruptions (Nguyen et al., 2016; Mazzetti et al., 2021). In offshore platforms, limited accessibility and harsh environmental conditions not only contribute to the occurrence of failures, but also create additional risks related to technical performance degradation, the sustainability of other subsystems, and personnel safety (Deyab et al., 2018; Adumene et al., 2023). Therefore, even small performance degradations in central components such as condensers can, if not appropriately controlled at an early stage, generate cascading effects that drive the system toward crisis and emergency scenarios.

This study presents a case study of failures occurring in the condenser, a critical component of an offshore energy system, and demonstrates why such failures are critical in the context of crisis and emergency management. The proposed Bayesian Network (BN)-based model is not only aimed to serve as a tool for failure detection, but also a probabilistic decision-support mechanism that assists mitigation, preparedness, response, and recovery processes under uncertainty. The model represents failure mechanisms probabilistically, addresses uncertainties using a fuzzy logic approach, and provides a dynamic assessment through risk updates based on observed symptoms. This approach aims enhancing system reliability on offshore platforms, and also offering a framework for understanding condenser-induced cascading failures, supporting operational decision-making, and systematically preventing crises in similar high-risk industrial systems. In this way, the study contributes to the development of resilience engineering and risk-based decision-support applications in offshore energy systems, while promoting the integrated consideration of potential failures within crisis and emergency management processes (Li et al., 2021).

2. Literature review

2.1. Fundamentals of combined cycle systems

One way to use energy sources more efficiently is through a combined cycle system, which is commonly used in electricity generation (Ersayin and Ozgener, 2015). In a combined cycle system, in addition to the gas turbine, a waste heat boiler and a steam turbine are also integrated into the system (Fig. 1). Therefore, the system includes two cycles that work together: a gas cycle and a steam cycle.

The combined cycle system produces electricity via gas and steam turbines by using the same source of heat. To achieve high thermal efficiency with current technologies, combined cycle systems need to optimize their performance and include a Heat Recovery Steam Generator (HRSG) cycle (Fig. 2) (Franco and Russo, 2002). The HRSG uses the heat from the gas turbine's exhaust to produce steam. This steam is then used by the steam turbine. Using steam at different pressure levels in various stages of the steam turbine helps improve energy efficiency.

Fig. 3 shows a comparison of efficiency calculations for a system with a power capacity of around 440 MW in both simple and combined cycle modes. In the simple cycle, the thermal efficiency is around 38%, while in the combined cycle it can be increased up to 60%.

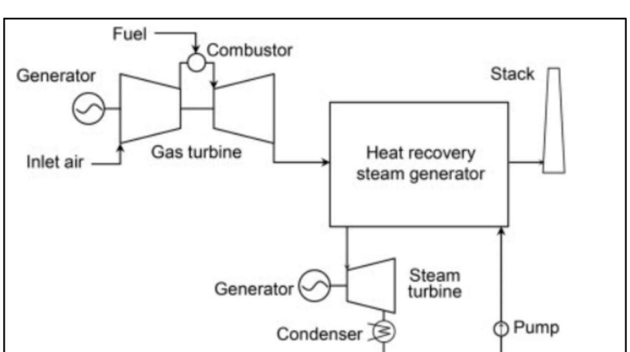

Fig. 1. Combined cycle system configuration (Shiozaki et al., 2021).

One of the key components of a combined cycle system is the condenser, which cools the steam coming from the steam turbine and converts it back into water. The condenser is made up of several parts, including the hotwell (condensate water tank), shell, tubesheets, support plates, tubes, baffle screens, and waterboxes (Fig. 4). Seawater flows through the condenser tubes to cool the steam. The water produced through condensation in the condenser is then pumped back to the waste heat boiler, where the steam generation process begins again. This cycle improves energy efficiency alongside power production in the steam turbine (Shiozaki et al., 2021).

A decline in the condenser's thermal performance not only reduces electricity production but also affects the overall efficiency of the system. One critical issue to watch for is the risk of seawater used for cooling mixing with the steam-water cycle (combined cycle system). If this happens, seawater can leak into the steam boiler and turbine, potentially causing catastrophic system failures. The main causes of heat exchanger tube failures include vibration-induced wear, fouling, cavitation, high fluid velocity, poor material quality, high temperatures, high pressure, weak tube material, water hammer effects, corrosion, metal erosion and structural damage to the tubes (Deyab et al., 2018).

2.2. Literature review on condenser failures

Performance of condensers, which are one of the key components of combined-cycle systems, is of crucial importance for the continuity of energy production and the safe execution of critical operations on offshore platforms. Studies in the literature have examined condenser performance based on parameters such as the heat transfer coefficient, cooling water flow rate and temperature, heat transfer area, and blockage ratio (Pattanayak et al., 2019). Laković et al. (Laković et al., 2010) investigated the effects of changes in cooling water properties on energy efficiency. Similarly, comparisons of evaporative coolers and different condenser types under fouling conditions have shown that efficiency reductions of up to 75% can occur (Anozie and Odejobi, 2011; Qureshi and Zubair, 2005). In systems using seawater, problems such as corrosion, sediment accumulation, and biological fouling are known to directly reduce heat transfer performance (Zeytin, 2008; Shalaby et al., 2011). Cristiani et al. (Cristiani et al., 2008) demonstrated that these effects can be partially controlled in some materials through the formation of protective oxide layers. These findings indicate that degradations in condenser performance can have critical impacts on energy efficiency and operational continuity.

The main causes of condenser failures include dezincification, high-temperature–induced fatigue, material cracking, vibration-related structural stresses, and the accumulation of sludge and biological deposits (Deyab et al., 2018; Zeytin, 2008; Shalaby et al., 2011; Pandey, 2006; Shen et al., 2016). Pandey (Pandey, 2006) reported that iron deficiency and biological fouling increase the frequency of failures in condensers operating with seawater, while Zeytin (Zeytin, 2008) showed that copper–zinc alloy tubes used in these systems weaken within 5–6 years due to dezincification. In titanium tubes, oxide layer formation and cracking mechanisms under high temperatures have been examined in detail by Shalaby et al. (Shalaby et al., 2011) and Shen et al. (Shen et al., 2016). Studies focusing on the root causes of failures indicate that early detection and appropriate maintenance strategies play a critical role in reducing performance losses. In this context, Sen et al. (Sen et al., 2023) proposed root cause analysis, Padilla et al. (Padilla et al., 2024) applied FMEA-based reliability assessments, Ju et al. (Ju et al., 2022) developed a hybrid diagnostic model combining Principal Component Analysis and the Deep Forest algorithm, and Mathews et al. (Mathews et al., 2020) introduced a thermo-hydraulic simulation model for maintenance scheduling. However, most of these studies focus on technical diagnosis and performance optimization, and do not address the socio-technical background of condenser failures, risk dynamics

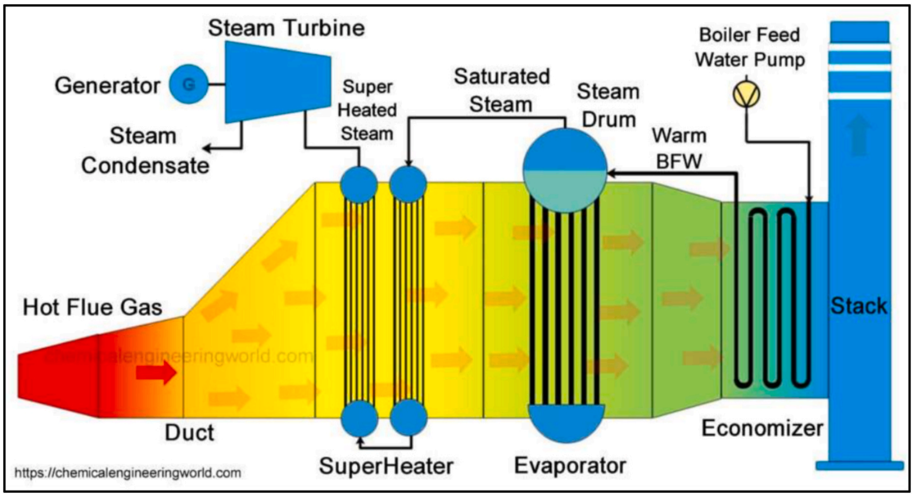

Fig. 2. Heat Recovery Steam Generator segments.

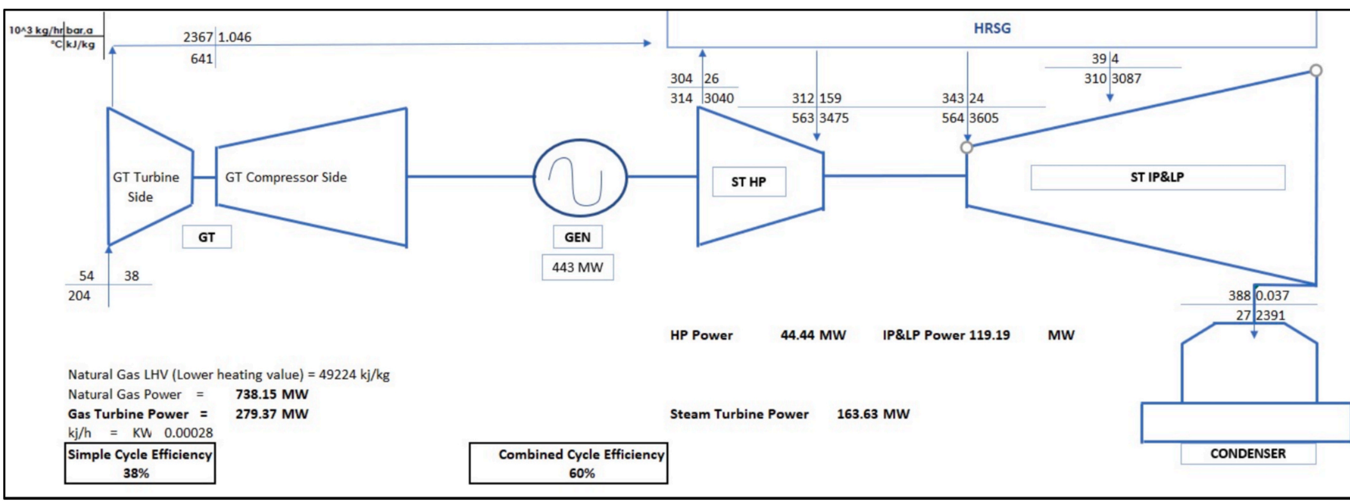

Fig. 3. Heat balance diagram.

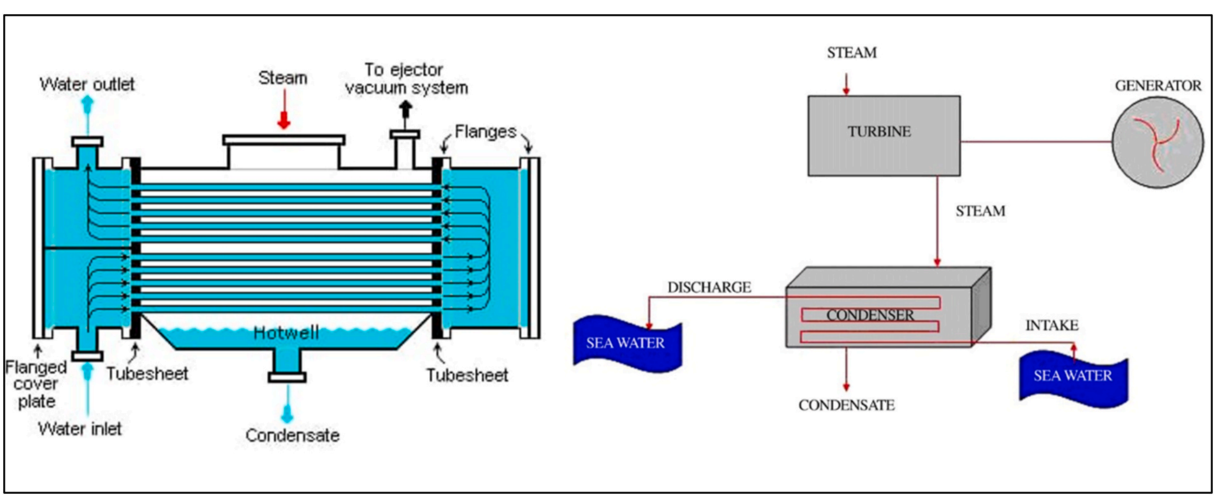

Fig. 4. Condenser structure and its position in the system configuration (Zeytin, 2008).

under uncertainty, or their integration into crisis and emergency management.

Offshore energy facilities are considered complex socio-technical systems in which technical components interact intensively with human, organizational, and environmental factors. In these systems, failures often exhibit non-linear behavior, where local degradation can produce system-level consequences through component interdependencies and operational interactions. The literature shows that component-based maintenance and diagnostic approaches are insufficient to capture these multiple interactions and the propagation of degradation across the system, and that neglecting human and organizational factors creates critical uncertainties (Keprate, 2023; França et al., 2021; França et al., 2022). Studies conducted under harsh offshore conditions have demonstrated that interdependencies between control systems, communication infrastructures, and human factors accelerate failure propagation and make isolation decisions critical for process safety (Deyab et al., 2018; Nitonye et al., 2021). In addition, research on shared infrastructure components and mooring systems indicates that the failure of a single component can turn into cascading failures under environmental loads (Lu et al., 2026; He et al., 2025). In the long term, corrosion, fatigue, and uncertainties in environmental loads gradually degrade material strength, push system reliability toward critical thresholds, and increase the likelihood of multiple failure scenarios (Adedipe et al., 2016; Adumene et al., 2021; Hajinezhadian and Behnam, 2024; Gholizad et al., 2012). Taken together, these studies indicate that performance degradations in safety–critical equipment on offshore facilities are not limited to local technical issues, but can evolve into systemic risks through socio-technical interactions and environmental degradation. These cascading interactions show that even a single equipment failure on an offshore platform can, under certain conditions, challenge process safety barriers and develop into scenarios requiring crisis and emergency management.

Because crises and emergencies at offshore facilities often develop under sudden, uncertain, and evolving conditions, addressing these systems only through reliability-based approaches is insufficient. The literature emphasizes that resilience in offshore infrastructure should be defined independently of reliability, based on the capacity to anticipate disruptive events, absorb their impacts, adapt operationally, and recover (Sarwar et al., 2018; Okoro et al., 2022). In remote and harsh offshore environments, limited resources, delayed intervention capabilities, and environmental uncertainties further complicate crisis management and make deterministic risk assessment methods inadequate (Adumene et al., 2023; Nathanael et al., 2024). In this context, studies show that probabilistic and dynamic risk models provide a more realistic representation in emergency scenarios where failure propagation, human responses, and environmental effects change over time. In particular, Bayesian and dynamic Bayesian networks stand out because of their ability to update the performance of safety barriers and human-environment-system interactions throughout the crisis process. However, data scarcity, sensor noise, and reliance on expert judgment make it necessary to support these models with hybrid uncertainty approaches such as fuzzy logic and evidence theory (Norazahar et al., 2018; Wang et al., 2021; Rahman, 2020; Chen, 2025). These methodological developments create a foundation for scenario-based, risk-informed decision support and early warning systems, enabling technical failures to be addressed within the context of crisis and emergency management (Li et al., 2022; Liu et al., 2023).

The reviewed literature shows that studies directly focusing on condensers are limited, and that existing knowledge is largely produced indirectly through general heat transfer processes, material degradation, and studies of similar offshore equipment. As a result, condensers operating within complex and tightly coupled socio-technical systems at offshore facilities are not adequately represented as potential sources of vulnerability in cascading failure processes. Although cascading failures and systemic risks are widely discussed in the literature, the roles of such less-studied safety–critical components in failure propagation have been addressed only to a limited extent. This gap makes it difficult to achieve a balanced understanding of the risk contributions of all components in complex systems and complicates the early management of crisis potential. Rather than treating condenser failures solely as a technical reliability problem, this study adopts a preventive perspective by evaluating their potential to trigger system-wide cascading effects that may evolve into crises and emergencies. Through Bayesian network and fuzzy logic-based analyses, the risk profile of condensers under uncertainty, their root causes, and possible intervention options are considered together. In this way, the study supports decision-makers and operators on offshore platforms in conducting more balanced and risk-informed assessments that also include less-studied components of complex systems.

3. Methodology

This study applies a BN framework, integrated with fuzzy logic where appropriate, to identify and model the causal relationships among major operational failures occurring in condenser systems. The BN structure and parameters were derived from both the literature and a case study of a significant operational failure at a power plant equipped with a condenser system comparable to those used on offshore platforms. Conditional probabilities were determined with input from eight domain experts, given the highly specific nature of the event and the limited dataset available. The resulting failure network was utilized to capture dominant failure pathways and to evaluate the impact of changes in component conditions and maintenance activities on overall failure probabilities. Furthermore, additional analyzers and automatic shutdown mechanisms that could prevent such failures were incorporated, and their effectiveness was tested using the BN model. The results demonstrate the applicability of the BN approach in supporting structured failure analyses and evidence-based reliability assessments of combined-cycle condenser systems. The methodology employed in this study is explained step by step and in detail in the following sections.

3.1. Real-life condenser failure in the case study

The chronological sequence leading to the failure of the condenser was as follows. The condenser was prepared for the Acoustic Eye test during the initial commissioning of the system. Acoustic Pulse Reflectometry is a technique that measures one-dimensional acoustic waves as they travel through the condenser tubes. If there is any defect or change in the cross-sectional area of the tube system, the waves reflect, and these reflections are recorded and analyzed. This test is a non-destructive inspection method (Surbled, 2024). It allows inspectors not only to detect the presence of tube failures but also to locate them accurately. The Acoustic Eye system works by sending an acoustic pulse along the entire length of a tube and displays any defects in real time.

In the method shown in Fig. 5, sound signals are sent into the tube using a probe, and the reflected signals are analyzed to detect any failures. Each defect inside the tube produces a unique signal pattern. Through this analysis, the location of the defect can be identified, and information about the type of defect, such as pitting, corrosion, or blockage, can also be obtained. As a result of the test, a tube damage map in Fig. 6 was created. Out of more than 10,000 tubes, the damaged ones were identified and plugged (Fig. 7). The combined cycle system was restarted and taken into operation mode. After about three years of regular operation, an alarm was received from the conductivity analyser which was located at the condensate pump discharge during a hot start-up phase after commercial shutdown of the combined cycle system. At the same time, several other components of the system also issued alarms during this intensive start-up process. The conductivity analyzer alarm at the outlet of the hotwell was reported for further inspection.

After 2–3 h, the steam inlet pressure of the High-Pressure Steam Turbine began to increase. Shortly after, an alarm indicating bearing vibration in the high-pressure steam turbine was received, leading to an emergency shutdown of the unit. After allowing the system to cool down, a borescope inspection was carried out at the steam inlet of the high-pressure steam turbine. This revealed white deposits inside the system.

When the turbine was opened for further inspection, it was confirmed, as shown in Fig. 8, that the damage was caused by saltwater

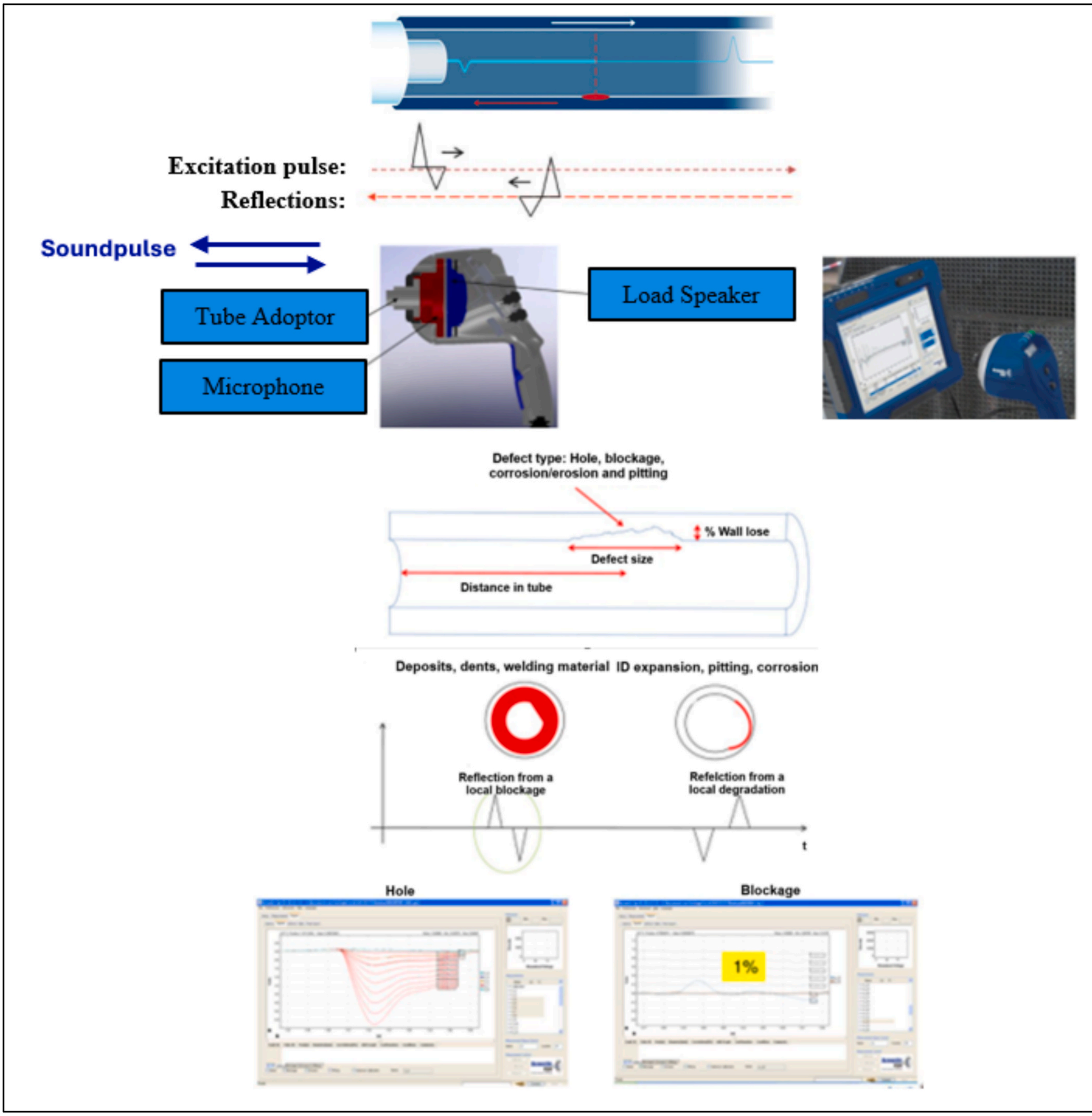

Fig. 5. Acoustic pulse reflectometry tests.

mixing into the steam phase. Then, the condenser was drained, and during the inspection, one of the previously plugged tubes was found with its plug detached or fallen into the waterbox (Fig. 9).

The condenser's steam side was tested by activating the vacuum pump, and it was found that one of the tubes had a hole or rupture. Using the tube damage map, it was confirmed that the detached plug belonged to this damaged tube. After this finding, all water-steam phase components were drained, and as shown in Fig. 10, maintenance activities were started for the steam turbine, boiler, and other water-steam system components such as valves and pipelines.

3.2. Dataset and proposed framework

3.2.1. Establishment of the BN-based on the case study

The structure of the Bayesian Network (the nodes and their causal relationships) was constructed through a rigorous, multi-source process. The structure was developed based on the following three pillars:

Causal Sequence from the Case Study: The chronological failure sequence described in Section 3.1 formed the primary backbone of the network. This provided the direct, cause-effect pathways observed in the real-world incident.

Integration of Literature Findings: To ensure comprehensiveness and to include potential failure causes not directly observed in the single case, relevant studies from the literature were integrated. For instance, the

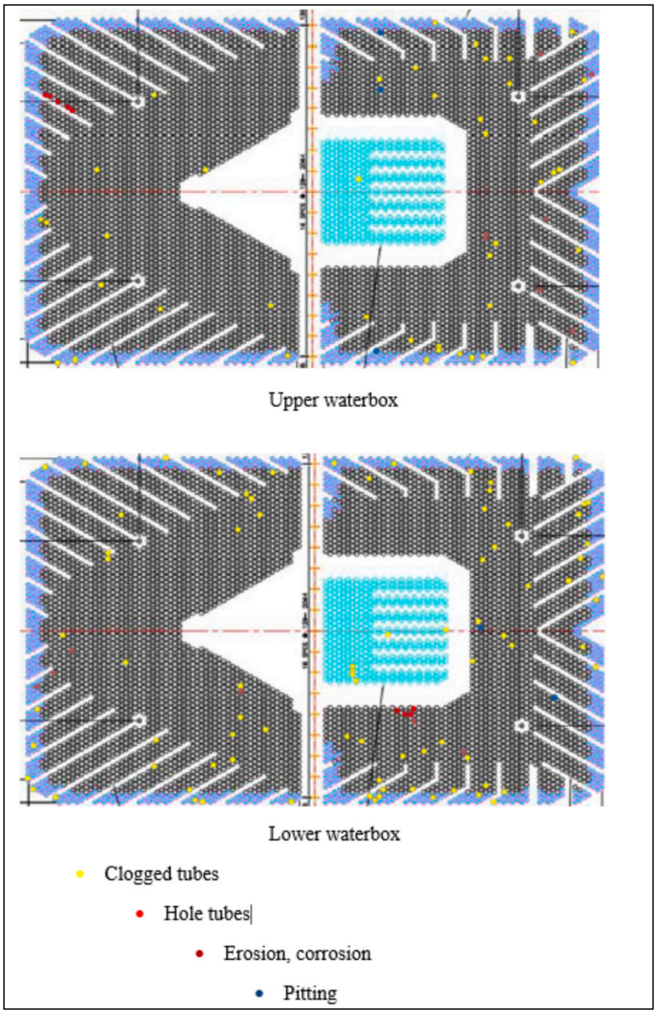

Fig. 6. Condenser upper/lower waterbox.

parent node "Fatigue" (Deyab et al., 2018) and "Contaminated Cooling Water" (Shalaby et al., 2011) were added based on their established role in condenser tube blockages and structural damage, as identified in prior research. The specific studies used for this purpose are summarized in Table 1.

Expert Validation: The preliminary network structure was reviewed by the domain experts to validate the logical consistency and completeness of the causal relationships. This step ensured that the model accurately represented the engineering reality of offshore condenser systems.

In this study, a "Catastrophic Failure" refers to a severe fault that leads to the prolonged and unplanned shutdown of the combined cycle system, resulting in substantial economic and operational losses. To align with commonly accepted criteria in maritime and offshore engineering (IMO, 2008; Wang et al., 2021), this classification is defined by meeting at least one of the followings:

- Repair or replacement costs exceeding US $1 million.
- A system downtime of more than 60 days, leading to a substantial loss in energy production.
- An incident that poses a significant threat to the structural integrity of the system or has the potential to cause a major environmental effect.

The failure scenario analyzed in this case study, which required extensive maintenance on the steam turbine, boiler, and associated systems over several months, clearly meets these criteria, particularly in terms of cost and downtime.

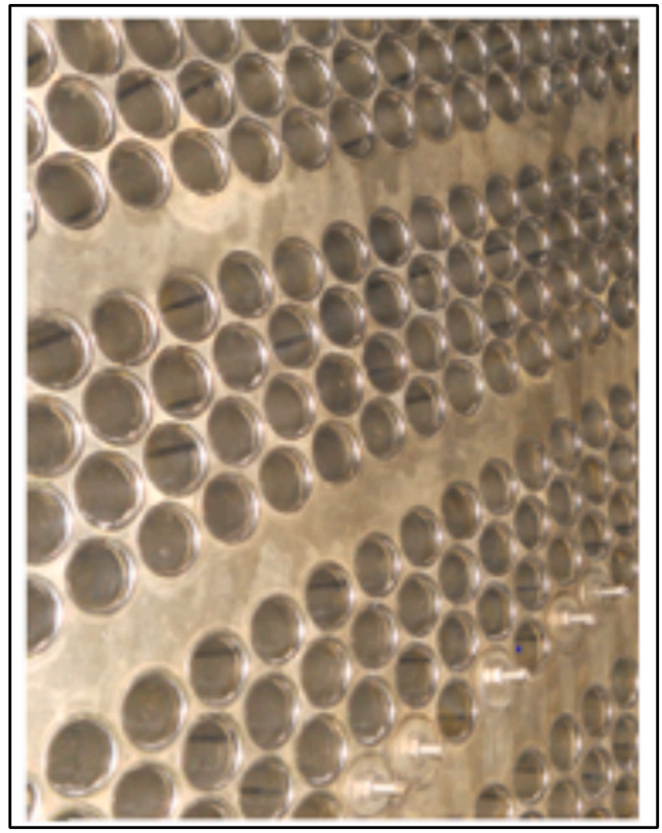

Fig. 7. Blind plug application.

Fig. 8. High-pressure steam turbine casing.

3.2.2. Bayesian network

A BN is a probabilistic graphical model based on Bayes' Theorem that shows the conditional dependency relationships between a set of random variables (Liu et al., 2015). It graphically represents the joint probability distribution of a group of discrete variables. In the model, each node (representing a factor contributing to the incident) has a probability of occurring, and this probability depends on the states of its parent nodes (Hänninen et al., 2014). The general mathematical equation of Bayes' Theorem is presented below.

$$P(A|B) = \frac{P(A) \times P(B|A)}{P(B)} \tag{1}$$

Fig. 9. Detached plug found in the condenser waterbox.

Fig. 10. Inspection and maintenance activities.

$P(A|B)$: Probability of event A occurring given that event B has occurred$P(A)$: Probability of event A occurring$P(B|A)$: Probability of event B occurring given that event A has occurred$P(B)$: Probability of event B occurring

In the Bayesian approach, a Directed Acyclic Graph (DAG) is created using nodes and arrows to understand the structure of events and to interpret upper (cause) and lower (effect) events (Loughney and Wang, 2017). In this model, statistical relationships between variables are represented through directional arrows, reflecting real-life event sequences within the network. In other words, nodes in a BN represent variables with a finite set of possible states, while arrows represent the relationships between these variables. It is also possible to reason about causal relationships between nodes in BN models. Therefore, creating the structure of a BN is considered a qualitative approach. The quantitative aspect of the model involves determining numerical values through Conditional Probability Tables (CPTs) linked to each node (Uğurlu, 2025).

To understand BN, it is first important to understand the concept of conditional probability. This concept explains that when calculating the likelihood of an event, additional known information about related events should be considered. For example, suppose events A and B are conditionally dependent, and B occurs when A occurs. The probability of B given that A is observed can be expressed as: $P(B|A) = p$. Based on this, the probability of event A occurring given that B has occurred can be expressed as follows (Uğurlu et al., 2020).

Table 1
Reference studies used in building BN.

Author(s)	Title of the study	Journal
Pandey (Pandey, 2006)	Failure analysis of refinery tubes of overhead condenser	Engineering Failure Analysis
Cristiani et al. (Cristiani et al., 2008)	Effect of chlorination on the corrosion of Cu/Ni 70/30 condenser tubing	Electrochimica Acta
Shalaby et al. (Shalaby et al., 2011)	Failure of titanium condenser tube	Engineering Failure Analysis
Zeytin (Zeytin, 2008)	Failure analysis of cooling water pipes used in the condensation system of a gas turbine	Materials characterization
Mazzetti et al. (Mazzetti et al., 2021)	Achieving 50% weight reduction of offshore steam bottoming cycles	Energy
Pattanayak et al. (Pattanayak et al., 2019)	Thermal performance assessment of steam surface condenser	Case Studies in Thermal Engineering
Gong et al. (Gong et al., 2019)	Failure analysis on leaked titanium tubes of seawater heat exchangers in recirculating cooling water system of coastal nuclear power plant	Engineering Failure Analysis
Haglind (Haglind, 2008)	A review on the use of gas and steam turbine combined cycles as prime movers for large ships. Part I: Background and design	Energy Conversion and Management
Deyab et al. (Deyab et al., 2018)	Failure analysis of the offshore process component considering causation dependence	Process Safety and Environmental Protection
Zhang (Zhang and Otahuhu, 2008)	Otahuhu B Power Station condenser in-leakage analysis and condensate monitoring system	Doctoral dissertation, Massey University Wellington, New Zealand

$$P(A|B) = \frac{P(A \cap \mathrm{B})}{\mathrm{P(B)}}, \quad P(B) > 0 \tag{2}$$

$$P(A \cap \mathrm{B}) = P(A|B) \times P(B) = P(B|A) \times P(A) \tag{3}$$

here $P(A|\mathrm{B})$ represents the conditional probability of event A occurring given that event B has already happened. $P(A \cap B)$ refers to the probability that both A and B happen together (the intersection of A and B). $P(B)$ is the probability of event B occurring, regardless of whether A happens (the prior probability of B).

In the concept of conditional probability, the mathematical expression of Bayes' Theorem assumes that there are k number of different events $A_1, A_2, \ldots, A_k$, that can intersect with event B. It is also assumed that the probability of each event A_i, given event B, is known:

$$P(A_i|B) = \frac{P(A_i) \times P(B|A_i)}{P(B)}, i = 1, 2, \cdots, k \tag{4}$$

$$P(B) = P(A_1) \times P(B|A_1) + P(A_2) \times P(B|A_2) + \cdots + P(A_k) \times P(B|A_k) \tag{5}$$

$P(A_i|B)$= Posterior probability of the hypothesis (the likelihood that A_i occurs given that B has occurred),$P(A_i)$= Prior probability of A_i (the probability of A_i occurring independently of B),$P(B|A_i)$= Conditional probability of event B, given that A_i has occurred, and.$P(B) =$ Marginal probability of B (the prior probability of B, independent of A_i).

3.2.3. *Fuzzy logic-based BN probabilities*

Fuzzy logic is used in the analysis process to manage, model, and handle uncertainty using verbal (linguistic) values (Zadeh, 1965). In classical logic, values are limited to two opposites, i.e., 0 and 1.

However, fuzzy logic allows for values that lie between these two extremes (Klir and Yuan, 1995). This method is usually based on expert opinions, and the evaluation of variables is expressed using verbal terms (Sarıalioğlu et al., 2020). A Fuzzy Bayesian Network (FBN) is used when statistical data is missing or insufficient. The fuzzy values gathered from expert opinions are used to define the prior conditional probabilities of the nodes. Since this study is based on a real accident, the conditional probabilities of the nodes (i.e., the factors causing the failure) were determined using fuzzy logic based on expert input.

After gathering expert assessments for all adverse conditions of the child nodes in the network, the expert opinions provided on the 7-point verbal scale were converted into triangular Fuzzy Numbers. A triangular Fuzzy Number represents the probability of a condition as a triplet set of Fuzzy Probability values, such as a_1, a_2, a_3. For each $x \varepsilon A$, where $\mu_{\tilde{A}}(x)$, A is a fuzzy number, and the range of R values were defined as $R \rightarrow [0,1]$. Assuming the value of A lies within the interval $[a_1, a_3]$ the membership function $\mu_{\tilde{A}}(x)$ was calculated using Eq. (6) (Sarıalioğlu et al., 2020; Lin and Wang, 1997):

$$\mu_{\tilde{A}}(x) = K_{I(i+1)} = \left\{ \begin{array}{c} 0 x \leq a_1 \\ (x - a_1)/(a_2 - a_1) a_1 \leq x \leq a_2 \\ (a_3 - x)/(a_3 - a_2) a_2 \leq x \leq a_3 \\ 0 x \geq a_3 \end{array} \right\} \tag{6}$$

After all expert opinions were converted from the verbal scale to a numerical scale (triangular fuzzy numbers), the fuzzy logic processing steps were sequentially followed to obtain fuzzy probabilities for each condition, as presented below. Combining expert opinions is essential, as experts in a heterogeneous group, as in this study, may have varying levels of experience, knowledge, and expertise, leading to different interpretations and conclusions about a conditional probability. Therefore, consolidating the data obtained from expert assessments and integrating their opinions is crucial. In this regard, Hsu and Chen proposed an algorithm for combining views from homogeneous and heterogeneous expert groups, which is frequently used in the literature (Sarıalioğlu et al., 2020; Hsu and Chen, 1994; Ma et al., 2024). Assuming:

$\tilde{R}_1, \tilde{R}_2$: Pair of expert opinions;

$S_{uv}(\tilde{R}_1, \tilde{R}_2)$: Degree of agreement (similarity) between two different expert opinions;

$S(\tilde{A}_1, \tilde{A}_2)$: Degree of similarity between two fuzzy numbers;

$AA(E_u)$: Average degree of agreement among the experts;

$RA(E_u)$: Relative degree of agreement among the experts;

$CC(E_u)$: Consensus coefficient of the experts; and.

$\tilde{R}_{AG}$: Aggregated result of the weighted expert opinions.

The aggregated expert opinions can be calculated by using Eqs. (5)–(9).

Initially, it is necessary to calculate the degree of compatibility (similarity) ($S_{uv}(\tilde{R}_1, \tilde{R}_2)$) between the opinions $\tilde{R}_1$ *and* $\tilde{R}_2$ of two different experts, Eu (u = 1 to M). According to this approach, two triangular fuzzy numbers $\tilde{A}_1 = (a_{11}, a_{12}, a_{13})$ and $\tilde{A}_2 = (a_{21}, a_{22}, a_{23})$ were created. The similarity degree between these two fuzzy numbers is obtained using the similarity function from Eq. (7):

$$S\left(\tilde{A}_1, \tilde{A}_2\right) = 1 - \left(\frac{1}{3}\right) \sum_{i=1}^{3} |a_{1i} - a_{2i}| \tag{7}$$

The average agreement degree of M number of experts ($AA(E_u)$) is calculated using Eq. (8):

$$AA(E_u) = \frac{1}{M-1} \sum_{u \neq v}^{M} S\left(\tilde{A}_u, \tilde{A}_v\right) \tag{8}$$

The relative agreement degree of M number of experts ($RA(E_u)$) is calculated using Eq. (9):

$$RA(E_u) = \frac{AA(E_u)}{\sum_1^M AA(E_u)} \tag{9}$$

The consensus coefficient of M number of experts ($CC(E_u)$) calculated using Eq. (10):

$$CC(E_u) = \beta \times w(E_u) + (1 - \beta) \times RA(E_u) \tag{10}$$

In Eq. (10), $\beta\ (0 \leq \beta \leq 1)$ is referred to as the relaxation factor of the proposed method. This value (β) represents the importance of the weight factor of expert E_u "$w(E_u)$" in relation to $RA(E_u)$. If $\beta = 0$, the weight factor of the experts is disregarded, assuming a homogeneous distribution among the experts. Conversely, when $\beta = 1$, it is assumed that the experts share the same consensus coefficient (CC) and weight importance. In this study, β=0.5 is used (Sarıalioğlu et al., 2020; Hsu and Chen, 1994; Ma et al., 2024).

The weighted results of the opinions of M number of experts ($\tilde{R}_{AG}$) are calculated using Eq. (11) below:

$$\tilde{R}_{AG} = CC(E_1) \times \tilde{R}_1 + CC(E_2) \times \tilde{R}_2 \cdots + CC(E_M) \times \tilde{R}_M \tag{11}$$

After calculating the weighted results of expert opinions ($\tilde{R}_{AG}$), it is necessary to perform defuzzification to obtain interpretable and measurable results. Transforming fuzzy numbers into clear, comprehensible values through defuzzification is critical for the decision-making process. If calculations are performed using triangular fuzzy numbers, the result will also be in the form of triangular fuzzy numbers. To fully understand the relationship among these values, a fuzzy number should be converted into a precise probability, termed the "Defuzzified Probability" (Buckley, 2006; Kaushik and Kumar, 2023). The Defuzzified Probability for each condition is derived from a membership function calculated during the aggregation of the expert opinions. Defuzzification methods include the mean of maximum membership method, centroid method, weighted average method, centre of area method, and centre of sums method (Sarıalioğlu et al., 2020; Lin and Wang, 1997; Gudder, 1998). In this study, the "centre of area" method, which is widely used due to its simplicity and clarity, has been employed to calculate the fuzzy probability values for each condition (Zhao and Govind, 1991; Arun and Mohan, 2017; Vahidnia et al., 2009). The defuzzification equation (X^*) is presented in Eq. (12):

$$X^* = \frac{\int \mu_i(x) x dx}{\int \mu_i(x) dx} \tag{12}$$

For the triangular fuzzy number $\tilde{A}_1 = (a_1, a_2, a_3)$, Eq. (13) is given as follows:

$$X = \frac{\int_{a_1}^{a_2} \frac{x - a_1}{a_2 - a_1} x dx + \int_{a_2}^{a_3} \frac{a_3 - x}{a_3 - a_2} x dx}{\int_{a_1}^{a_2} \frac{x - a_1}{a_2 - a_1} dx + \int_{a_2}^{a_3} \frac{a_3 - x}{a_3 - a_2} dx} = \frac{1}{3}(a_1 + a_2 + a_3) \tag{13}$$

After determining the probabilities for all conditions as described above, the condenser failure probabilities were entered into the Genie 4.1 Academic Bayes software, and the network was executed. In BN studies, the analytical validation of the developed network is the most critical condition to ensure that the results are consistent, reliable, and effective. A commonly used validation approach in the literature for BN validation, based on three axioms, is frequently preferred (Goerlandt et al., 2017; Uğurlu et al., 2020; Animah, 2024). This study also employs this three-axiom-based method to validate the failure network. The three axioms provided by the network are presented below.

- Axiom 1 Any slight increase or decrease in the probabilities of each parent node should result in a corresponding relative increase or decrease in the final probabilities of the child node.
- Axiom 2: The impact of changes in the subjective probability distributions of each parent node on the child nodes should be continuous and consistent. In other words, changes (increase or decrease)

in the parent nodes should be reflected similarly in the child nodes (increase-increase/decrease-decrease).

- Axiom 3 The combined effect magnitudes of probability variations originating from any set of attributes “x” (evidence) should always be greater than those from “$x - y$” (where ($x \in y$)). In other words, the total effect magnitude of probability variations should always be greater than the impact of a single attribute (the individual effects of parent nodes).

3.2.4. Modelling and analysis of system improvements

Through fault analysis conducted using Bayesian Network and fuzzy logic methods, areas requiring improvement to reduce the probability of ‘catastrophic failure’ were identified within the system. Based on the findings obtained from the analysis of the Bayesian Network developed on the case study, additional analyzers and an automatic system shutdown command mechanism were proposed to eliminate operator errors and enhance system resilience (Pandey, 2006). The technical details and system integration of these improvements are provided in Section 4.1. By integrating these proposals into the existing network structure, the model was revised, and the impact of these improvements was re-evaluated. Similarly, in studies conducted in (Shen et al., 2016), recommendations to enhance system safety were developed following detailed analysis of failure causes.

The two main components ensuring system safety, namely the Alarm System and the Operator’s working protocol, were identified for improvement in this context. While the Alarm System was strengthened by deploying additional analyzers, the automatic shutdown mechanism was designed to support the operator’s working protocol. Using the revised Bayesian Network, the effects of these improvements on the system’s self-protection capacity and the probability of catastrophic scenarios were evaluated. The overall methodology and process steps are presented in Fig. 11.

3.3. Application of methodology

BNs are powerful tools for decision-making under uncertainty and for modelling cause-effect relationships. In this study, a Bayesian accident network was constructed to represent the sequence of events leading to the accident and to include all relevant causes and causal factors. During the construction of the accident network, all primary and secondary events identified in the case study were modelled using nodes and directed arrows to accurately reflect the accident scenario (Fig. 12). After the network was established, fuzzy probability values were assigned to each node, considering their role in the accident. The integration of fuzzy logic and the assignment of probabilities within the BN are demonstrated through an example node.

In this study, the relationships between the nodes in the Bayesian network are defined based on the considered case study, current operating conditions, and the modelling objective of the study. If a different system design, operating regime, or case study is considered, the relationships between the nodes may change or vary. This is one of the main limitations of the study. Therefore, the absence of some direct

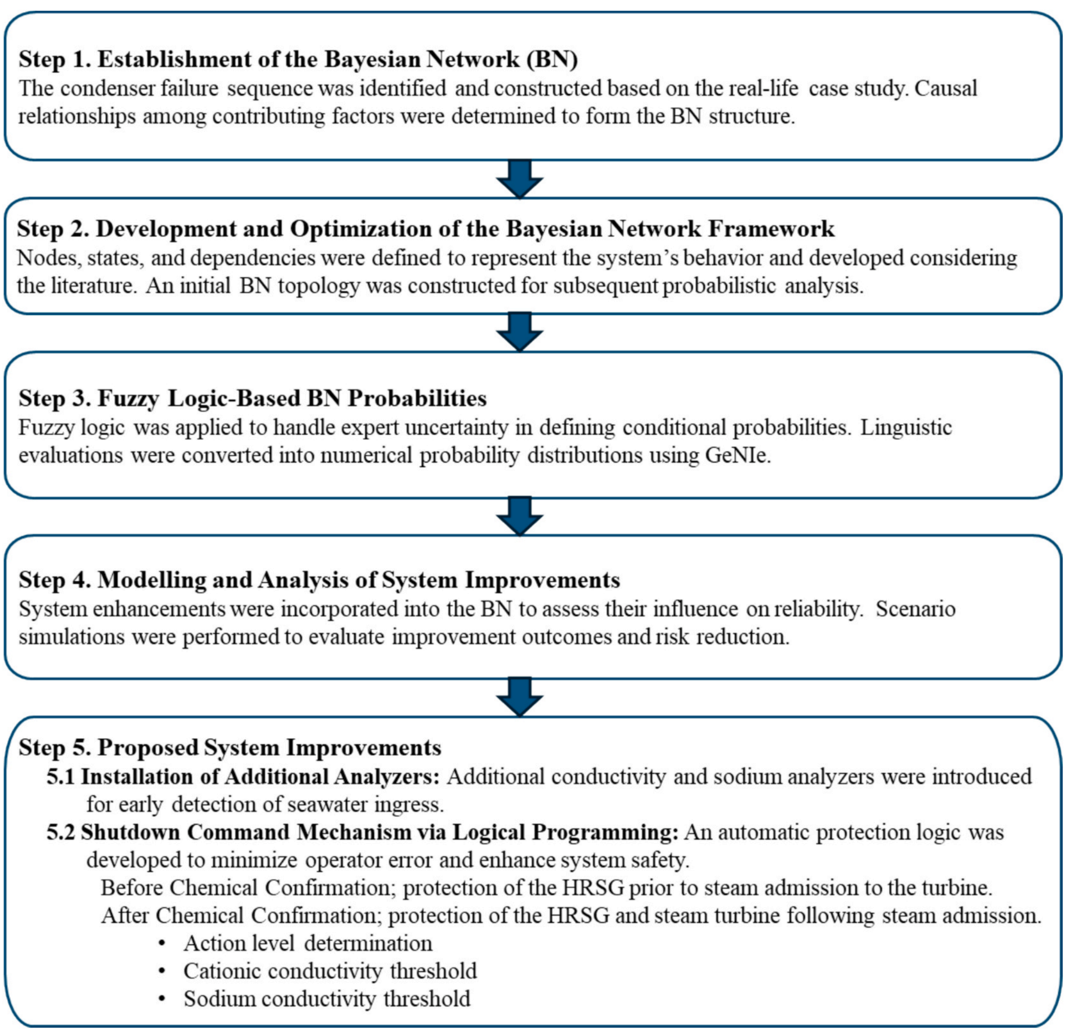

Fig. 11. Methodology flowchart.

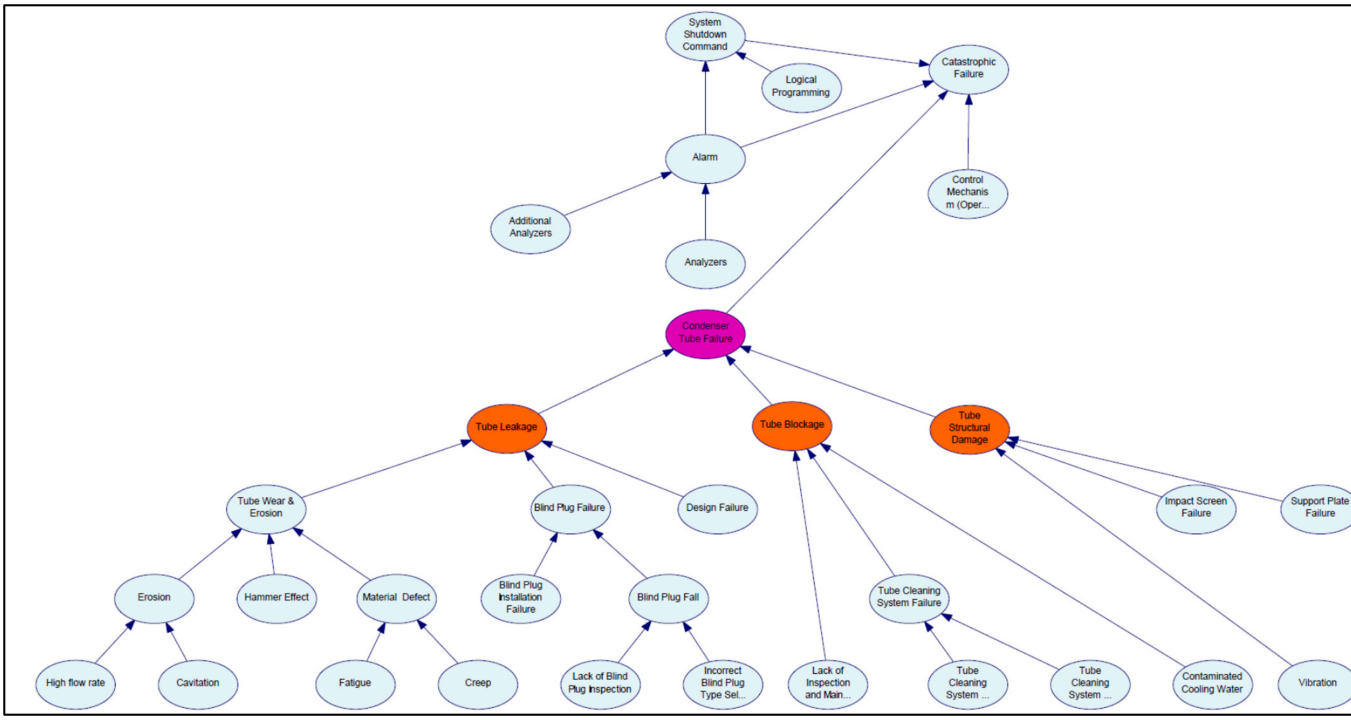

Fig. 12. General view of the BN summarizing the accident sequence.

connections between nodes does not mean that the related failure mechanisms are physically impossible. Rather, this choice indicates that these relationships are not modelled as direct causal links within the scope and assumptions of this study. Within this framework, the causal dependency and independence relationships defined among the nodes are explained below.

The Bayesian network presented in Fig. 12 is structured to distinguish direct and indirect mechanisms leading to catastrophic failure in condenser tubes. The "condenser tube failure" node, which results in catastrophic failure, is assumed to be directly independent of the operator error and alarm deficiency nodes in the considered case study. This independence assumption is based on the observation that, in the case study, these factors did not trigger each other but occurred as parallel and separate failure chains. System shutdown commands and the installation of additional analysers are treated as preventive and independent safety layers that directly reduce the probability of catastrophic failure. Therefore, these nodes are represented as independent in the network structure. However, it is acknowledged within the limitations of the study that this independence assumption may not hold in systems where different operational cultures, alarm management approaches, or human and machine interactions play a more prominent role.

In the network structure, Condenser Tube Failure is defined as a central intermediate node and is conditioned by the main failure modes: Tube Leakage, Tube Blockage, and Tube Structural Damage. These three nodes represent different classes of failures with distinct physical mechanisms and different levels of operational detectability.

In this study, Tube Leakage is considered the result of physical and material-based failure mechanisms that directly lead to loss of tightness in condenser tubes. As shown in Fig. 12, tube leakage mainly arises from the Tube Wear and Erosion, Blind Plug Failure, and Design Failure nodes. These factors represent failure modes that directly compromise tube integrity. Tube Wear and Erosion refers to a failure mode that develops due to the combined effects of hydrodynamic stresses caused by erosion, cavitation, high flow velocities, and water hammer (hammer effect), as well as microstructural degradation mechanisms such as fatigue, creep, and material defects. These effects lead to gradual and cumulative reduction in tube wall thickness, which can result in tube leakage once a critical threshold is exceeded. In particular, the hammer effect, characterized by sudden pressure waves, is modelled as a direct mechanism that can trigger tube leakage even when no significant prior wear or erosion is observed. Under the Blind Plug Failure node, conditions such as installation errors, inappropriate plug selection, plug dislodgement, and insufficient inspection are defined as failure modes that directly eliminate tube tightness. Since such failures can cause sudden tube outage and leakage during operation, they are included in the network as direct parent nodes of Tube Leakage. Design Failure is considered a failure mode that can directly cause tube leakage when the tube material, wall thickness, or design conditions are incompatible with operational loads. Inappropriate design decisions may lead to early damage and loss of tightness in the tubes even under normal operating conditions.

In contrast, the Tube Blockage and Tube Structural Damage nodes are not modelled in this study as mechanisms that directly and rapidly lead to tube leakage. It is assumed that these failure modes can be detected and controlled at an early stage through monitoring and maintenance systems, and their potential effects are represented indirectly through common causes or higher-level nodes. However, it is explicitly acknowledged that if the effectiveness of monitoring systems decreases, design assumptions change, or different operating conditions apply, the relationship between these two nodes and Tube Leakage may become direct (Zeytin, 2008; Yilin et al., 2025). This is considered one of the main limitations of the network structure.

In this study, Tube Blockage is considered the result of operational and environmental mechanisms that cause narrowing or partial or complete blockage of the flow area in condenser tubes. As shown in the figure, tube blockage is mainly represented by nodes such as Tube Cleaning System Failure, Lack of Inspection and Maintenance, and Contaminated Cooling Water. These factors include failure modes that disrupt flow by triggering processes such as fouling, particle accumulation, or the retention of foreign materials on the inner tube surface. The Tube Cleaning System Failure node represents conditions in which the online tube cleaning system is out of service, operates insufficiently, or fails to achieve its intended performance. Reduced effectiveness of the cleaning system can lead to a gradual increase in deposits and biological fouling on the tube inner surface, thereby creating conditions for blockage. Therefore, cleaning system failure is modelled as a direct parent node of Tube Blockage. The Lack of Inspection and Maintenance node represents an organizational failure mode in which periodic inspection of tube conditions is not performed or maintenance activities are delayed, allowing small-scale deposits to grow to critical levels over time. Since this can prevent early detection of blockage and increase its operational impact, it is treated as a direct contributing factor to the occurrence of Tube Blockage. The Contaminated Cooling Water node refers to the formation of deposits on the tube inner surface due to high particle loads, biological organisms, or chemical contaminants in the cooling water. Especially under insufficient filtration or variable water quality conditions, such contamination can significantly increase the risk of tube blockage. For this reason, cooling water quality is included in the network structure as one of the main environmental determinants of Tube Blockage.

In this model, Tube Blockage is not defined as a failure mode that directly leads to Tube Leakage in the short term. The main reason for this is that, in the considered system, online cleaning, monitoring, and operational control mechanisms are designed to prevent blockage from progressing into tube leakage. However, it is acknowledged that under reduced effectiveness of monitoring and maintenance systems, different design assumptions, or more severe operating conditions, Tube Blockage may contribute to tube leakage through secondary effects (Shalaby et al., 2011; Rao, 2015). This is explicitly stated as one of the main limitations of the network structure.

In this study, Tube Structural Damage is defined as a failure mode representing structural degradation caused by mechanical stresses acting on condenser tubes under supporting structures and flow-induced dynamic loads. As shown in Fig. 12, this node is associated with physical interaction and loading mechanisms such as Support Plate Failure, Impact Screen Failure, and Vibration. These factors represent processes that can gradually weaken the geometric integrity of the tubes, leading to local deformation, ovalization, or surface damage over time. The Support Plate Failure node represents situations in which support plates shift, lose stiffness, or experience increased loads due to operational reasons, causing the tubes to operate under unexpected boundary conditions. In such cases, the tubes may be exposed to unanticipated contact and loading, leading to structural damage. Therefore, support plate–related issues are modelled as direct parent nodes of Tube Structural Damage. The Impact Screen Failure node represents cases in which impact screens are damaged or lose functionality, allowing steam or fluid to interact directly with the tubes at high velocity. This interaction can create local mechanical stresses and deformations on the tube surfaces, contributing to structural damage. For this reason, impact screen-related failures are also included in the network as direct mechanisms influencing the occurrence of Tube Structural Damage. The Vibration node represents flow-induced vibrations that generate dynamic stresses on the tubes and gradually reduce their structural strength over time. In the network structure, vibration is considered one of the main contributing factors that can trigger Tube Structural Damage.

In the BN developed in this study, Tube Structural Damage is not defined as a failure mode that directly leads, in the short term, to Tube Leakage or Tube Blockage. The main reason is that the system includes a multi-layer monitoring architecture consisting of vibration sensors, Acoustic Eye testing, a tube blockage prevention system, and operational/maintenance control mechanisms. Within this scope, these systems operate as defence layers that function independently from one another, each having its own failure detection mechanisms (i.e., alarms/sensor failures) and periodic verification procedures (maintenance and calibration in every 6–12 months). Since each layer can detect structural deterioration and allow intervention independently of the others, this structure has been considered not as a single monitoring mechanism but as a multi-layer monitoring architecture. Based on the expert opinions and field observations, the probability that these layers fail simultaneously was considered negligible. The main reason is that it is practically impossible for all layers to fail at the same time without being detected, which strengthens the reliability and transparency of the probabilistic assumptions underpinning the model. This architecture is expected to detect structural deterioration at an early stage and allow corrective actions to be taken. These monitoring layers are designed as complementary and partially independent defence barriers. The absence of a direct causal link between the related nodes in the network does not mean that the failure modes are absolutely independent. Instead, the model is based on the assumption of conditional independence, which is valid under conditions where the multi-layer monitoring architecture operates effectively. Structural damage could directly progress to leakage or blockage only if multiple monitoring and control layers lose effectiveness simultaneously and for an extended period. Based on expert judgment and field observations, the joint probability of such common failure scenarios was assessed as negligible in this study. Therefore, no direct connection between the relevant nodes was modelled. The model does not assume perfect system performance; rather, it provides a probabilistic framework that represents operational conditions under a multi-layer monitoring architecture.

To demonstrate the fuzzy logic and BN processes on a case study, the child node “Condenser Tube Failure” was selected. This node has three parent nodes: “Tube Leakage”, “Tube Blockage”, and “Tube Structural Damage” (Fig. 13). These parent nodes create eight conditional probability scenarios for the “Condenser Tube Failure” node. For each of these scenarios, the presence of the condenser tube failure was evaluated by experts using linguistic terms. These linguistic assessments were then quantified using the seven-point fuzzy linguistic scale shown in Table 2. As in the overall network (Fig. 12), Fig. 13 also includes directed arrows only between nodes that have direct conditional dependencies, consistent with the BN approach. For example, since “tube blockage” does not influence “tube structural damage”, there is no directed link between them. Therefore, because the Condenser Tube Failure or its descendants are not conditioned upon, these two parent nodes (“tube blockage” and “tube structural damage”) are marginally independent, in accordance with the separation principle.

To enhance the robustness and accuracy of the assessment, experts were weighted based on their experience, occupation, and professional position. Experience reflects an expert’s accumulated knowledge from past events and problem-solving ability; experts with more experience can identify and assess potential risks more accurately. Occupation indicates the expert’s field of technical expertise and its direct relevance to the type of risk being evaluated; for example, specific engineering disciplines such as Mechanical/Marine Engineers have a deeper capacity to understand related risks. Professional position, on the other hand, represents the expert’s level of responsibility within the organization and their broad perspective on overall operational risks; senior managers are assigned higher weights because they possess the ability to evaluate both the technical and strategic dimensions of risks. By combining these criteria, the knowledge, experience, and authority levels of the experts involved in the risk assessment are objectively reflected, enabling a more reliable and comprehensive evaluation. The scoring distribution

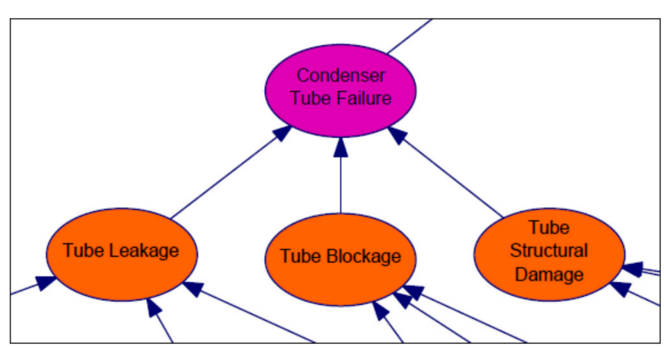

Fig. 13. “Condenser Tube Failure” node and its parent nodes.

Table 2
Verbal expressions and corresponding triangular fuzzy number values (Rajakarunakaran et al., 2015).

verbal term	Abbreviation	Triangular fuzzy numbers		
		a_1	a_2	a_3
Very Low	VL	0.00	0.04	0.08
Low	L	0.07	0.13	0.19
Reasonable Low	ML	0.17	0.27	0.37
Medium	M	0.35	0.50	0.65
Reasonable High	MH	0.63	0.73	0.83
High	H	0.81	0.87	0.93
Very High	VH	0.92	0.96	1.00

reflects the heterogeneity of the expert panel (Table 3). The demographic characteristics and calculated weight factors for the expert group are provided in Table 4.

By converting the linguistic terms provided by the experts into numerical values and processing them through fuzzy logic procedures, CPTs were generated. As an example, conditional probability scenario number 73 (CPT 73) is presented, along with the expert assessments and associated calculations in Tables 5 and 6.

The fuzzy probability values calculated for CPT 73 are then defuzzified using Eq. (13).

$$DefuzzificationofCPT73 = \left(\tfrac{1}{3}\right)\times \left(a_{1\tilde{R}_{AG}} + a_{2\tilde{R}_{AG}} + a_{3\tilde{R}_{AG}}\right) = .\left(\frac{1}{3}\right)\times (0.81 + 0.87 + 0.93) = 0.87$$

In the BN developed in this study, there are 104 conditional probability scenarios generated by 33 nodes. The calculations presented for CPT 73 were repeated for all others. As a result, CPTs were established for each of the 104 scenarios, containing fuzzy and defuzzified probability values (Appendix Tables 1–13). The conditional probability table for the “Condenser Tube Failure” node, which includes its 8 associated scenarios, is presented in Table 7.

To illustrate the general formulation of CPTs within the BN, the CPT of the “Condenser Tube Failure” child node is presented as an example. This node has three parent nodes, “Tube Leakage”, “Tube Blockage” and “Tube Structural Damage”, each with two possible states: present or absent. The state of the “Condenser Tube Failure” node (present or absent) depends on the combinations of these three parent node states (Fig. 14).

The posterior probability of the “Tube Leakage” node being in the “present” state is 76%, the posterior probability of the “Tube Blockage” node being in the “present” state is 61%, and the posterior probability of the “Tube Structural Damage” node being in the “present” state is 43% (Fig. 14).

Table 3
Evaluation criteria and their weights.

Criterion	Description	Weight
Experience	20 ≤ years	5
	15–20 years	4
	10–15 years	3
	5–10 years	2
	5 ≥ years	1
Occupation	Mechanical/Marine Engineer	5
	Metallurgical/Materials Engineer	4
	Chemical Engineer	3
	Academic/Researcher	2
	Electrical/Electronics Engineer	1
Professional Position	Power Plant Manager, Commercial Director, Occupational Safety Engineer	5
	Maintenance Manager, Operations Manager	4
	Chief Mechanical Maintenance Engineer, Chief Control Engineer	3
	Engineer	2
	Technician	1

According to the BN developed in the study, there are eight parent combinations representing the present or absent states of “Condenser Tube Failure”. The conditional probability values for these eight combinations are presented in Table 8. Based on these conditions, the posterior probability of the “Condenser Tube Failure” node being in the present state is calculated as 88% and 12% for the absent state.

According to Eqs. (3) and (5), the probability of the “Condenser Tube Failure” node being in the present state is calculated as follows:

Let $T = Condenser\ Tube\ Failure\ (present)$, $A = Tube\ Leakage\ (present)$, $B = Tube\ Blockage\ (present)$, $C = Tube\ Structural\ Damage\ (present)$, and $\overline{A}$, $\overline{B}$, C^{-} their absent complements.

$$\begin{aligned} P(T) = {} & [(P(T|A,B,C)\times P(A)\times P(B)\times P(C)] + [(P(T|A,B,\overline{C}) \\ & \times P(A)\times P(B)\times P(\overline{C})] + [(P(T|A,\overline{B},C)\times P(A)\times P(\overline{B}) \\ & \times P(C)] + [(P(T|A,\overline{B},\overline{C})\times P(A)\times P(\overline{B}) \\ & \times P(\overline{C})] + [(P(T|\overline{A},B,C)\times P(\overline{A})\times P(B) \\ & \times P(C)] + [(P(T|\overline{A},B,\overline{C})\times P(\overline{A})\times P(B) \\ & \times P(\overline{C})] + [(P(T|\overline{A},\overline{B},C)\times P(\overline{A})\times P(\overline{B}) \\ & \times P(C)] + [(P(T|\overline{A},\overline{B},\overline{C})\times P(\overline{A})\times P(\overline{B})\times P(\overline{C})] \end{aligned}$$

$$\begin{aligned} P(Condenser\ Tube\ Failure\ (Present)) = {} & (0.96\times 0.76\times 0.61 \\ & \times 0.43) + (0.96\times 0.76\times 0.61 \\ & \times 0.57) + (0.96\times 0.76\times 0.39 \\ & \times 0.43) + (0.95\times 0.76\times 0.39 \\ & \times 0.57) + (0.87\times 0.24\times 0.61 \\ & \times 0.43) + (0.73\times 0.24\times 0.61 \\ & \times 0.57) + (0.78\times 0.24\times 0.39 \\ & \times 0.43) + (0.04\times 0.24\times 0.39 \\ & \times 0.57) \\ = {} & 0.88\,(88\%) \end{aligned}$$

$$P(Condenser\ Tube\ Failure\ (Absent)) = 1 - 0.88 = 0.12\,(12\%)$$

4. Results

This study analyses a failure event in a condenser, addressing potential system-related issues and providing guidance on how such failures may be avoided through appropriate actions. The condenser, as examined in this study, is a common piece of equipment used across various sectors of the energy industry, including offshore platforms, power plants, and industrial facilities (Laskowski et al., 2020).

In the initial BN developed based on the accident scenario, Additional Analyzers and Shutdown Command Mechanisms were not included. The initial network is presented in Fig. 15, where the nodes not included in the system are marked in orange (100% Absent). In this system, if a Condenser Tube Failure emerges (100%), and the available Analyzers detect the fault (100%) and trigger an Alarm (100%), it was observed that in the presence of a Control Mechanism (Operator) Failure (100%), the probability of a Catastrophic Failure is as high as 94%. Indeed, in the case examined, the sequence followed this exact progression, ultimately leading to a catastrophic failure.

The analysis conducted using the initial network highlighted the necessity of an additional safety layer (second line of defence) in cases where a Condenser Tube Failure occurs and an Alarm is triggered by the Analyzers, but a Control Mechanism (Operator) Failure also takes place. Based on these insights, improvements were made to the network. Specifically, the Additional Analyzers and System Shutdown Command, which were absent in the initial network, were integrated into the system using Logical Programming. The improved network is presented in Fig. 16, with the newly added nodes marked in green (100% Present). In

Table 4
Expert weights.

No	Professional position	Occupation	Experience	Weight factor			Total weight	Evaluation impact
1	Maintenance Manager	Marine Engineer	16	4	5	4	13	0.138
2	Operations Manager	Mechanical Engineer	22	4	5	5	14	0.149
3	Chief Mechanical Maintenance Engineer	Mechanical Engineer	10	3	5	2	10	0.106
4	Power Plant Manager	Electrical Engineer	30	5	1	5	11	0.117
5	Chief Control Engineer	Electrical Engineer	17	3	1	4	8	0.085
6	Chief Control Engineer	Marine Engineer	16	3	5	4	12	0.128
7	Commercial Director	Marine Engineer	16	5	5	4	14	0.149
8	Occupational Safety Engineer	Mechanical Engineer	21	5	5	2	12	0.128
				Sum			94	1.000

Table 5
Experts' verbal assessment for CPT 73.

Expert no	Verbal assessment	Triangular fuzzy number
Expert 1	VH	(0.92, 0.96, 1.00)
Expert 2	H	(0.81, 0.87, 0.93)
Expert 3	H	(0.81, 0.87, 0.93)
Expert 4	H	(0.81, 0.87, 0.93)
Expert 5	VH	(0.92, 0.96, 1.00)
Expert 6	MH	(0.63, 0.73, 0.83)
Expert 7	H	(0.81, 0.87, 0.93)
Expert 8	H	(0.81, 0.87, 0.93)

this enhanced network, when all other nodes remain constant, and if a Condenser Tube Failure is present (100%), and the existing Analyzers detect it (100%) and an Alarm is triggered (100%), even in the event of a Control Mechanism (Operator) Failure (100%), the Additional Analyzers (100%) will detect the failure and activate the System Shutdown Command, halting the system. As a result, the probability of a catastrophic failure decreases significantly, from 94% to 6%.

To ensure the internal validity of the BN model developed in this study, a three-axiom-based sensitivity verification approach was also applied, as introduced in Section 3.2.3. These axioms were systematically tested using the constructed network. Axiom 1 was validated by slightly varying the probabilities of each parent node (e.g., failure detection, alarm triggering) and observing that the resulting changes in their child node probabilities (e.g., catastrophic failure) were proportionally consistent. Axiom 2 was confirmed through continuous adjustments in parent node distributions, which yielded smooth and directionally coherent changes in the associated child node outputs, ensuring that increase-increase and decrease-decrease relationships reflecting correctly. Lastly, Axiom 3 was tested by comparing the impact magnitudes between the full set of contributing factors and various reduced subsets, confirming that the combined influence of all relevant attributes was higher than individual or partial contribution. Accordingly, this systematic validation process based on the three axioms has reliably demonstrated the internal consistency of the developed Bayesian network model and its capacity to accurately reflect causal relationships. Based on the data generated through BN and fuzzy logic in this study, a sensitivity analysis has been conducted and is presented below.

4.1. Improvements made to the system

The risk of condenser tube leakage, which poses a significant threat to system reliability by allowing seawater to contaminate the feedwater system, was identified through fault analysis using Bayesian Network and fuzzy logic methods. These analyses revealed a critical need for enhancements to mitigate operator error and increase the system's self-protection capabilities. Consequently, two principal components were designed for improvement: the deployment of additional analyzers to strengthen the existing alarm system, and the implementation of an automatic shutdown command mechanism to support the operator protocol. The objective of these improvements is to enable the earliest possible detection of seawater ingress-induced contamination, thereby protecting critical equipment and preventing potential catastrophic failure scenarios. The technical details and system integration of these proposed improvements are elaborated in the subsequent sections.

4.1.1. Installation of additional analyzers

In the event of a leak in the condenser tubes, seawater may enter the steam side, particularly the hotwell, since this side is under vacuum. To detect seawater ingress directly within the hotwell, before it spreads to the High Pressure-Intermediate Pressure-Low Pressure (HP-IP-LP) drums and the rest of the process, additional cationic conductivity and sodium (Na) analyzers were installed at the hotwell, at the condensate pump outlet, and at the LP drum.

Although analyzers exist at other points in the process, this approach was chosen to ensure faster and accurate detection, to prevent contamination of other system components and to detect leakage during downtime when the condensate pump is not running. If seawater enters the hotwell, the sodium and conductivity levels will rise, triggering an early alarm in the affected area. Zhang (Zhang and Otahuhu, 2008) demonstrated in his study that installing additional analyzers enhances system reliability. Similarly, Vidojkovic et al. (Vidojkovic et al., 2013) focused on monitoring and controlling feedwater quality from the condenser to the boiler, helping to prevent damage to boiler tubes.

Locations of the additional analyzers are shown in red boxes in Fig. 17. These upgrades have made the system more resilient and capable of issuing earlier warnings. The improvements provide the following benefits:

- In the existing system, analyzers are located only at the Condensate Discharge Pump (CDP) outlet. In case of seawater leakage, the high-capacity pumps (with flow rates over 400 m^3/h) would feed contaminated hotwell water to the HRSG, resulting in boiler water contamination. The newly installed analyzers now act as an early warning system.
- During the start-up of the existing analyzers, unstable readings caused delays. With the newly installed analyzers, a redundant setup has been achieved, enhancing system safety and reliability.
- The sodium analyzers in the existing system are dual-channel units and perform measurements every 15 min. Therefore, in case of a leak, sodium values may not be detected for up to 15 min at the CDP outlet. The new single-channel analyzers provide continuous, real-time measurements.
- With the new system, additional analyzers are installed upstream of the HRSG and steam turbine, enabling the early detection of seawater intrusion before it reaches the HRSG and steam turbine. This ensures protection for both equipment.

4.1.2. Shutdown command mechanism via Logical Programming of the system

In the event of a failure or leak in the condenser tubes that causes seawater ingress to the hotwell and subsequently the boiler feedwater, a shutdown command mechanism has been integrated into the control system to enable the earliest possible detection of seawater presence.

Table 6
Aggregation calculations for CPT 73.

Step1. Degree of similarity for CPT 73 using Eq. (7).

$S(E_1, E_2)$ 0.91

$$S\left(\tilde{A}_1, \tilde{A}_2\right) = 1 - (1/3)\sum_{i=1}^{3}|a_{1i} - a_{2i}|$$

$$S(E_1, E_2) = 1 - \left(\frac{1}{3}\right)(0.11 + 0.09 + 0.07) = 0.91$$

$S(E_1, E_3)$	0.91	$S(E_2, E_6)$	0.86	$S(E_4, E_6)$	0.86
$S(E_1, E_4)$	0.91	$S(E_2, E_7)$	1.00	$S(E_4, E_7)$	1.00
$S(E_1, E_5)$	1.00	$S(E_2, E_8)$	1.00	$S(E_4, E_8)$	0.96
$S(E_1, E_6)$	0.77	$S(E_3, E_4)$	0.86	$S(E_5, E_6)$	0.77
$S(E_1, E_7)$	0.91	$S(E_3, E_5)$	0.91	$S(E_5, E_7)$	0.91
$S(E_1, E_8)$	0.91	$S(E_3, E_6)$	0.86	$S(E_5, E_8)$	0.91
$S(E_2, E_3)$	1.00	$S(E_3, E_7)$	1.00	$S(E_6, E_7)$	0.86
$S(E_2, E_4)$	1.00	$S(E_3, E_8)$	1.00	$S(E_6, E_8)$	0.86
$S(E_2, E_5)$	0.91	$S(E_4, E_5)$	0.91	$S(E_7, E_8)$	1.00

Step2. Average of agreement for CPT 73 using Eq. *(8)*.

$AA(E_1)$ 0.90

$$AA(E_u) = \frac{1}{M-1}\sum_{u\neq v}^{M} S\left(\tilde{A}_u, \tilde{A}_v\right) AA(E_1) = \left(\frac{1}{8-1}\right)(0.91 + 0.91 + 0.91 + 1.00 + 0.77 + 0.91 + 0.91) = 0.90$$

$AA(E_2)$	0.95		
$AA(E_3)$	0.95	$AA(E_6)$	0.83
$AA(E_4)$	0.95	$AA(E_7)$	0.95
$AA(E_5)$	0.90	$AA(E_8)$	0.95

Step3. Relative agreement for CPT 73 using Eq. *(9)*.

$RA(E_1)$ 0.12

$$RA(E_u) = \frac{AA(E_u)}{\sum_{u=1}^{M} AA(E_u)} RA(E_1) = \frac{0.90}{0.90 + 0.95 + 0.95 + 0.95 + 0.90 + 0.83 + 0.95 + 0.95} = 0.12$$

$RA(E_2)$	0.13		
$RA(E_3)$	0.13	$RA(E_6)$	0.11
$RA(E_4)$	0.13	$RA(E_7)$	0.13
$RA(E_5)$	0.12	$RA(E_8)$	0.13

Step4. Consensus coefficient for CPT 73 using Eq. *(10)*.

$CC(E_1)$ 0.13

$$CC(E_u) = \beta \cdot w(E_u) + (1-\beta)\cdot RA(E_u) CC(E_1) = 0.5 \times 0.138 + 0.5 \times 0.12 = 0.13$$

$CC(E_2)$	0.14		
$CC(E_3)$	0.12	$CC(E_6)$	0.12
$CC(E_4)$	0.12	$CC(E_7)$	0.14
$CC(E_5)$	0.10	$CC(E_8)$	0.13

Step5. Aggregation of experts' opinion for CPT 73 using Eq. *(11)*.

$$\tilde{R}_{AG} = CC(E_1) \times \tilde{R}_1 + CC(E_2) \times \tilde{R}_2 + \cdots + CC(E_M) \times \tilde{R}_M$$

$$0.13 \times (0.92, 0.96, 1.00) + 0.14 \times (0.81, 0.87, 0.93) + 0.12 \times (0.81, 0.87, 0.93) + 0.12 \times (0.81, 0.87, 0.93) + 0.10 \times (0.92, 0.96, 1.00) + 0.12 \times (0.63, 0.73, 0.83) + 0.14 \times (0.81, 0.87, 0.93) + 0.13 \times (0.81, 0.87, 0.93) = (0.81, 0.87, 0.93)$$

Table 7
Fuzzy and defuzzified probabilities for the "Condenser Tube Failure" conditional probability scenarios.

Conditional probability no.	Fuzzy probability			Defuzzified probability
69	0.92	0.96	1.00	0.96
70	0.92	0.96	1.00	0.96
71	0.92	0.96	1.00	0.96
72	0.91	0.95	0.99	0.95
73	0.81	0.87	0.93	0.87
74	0.66	0.73	0.81	0.73
75	0.69	0.78	0.87	0.78
76	0.00	0.04	0.08	0.04

This alarm system is based on parameters measured by analyzers located in the hotwell, the condenser discharge line, and downstream components.

The purpose of the shutdown command mechanism is to ensure that any deterioration in the water-steam parameters caused by seawater leakage is identified before damage occurs to boiler tubes or turbine blades. Additionally, it ensures that decisions regarding when to shutdown units, based on analyzer readings, are not left solely to the attention and judgement of the control room operator.

Khalid et al. have studied smart techniques for identifying potential failures in boilers and steam turbines in thermal power plants (Khalid et al., 2023). Similarly, Yasmal et al. (Yasmal et al., 2023) applied an autoencoder-based method for data-driven leak detection in heat exchangers at oil refineries.

When a condenser tube leak occurs, the operator should not rely on a single analysis to determine the level of contamination. Before taking action, the operator must verify whether the data received is accurate. In such situations, a decision may need to be made within minutes, depending on the severity of the leakage. Otherwise, the deterioration of water/steam chemical parameters may lead to damage or deformation of equipment in contact with the fluid (Kannan et al., 2013).

It is therefore critical that the operator is immediately informed of the required action level, as this will enable an appropriate and timely response based on the degree of contamination. In the event that seawater infiltrates the process water due to a condenser tube leak, both the conductivity and sodium levels in the process water will rise rapidly. As a result, the initial contamination will occur in the hotwell. Subsequently, the contaminated water will be pumped by the condensate discharge pumps through the LP economizer and eventually reach the LP drum. The proposed alarm system is working as presented below.

4.1.2.1. Before the chemical confirmation: protection of the boiler prior to steam admission to the turbine. During the start-up process, the chemical

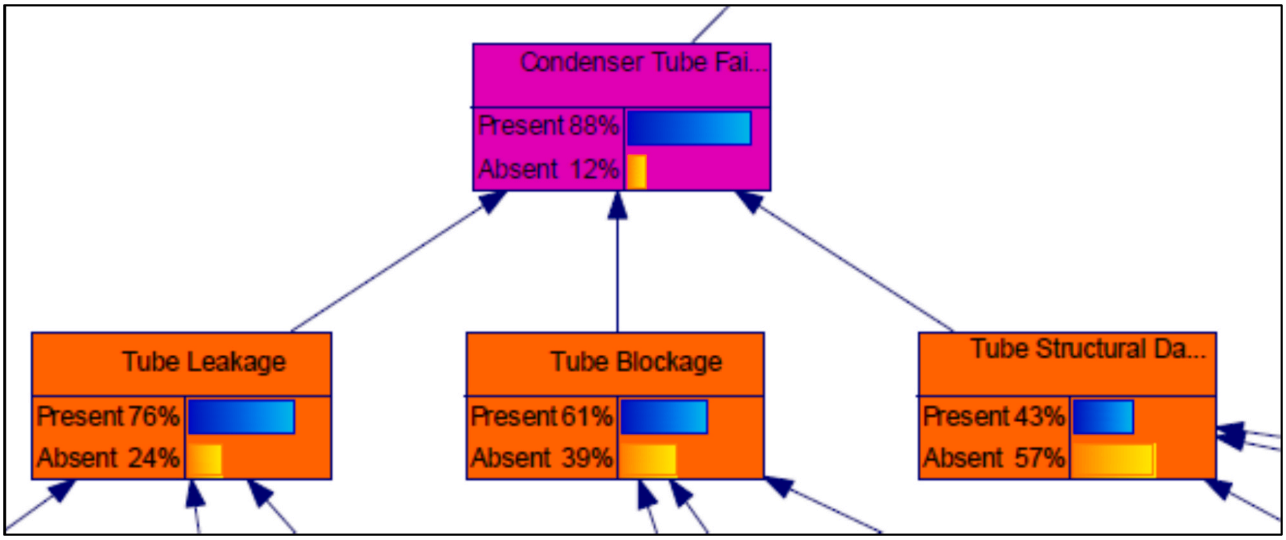

Fig. 14. "Condenser Tube Failure" and probabilities in the BN.

Table 8
Conditional probability scenarios and values for "Condenser Tube Failure".

Conditional probability no	Tube leakage	Tube blockage	Tube structural damage	Defuzzified probability
69	Present	Present	Present	0.96
70	Present	Present	Absent	0.96
71	Present	Absent	Present	0.96
72	Present	Absent	Absent	0.95
73	Absent	Present	Present	0.87
74	Absent	Present	Absent	0.73
75	Absent	Absent	Present	0.78
76	Absent	Absent	Absent	0.04

parameters of the boiler water must reach acceptable levels (Choi and Yun, 2025). Until the Chemical Confirmation phase is completed, the analyzers located downstream of the condenser discharge line may not yet be fully stabilized. Therefore, monitoring for salt ingress will be carried out using the additional analyzers installed at the condenser hotwell.

4.1.2.2. After chemical confirmation: protection of the boiler and steam turbine following steam admission

4.1.2.2.1. Determination of the action level. According to the guidelines of the Electric Power Research Institute (EPRI), contamination in the condenser resulting from a tube leak is classified into four action levels, each with a specified allowable operating duration (EPRI, 2025).

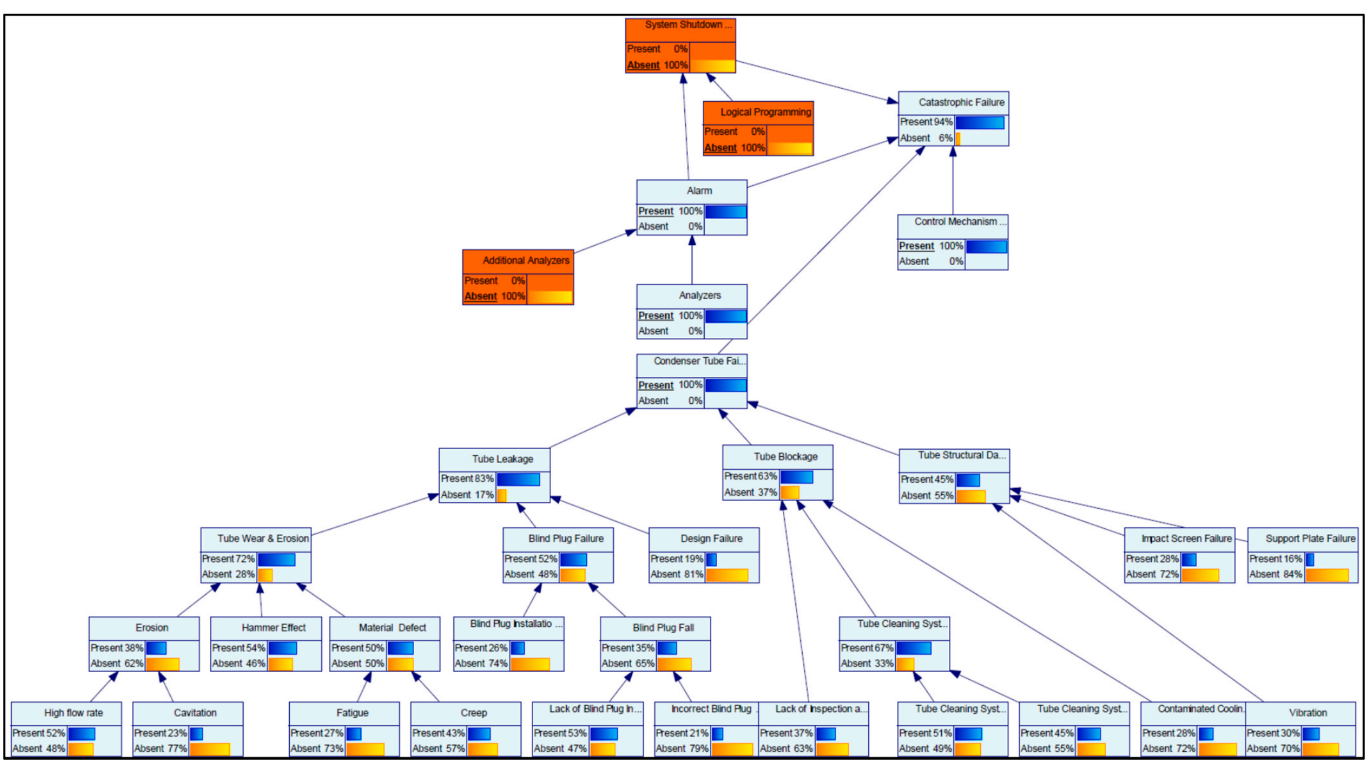

Fig. 15. BN constructed based on the accident, no additional analyzers or system shutdown command mechanism present.

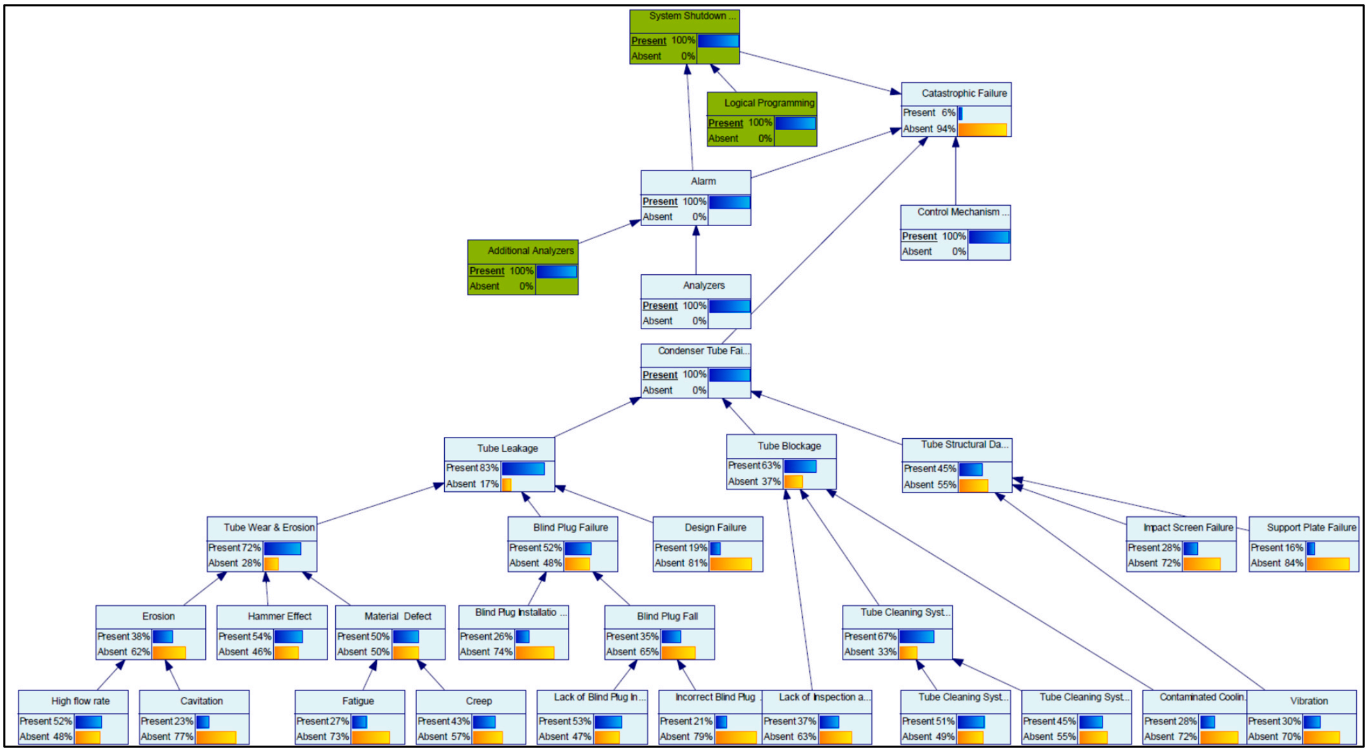

Fig. 16. Improved BN presented in the study; includes additional analyzers and system shutdown command mechanism.

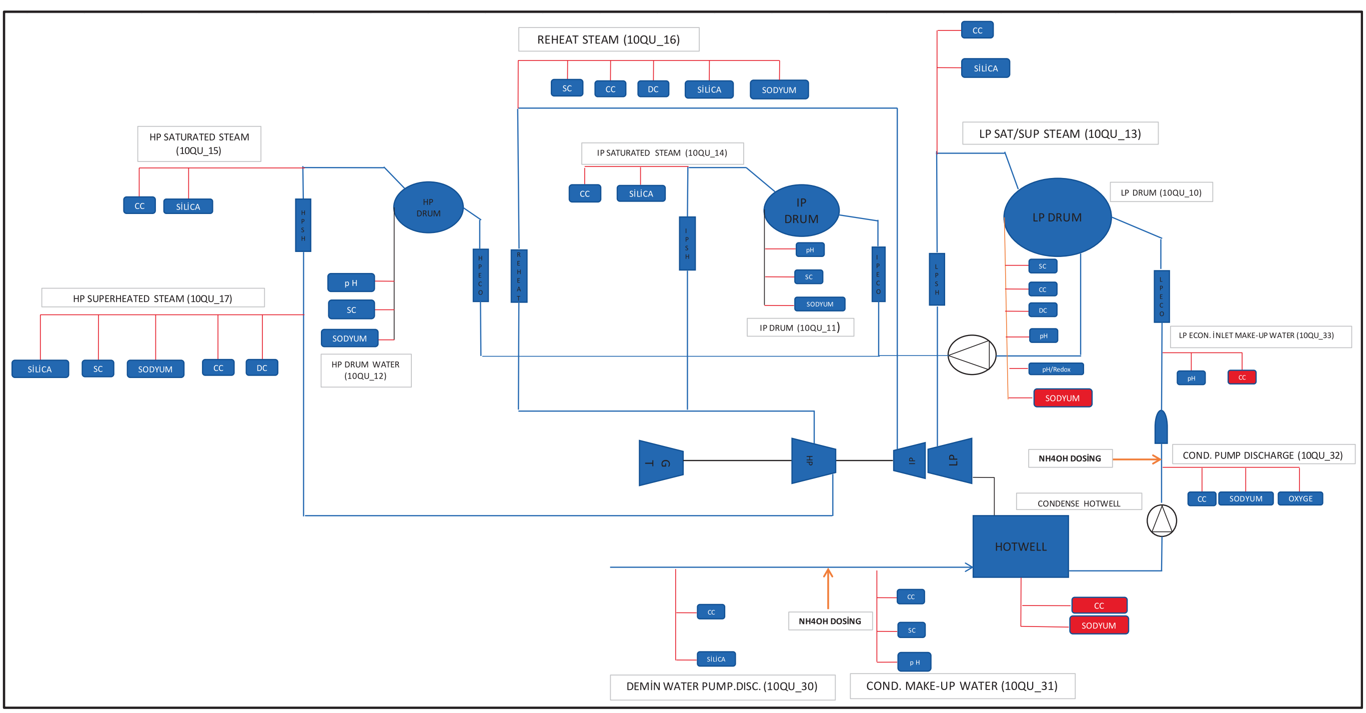

Fig. 17. Additional analyzers installed for condenser tube failure detection.

The determination of the action level depends on both the sodium concentration and the cationic conductivity values. Therefore, the active analogue signals from the Na and cationic conductivity measurements have been calibrated to correspond to four distinct values, each representing one of EPRI's defined action levels. The combined action level matrix, shown in Table 9, is based on experimental studies and follows guidance from EPRI. In the table, the top row represents the action levels detected by the sodium analyzers, while the left column represents the action levels detected by the cationic conductivity analyzers. Each cell in the table, highlighted with different colours, indicates the action level determined by the combined logic of sodium and cation conductivity readings.

For example, if the cationic conductivity action level is 3 and the Na action level is 2, the final action level is determined to be Level 2; and if

Table 9
Combined action level matrix (EPRI, 2025).

		Na				
		0	1	2	3	4
Cationic Conductivity	0	0	0	0	0	0
	1	0	1	2	3	4
	2	0	1	2	3	4
	3	0	1	2	3	4
	4	0	3	3	3	4

the cationic conductivity action level is 4 and the Na action level is between 1 and 3, the final action level is Level 3. The determined final action level is used to activate both the contamination level alarm and the contamination duration timing function.

4.1.2.2.2. Determination of cationic conductivity action level. If the cationic conductivity value measured by the analyzers in the hotwell section increases, the action level is determined as follows:

- If 0.20 μS/cm < cationic conductivity ≤ 0.35 μS/cm, then Action Level 1 is implemented.
- If 0.35 μS/cm < cationic conductivity ≤ 0.5 μS/cm, then Action Level 2 is implemented.
- If 0.50 μS/cm < cationic conductivity ≤ 1.0 μS/cm, then Action Level 3 is implemented.
- If cationic conductivity > 1.0 μS/cm, then Action Level 4 is implemented.

4.1.2.2.3. Determination of sodium conductivity action level. According to the defined sodium thresholds, if the sodium concentration measured by the Na analyzers in the hotwell section increases, the action levels are determined as follows:

- If 3 ppb < Na ≤ 6 ppb, then Action Level 1 is implemented.
- If 6 ppb < Na ≤ 12 ppb, then Action Level 2 is implemented.
- If 12 ppb < Na ≤ 19 ppb, then Action Level 3 is implemented.
- If Na > 19 ppb, then Action Level 4 is implemented.

If Action Level 3 is reached based on sodium values, the steam turbine must be shut down within a maximum of 4 h. Due to this short operating window, the range for Action Level 3 has been specifically defined as 12 ppb < Na ≤ 19 ppb.

Upon reaching Action Level 4, an automatic shutdown command will be issued for the system immediately.

4.1.2.2.4. Action level timing. The remaining time shown in Table 10 represents the maximum duration that the facility can continue operating at the specified final action level without shutting down the steam turbine. As the level of contamination increases, the permitted operating time decreases. When contamination reaches Action Level 4, the allowed operating time becomes zero, and the system must be shut down immediately.

It is likely that Action Level 4 will be reached shortly after condenser fouling begins. Therefore, it is essential to record the time spent at each action level. It is also critical that the control system interface displays the remaining time, allowing the operator to determine how much time is left before the steam turbine must be shutdown. As illustrated in Fig. 18, the "Condenser Monitoring System" shows whether an action level has been triggered, which action level is currently active, and how many minutes remain before an emergency shutdown is required.

The remaining time at a given action level is not the full permitted duration for that level when transitioning from one action level to another. For example, if contamination increases from Action Level 2 to Action Level 3 after 21 h, the remaining time at Level 3 is not automatically 4 h. Assigning a default of 4 h at Level 3 without accounting for the elapsed time in previous levels is not meaningful. When calculating the remaining time at a new action level, the time already spent at preceding levels must also be considered. To calculate the remaining time during a condenser leakage event, the following algorithm has been developed (Zeytin, 2008). Action Level 4 is excluded from this algorithm because no operating time is permitted once it is reached. In the algorithm below, all time units are expressed in minutes.

$$t = \left(1 - \frac{a}{100 \times 60} - \frac{b}{24 \times 60} - \frac{c}{4 \times 60}\right) \times k \times 60 \tag{14}$$

t = remaining time (in minutes)a = total operating time at Action Level 1 (in minutes)b = total operating time at Action Level 2 (in minutes)c = total operating time at Action Level 3 (in minutes)k = total permitted time (in hours) at the current action level

Table 10
Action level/Remaining time schedule (EPRI, 2025).

Action level	1	2	3	4
Remaining time (hours)	100	24	4	0

4.2. Findings obtained through BN and fuzzy logic

When the system operates without the implemented improvements, and in a scenario where a condenser tube failure occurs and an alarm is triggered but there is no control mechanism (operator) failure, the probability of a catastrophic failure is 7%, as shown in Table 11. Under the same conditions, if a control mechanism (operator) failure is also present, this probability increases significantly to 94%, as shown in Table 12.

As shown in Table 13, even in the absence of a control mechanism (operator) failure, if a condenser tube failure occurs but the alarm does not activate, the probability of a catastrophic failure reaches a critical level of 90%.

These results emphasize the importance of the alarm system and the control mechanism (operator). The modifications made to the system are aimed at minimizing the impact of these two risk factors on catastrophic failure. To mitigate the risk, a system shutdown command and additional analyzers were integrated into the system, which was subsequently revised (Fig. 16).

After adding the system shutdown command mechanism, the probability of a catastrophic failure, under the same risk conditions, was reduced from 94% to 6%, based on calculations using fuzzy logic, as presented in Table 14. This outcome demonstrates that the improvements implemented in the study significantly reduce the risk of catastrophic failure.

The installation of additional analyzers is another improvement aimed at addressing the previously highlighted issue of alarm deficiency. As shown in Table 15, the presence of additional analyzers reduces the probability of alarm deficiency from 18% to 4%.

When the nodes influencing catastrophic failure in the BN are examined individually, Table 16 shows that the alarm system and control mechanism (operator) failure play a significant role. System shutdown command when changed from present to absent, the probability of catastrophic failure changes from 6% to 45%, showing a significant reducing effect when it is present. Similarly alarm absence and presence change the probability of catastrophic failure from 30% to 80%, showing that it is a critical detection component. Changes from absent to present in condenser the tube failure node increases the catastrophic failure probability from 4% to 41%, showing its role as a failure initiator. Control mechanism failure (Operator) has one of the strongest effects, with the catastrophic failure probability ranging from 15% to 67%, emphasizing the importance of human reliability in the system.

The study primarily aims to minimize the probability of catastrophic failure arising from these two critical factors. The system shutdown command mechanism ensures protection even in cases of operator error. Meanwhile, the installation of additional analyzers strengthens the reliability of the alarm system.

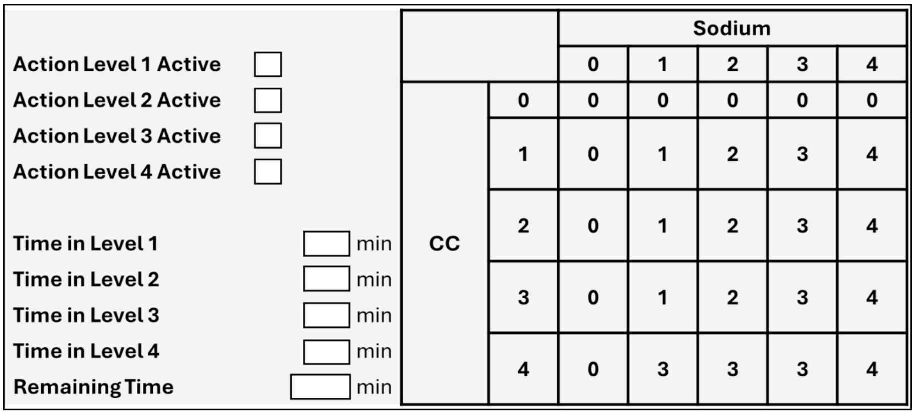

Fig. 18. Condenser monitoring system interface.

Table 11
Sensitivity analysis 1.

Nodes	Catastrophic failure (present) probability (%)
Condenser Tube Failure (Present) Control Mechanism Failure (Absent) Alarm (Present) System Shutdown Command (Absent)	7

Table 12
Sensitivity analysis 2.

Nodes	Catastrophic failure (present) probability (%)
Condenser Tube Failure (Present) Control Mechanism Failure (Present) Alarm (Present) System Shutdown Command (Absent)	94

Table 13
Sensitivity analysis 3.

Nodes	Catastrophic failure (present) probability (%)
Condenser Tube Failure (Present) Control Mechanism Failure (Absent) Alarm (Absent) System Shutdown Command (Absent)	90

Table 14
Sensitivity analysis 4.

Nodes	Catastrophic failure (present) probability (%)
Condenser Tube Failure (Present) Control Mechanism Failure (Present) Alarm (Present) System Shutdown Command (Present)	6

Analyzing the probabilities related to Condenser Tube Failure, it is observed that Blind Plug Failure leads to tube failure with a high probability of 94%. Further, the sub-node incorrect blind plug type selection, identified in the case study, shows a high probability of 88%. These high values confirm that the findings of the study are consistent with real-world conditions (Table 17). The case study also considered that the blind plugs installed in the system may be suitable for commissioning or testing purposes but may pose a risk under normal operating conditions. The probability figures above support this consideration.

As shown in Table 18, contaminated cooling water is identified as the most significant factor contributing to tube blockage events. On the other hand, the proper functioning of the tube cleaning system emerges as the most effective factor in minimizing the risk of tube blockage.

When examining the factors contributing to tube structural damage, no major differences are observed among the relative probabilities of the nodes. As presented in Table 19, the minimum probabilities range between 29% and 37%, while the maximum probabilities vary between

Table 15
Sensitivity analysis 5–6.

Nodes	Alarm (absent) probability (%)
Analysers (Present), Additional Analysers (Absent)	18
Analysers (Present), Additional Analysers (Present)	4

Table 16
Sensitivity analysis 7.

Nodes	Catastrophic failure (present) min. (%)	Catastrophic failure (present) max. (%)
System Shutdown Command	6	45
Alarm	30	80
Condenser Tube Failure	4	41
Control Mechanism Failure	15	67

Table 17
Sensitivity analysis 8–9.

Nodes	Tube leakage (present) min. (%)	Tube leakage (present) max. (%)
Tube Wear & Erosion	53	87
Blind Plug Failure	60	94
Design Failure	74	89
Nodes	**Blind plug fall (present) min. (%)**	**Blind plug fall (present) max. (%)**
Lack of Blind Plug Inspection	22	43
Incorrect Blind Plug Type Selection	20	88

Table 18
Sensitivity analysis 10.

Nodes	Tube blockage (present) min. (%)	Tube blockage (present) max. (%)
Lack of Inspection and Maintenance	52	75
Tube Cleaning System Failure	35	74
Contaminated Cooling Water	51	86

Table 19
Sensitivity analysis 11.

Nodes	Tube structural damage (present) min. (%)	Tube structural damage (present) max. (%)
Impact Screen Failure	29	80
Vibration	30	72
Support Plate Failure	37	75

72% and 80%.

In Table 20, when evaluating the most influential causes of tube wear and erosion, although there are no major differences among the scenarios, material damage caused by fatigue and creep stands out as the leading factor.

5. Discussion

Power generation and energy efficiency on offshore platforms are critical to the sustainability of operations. A significant share of energy demand is met through generators, renewable energy sources, and hybrid systems (Itiki et al., 2019; Nord et al., 2014; Du et al., 2024; Oliveira Pinto et al., 2019). Continuous energy supply is a fundamental factor that determines not only production efficiency but also the operability of safety–critical systems, such as emergency response, firefighting, and control/communication systems. As noted in the literature, disruptions in the power generation chain weaken safety barriers, reduce response capacity, and may cause operational disturbances to escalate into crisis scenarios through cascading failures (Sarwar et al., 2018; Adumene et al., 2021; Deyab et al., 2018). In this context, reliability and safety in offshore energy systems must be considered together with operational efficiency (Walnum et al., 2013), since even single failures under harsh offshore conditions can lead to serious operational and financial consequences (Al-Ballam et al., 2022; Hao et al., 2016; Pelenev et al., 2019). The findings of this study quantitatively demonstrate that failures occurring in the condenser, which is a safety–critical component of the energy generation chain, can have system-wide disruptive effects when they are not supported by appropriate testing, monitoring, and maintenance strategies. Bayesian Network and fuzzy logic-based analyses show that condenser-related degradation, if not detected at an early stage, can evolve into cascading risks that directly affect crisis and emergency management. In particular, maintenance practices targeting mechanisms such as stress corrosion cracking were found to contribute directly to failure reduction and preparedness processes.

Table 20
Sensitivity analysis 12.

Nodes	Tube wear & erosion (present) min. (%)	Tube wear & erosion (present) max. (%)
Erosion	60	85
Hammer Effect	57	80
Material Defect	50	90

The findings of this study demonstrate that, in the event of a blind plug failure, the likelihood of a tube failure can reach as high as 94%. Root cause analysis identified the selection of an incorrect type of blind plug as a major contributing factor, with a probability of 88% (Table 17). Prior research has similarly emphasized that the use of unsuitable equipment in such systems can result in catastrophic failures (Gong et al., 2019). In offshore facilities, blind plug solutions applied after damage detection are often part of early isolation decisions made under uncertainty and time pressure. The correctness of these decisions is critically important for preventing cascading failures (Sarwar et al., 2018; Deyab et al., 2018). Particularly following the detection of damage, the appropriateness of the blind plugs used to isolate tubes deemed unfit for continued operation remains a subject of ongoing debate. This issue encompasses uncertainties related not only to the selection of the plug type but also to potential errors in the implementation of plugging methods. The findings suggest that the processes related to plug type/selection and installation procedures should be addressed separately and supported through field testing.

Another key finding from the failure analysis is that contaminated cooling water is among the most influential factors leading to tube blockage (Table 18). On the other hand, it was found that the pipe cleaning system is the most effective factor in minimizing blockage failures. Existing literature highlights the critical safety role of pipe cleaning systems in maintaining system reliability (Li et al., 2021; Oñoro, 2024; Xu et al., 2022). A practical implication is the conditional adjustment of offline cleaning intervals and online cleaning parameters (e.g., ball cleaning) based on fouling indicators. This represents a risk-based approach that supports the prioritization of maintenance resources during the preparedness phase. Future research may focus on addressing current gaps in this area and further improving system performance.

The sensitivity analyses conducted in this study revealed that operator errors play a critical role in the prevention of system failures. In scenarios where no alarm deficiency is present and the operator functions correctly, the probability of a catastrophic failure remains low at 7% (Table 11). However, when only an operator error occurs, this probability increases significantly to 94% (Table 12). Previous studies show that approximately 80% of offshore platform accidents are caused by human error (Islam et al., 2020; Arena et al., 2022; Yildiz et al., 2021; Yıldız et al., 2024). These findings further confirm the critical importance of human reliability in socio-technical systems. Under harsh offshore conditions, operational decisions made with limited time and information increase the likelihood that human errors will escalate into crisis and emergency scenarios (Sarwar et al., 2018; Adumene et al., 2021). Therefore, decision-support and automation-based intervention mechanisms are becoming increasingly important to limit the consequences of human error. To mitigate the potentially severe consequences of human error, additional analyzers and a shutdown command mechanism were integrated into the system. The analysis demonstrated that these new components, representing targeted system improvements, reduced the probability of catastrophic failure from 94% to 6% (Table 14). In this context, the “shutdown command mechanism” can be considered a decision-support tool that reduces the decision burden on the operator and supports reliable operational processes under crisis conditions. The results suggest that such enhancements could serve as an effective solution for minimizing human error in power generation systems, including those on offshore platforms.

The analysis also showed that in the presence of alarm deficiencies, the probability of catastrophic failure could reach as high as 90%. In particular, failure of the analyzer to trigger the alarm system was identified as a critical risk factor, with a high potential to lead to system-wide failures (Table 13). Such deficiencies in alarm systems should be considered not only as technical failures but also as structural vulnerabilities, since the loss of early warning capability can delay responses to crises and emergency situations (Sarwar et al., 2018; Adumene et al., 2021). To reduce this risk, additional analyzers were installed, thereby enhancing system safety. While the probability of alarm deficiency with existing analyzers was calculated at 18%, this figure was reduced to 6% with the addition of new analyzers. Early fault detection and prediction are essential functions for ensuring safe operations (Arunthavanathan et al., 2021). In this context, additional analyzers not only improve the accuracy of fault detection but also provide an early warning infrastructure that supports timely and correct decision-making by enabling on-site identification of potential seawater leakage. Similar to the shutdown command mechanism, the additional analyzers significantly contribute to risk reduction in power generation systems (Zhang and Otahuhu, 2008).

In complex socio-technical systems, failure modes may theoretically interact with each other. However, as explained in Section 3.3. Application of Methodology, the BN structure in this study was intentionally limited to a manageable size so that it exclude causal paths deemed negligible in the operational context. In Bayesian networks, the graphical structure encodes assumptions of conditional independence between variables, and each variable is represented as dependent only on its parent nodes (Sattari et al., 2021). Therefore, instead of constructing a fully connected model that includes all possible interactions, the model focuses on failure patterns supported by field observations and expert judgment. The decision not to directly model scenarios with negligible joint probabilities, such as the simultaneous failure of multiple monitoring layers, was a deliberate modelling choice. This approach ensures manageable model complexity and reliable parameter estimation. Accordingly, the findings represent the system's operational behaviour under a multi-layer monitoring architecture. More extreme and rare combinations may be explored in future studies using alternative network topologies.

6. Conclusion

In this study, based on a representative accident scenario, a risk analysis was conducted on the potential impacts of condenser tube failures in seawater-cooled systems and the contributing factors that led to the incident. A BN and fuzzy logic-based accident model was developed, and potential system improvements aimed at preventing future accidents were evaluated within this framework. The analysis revealed that operator errors and alarm deficiencies significantly increase the risk of catastrophic failure. However, the enhancements introduced to improve system protection, namely the integration of additional analyzers and a shutdown command mechanism, proved to be effective solutions in mitigating such risks. These improvements reduced the probability of catastrophic failure approximately by a factor of 16 (from 94% to 6%), resulting in a substantial increase in system safety.

One of the main contributions of the proposed network and system enhancements is the enablement of timely intervention and increased operational safety. Failures in seawater-cooled condensers, if not addressed promptly, can lead to severe and catastrophic consequences. Therefore, it is essential to rigorously implement safety measures during operation and maintenance processes. Deficiencies in alarm systems and control mechanisms can lead to the escalation of failures and greater losses. As such, emergency preparedness should be a priority, and robust and responsive alarm and control systems must be established. As recommended in the study, the addition of shutdown command mechanism and additional analyzers can significantly reduce failure risks. These types of improvements enhance both the safety and reliability of the system, helping to prevent potentially large financial losses.

Based on the findings of this study, it is recommended that future research and operational improvements begin with a comprehensive review of equipment selection and operational conditions, as these factors can directly influence system performance. The use of the network model presented in this study may support the proactive prediction and management of failures and system deficiencies. Furthermore, considering the impact of human factors, particularly operational errors and shortcomings in maintenance practices, it is recommended that training programs and operational procedures be regularly updated to reflect best practices and minimize risks.

Seawater exposure presents significant risks of corrosion and erosion to turbine blades and other critical system components. In this context, considering the system components identified in the proposed network as influencing accident scenarios, future research in the fields of materials science and protective coatings is essential. Such research would contribute to the development of optimal material choices and protective strategies aimed at minimizing damage caused by these environmental stressors.

Condensers operating on offshore platforms may be exposed to more challenging environmental conditions compared to condensers in onshore facilities; these conditions include high vibration levels, increased humidity, and impurities specific to the marine environment. These factors can affect equipment failure frequency and maintenance requirements. The additional effects that offshore conditions can create are among the limitations of this study, and it is recommended that the BN model be tested on different environmental stress profiles in future research.

Finally, conducting regular risk analyses and system improvements in such critical systems is essential for ensuring the sustainability of operational safety. In high-risk environments such as offshore platforms, the implementation of continuous improvement and monitoring processes will enhance system resilience, while also minimizing operational disruptions and associated costs. This study offers practical solutions applicable to similar equipment in the offshore energy sector and can serve as a valuable reference for the design of future systems.

CRediT authorship contribution statement

Furkan Ertan: Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Özkan Uğurlu:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Conceptualization. **Fatih Tonoğlu:** Writing – original draft, Software, Methodology. **Fırat Sivri:** Writing – original draft, Software, Methodology. **Serdar Yıldız:** Writing – review & editing, Writing – original draft, Formal analysis. **Jin Wang:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ssci.2026.107272.

Data availability

Data will be made available on request.

References

Eneh, O.C., 2011. A review on petroleum: source, uses, processing, products and the environment. J. Appl. Sci. 11 (12), 2084–2091.
Zhang, B.L., Han, Q.L., Zhang, X.M., 2017. Recent advances in vibration control of offshore platforms. Nonlinear Dyn. 89, 755–771.
Itiki, R., Di Santo, S.G., Itiki, C., Manjrekar, M., Chowdhury, B.H., 2019. A comprehensive review and proposed architecture for offshore power system. Int. J. Electr. Power Energy Syst. 111, 79–92.
Karlilar Pata, S., Balcilar, M., 2024. Decarbonizing energy: evaluating fossil fuel displacement by renewables in OECD countries. Environ. Sci.Pollut. Res. 31 (21), 31304–31313.

Sarwar, A., Khan, F., Abimbola, M., James, L., 2018. Resilience analysis of a remote offshore oil and gas facility for a potential hydrocarbon release. Risk Anal. 38 (8), 1601–1617.
Adumene, S., Khan, F., Adedigba, S., Zendehboudi, S., Shiri, H., 2021. Dynamic risk analysis of marine and offshore systems suffering microbial induced stochastic degradation. Reliab. Eng. Syst. Saf. 207, 107388.
Deyab, S.M., Taleb Berrouane, M., Khan, F., Yang, M., 2018. Failure analysis of the offshore process component considering causation dependence. Process Saf. Environ. Prot. 113, 220–232.
Nord, L.O., Martelli, E., Bolland, O., 2014. Weight and power optimization of steam bottoming cycle for offshore oil and gas installations. Energy 76, 91–898.
Haglind, F., 2008. A review on the use of gas and steam turbine combined cycles as prime movers for large ships. Part II: previous work and implications. Energ. Conver. Manage. 49 (12), 3468–3475.
Berkeley, A.R., Wallace, M., Coo, C., 2010. A framework for establishing critical infrastructure resilience goals. In: Final Report and Recommendations by the National Infrastructure Advisory Council, pp. 1–26.
Sarwar, A., Khan, F., James, L., Abimbola, M., 2018. Integrated offshore power operation resilience assessment using object-oriented Bayesian network. Ocean Eng. 167, 257–266.
Nguyen, T.V., Voldsund, M., Breuhaus, P., Elmegaard, B., 2016. Energy efficiency measures for offshore oil and gas platforms. Energy 117, 325–340.
Mazzetti, M.J., Hagen, B.A., Skaugen, G., Lindqvist, K., Lundberg, S., Kristensen, O.A., 2021. Achieving 50% weight reduction of offshore steam bottoming cycles. Energy 230, 120634.
Guikema, S., McLay, L., Lambert, J.H., 2015. Infrastructure systems, risk analysis, and resilience-research gaps and opportunities. Risk Anal. 35 (4), 560–561.
Islam, R., Anantharaman, M., Khan, F., Abbassi, R., Garaniya, V., 2020. A hybrid human reliability assessment technique for the maintenance operations of marine and offshore systems. Process Saf. Prog. 39, e12118.
Adumene, S., Khan, F., Adedigba, S., Mamudu, A., Rosli, M.I., 2023. Offshore oil and gas development in remote harsh environments: Engineering challenges and research opportunities. Saf. Extreme Environ. 5 (1), 17–33.
Li, J., Goerlandt, F., Reniers, G., 2021. An overview of scientometric mapping for the safety science community: Methods, tools, and framework. Saf. Sci. 134, 105093.
Ersayin, E., Ozgener, L., 2015. Performance analysis of combined cycle power plants: a case study. Renew. Sustain. Energy Rev. 43, 832–842.
Shiozaki, S., et al., 2021. 6 - gas turbine combined cycle. In: Ozawa, M., Asano, H., Ozawa, M., Asano, H. (Eds.), Advances in Power Boilers. Elsevier, pp. 305–344.
Franco, A., Russo, A., 2002. Combined cycle plant efficiency increase based on the optimization of the heat recovery steam generator operating parameters. Int. J. Therm. Sci. 41 (9), 843–859.
Zeytin, H.K., 2008. Failure analysis of cooling water pipes used in the condensation system of a gas turbine. Mater Charact 59 (2), 167–172.
Pattanayak, L., Padhi, B.N., Kodamasingh, B., 2019. Thermal performance assessment of steam surface condenser. Case Stud. Therm. Eng. 14, 100484.
Laković, M.S., Stojiljković, M.M., Laković, S.V., Stefanović, V.P., Mitrović, D.D., 2010. Impact of the cold end operating conditions on energy efficiency of the steam power plants. Therm. Sci. 14 (suppl.), 53–66.
Anozie, A., Odejobi, O., 2011. The search for optimum condenser cooling water flow rate in a thermal power plant. Appl. Therm. Eng. 31 (17–18), 4083–4090.
Qureshi, B.A., Zubair, S.M., 2005. The impact of fouling on performance evaluation of evaporative coolers and condensers. Int. J. Energy Res. 29 (14), 1313–1330.
Shalaby, H., Al-Mazeedi, H., Gopal, H., Tanoli, N., 2011. Failure of titanium condenser tube. Eng. Fail. Anal. 18 (8), 1990–1997.
Cristiani, P., Perboni, G., Debenedetti, A., 2008. Effect of chlorination on the corrosion of Cu/Ni 70/30 condenser tubing. Electrochim. Acta 54 (1), 100–107.
Pandey, R., 2006. Failure analysis of refinery tubes of overhead condenser. Eng. Fail. Anal. 13 (5), 739–746.
Shen, S., Li, X., Zhang, P., Nan, Y., Song, X., 2016. Failure analysis and fatigue investigation on titanium tubes in a condenser. J. Fail. Anal. Prev. 16, 975–981.
Sen, S., Bahrami, A., Ghosh, M., Fallah Arani, H., Mahdizadeh, M., 2023. Establishing the root cause of a failure in condenser tubes in a power plant. J. Fail. Anal. Prev. 23 (5), 1991–2002.
Padilla, M.P., Maria, P.S., Faizal, A., 2024. A reliability analysis of steam condenser instrumentation using failure mode and effect analysis (FMEA). Jurnal Sistem Cerdas 7 (2), 155–162.
Ju, Y., Cui, Z., Xiao, Q., 2022. Fault diagnosis of power plant condenser with the optimized deep forest algorithm. IEEE Access 10, 75986–75997.
Mathews, I., Mathews, E., Van Laar, J., Hamer, W., Kleingeld, M., 2020. A simulation-based prediction model for coal-fired power plant condenser maintenance. Appl. Therm. Eng. 174, 115294.
Keprate A. Limitations and opportunities in PHM for offshore wind farms: A socio-technical-ecological system perspective. Annual Conference of the PHM Society 2023;15(1).
França, J.E., Hollnagel, E., dos Santos, I.J.L., Haddad, A.N., 2021. Analysing human factors and non-technical skills in offshore drilling operations using FRAM (functional resonance analysis method). Cogn. Tech. Work 23 (3), 553–566.
França, J.E., Hollnagel, E., Praetorius, G., 2022. Analysing the interactions and complexities of the operations in the production area of an FPSO platform using the functional resonance analysis method (FRAM). Arab. J. Geosci. 15 (7), 573.
Nitonye, S., Adumene, S., Orji, C.U., Effiong, U.A., 2021. Operational failure assessment of remotely operated vehicle (ROV) in harsh offshore environments. Pomorstvo 35 (2), 285–296.
Lu, W., Cai, D., Li, J., Wang, A., 2026. The role of shared suction anchors for mitigating cascading failure in floating offshore wind farms. Comput. Geotech. 189, 107655.
He, L., Chai, W., Gu, J., Chen, W., Shi, W., Liu, Z., Zhang, W., 2025. Extreme value prediction for the dynamic responses of a semi-submersible platform in harsh environments with consideration of mooring line failure accidents. Ocean Eng. 333, 121428.
Adedipe, O., Brennan, F., Kolios, A., 2016. Review of corrosion fatigue in offshore structures: present status and challenges in the offshore wind sector. Renew. Sustain. Energy Rev. 61, 141–154.
Adumene, S., Khan, F., Adedigba, S., Zendehboudi, S., Shiri, H., 2021. Offshore pipeline integrity assessment considering material and parametric uncertainty. J. Pipeline Sci. Eng. 1 (3), 265–276.
Hajinezhadian, M., Behnam, B., 2024. A corrosion- and repair-based reliability framework for offshore platforms. J. Marine Sci. Eng. 12 (3), 504.
Gholizad, A., Golafshani, A.A., Akrami, V., 2012. Structural reliability of offshore platforms considering fatigue damage and different failure scenarios. Ocean Eng. 46, 1–8.
Okoro, A., Khan, F., Ahmed, S., 2022. A methodology for time-varying resilience quantification of an offshore natural gas pipeline. J. Pipeline Sci. Eng. 2 (2), 100054.
Nathanael, J., Khairilmizal, S., MF, H., 2024. Challenges in managing emergency offshore: a comparison of offshore and onshore perspectives. J. Loss Prev. Process Ind. 88, 105275.
Norazahar, N., Khan, F., Veitch, B., MacKinnon, S., 2018. Dynamic risk assessment of escape and evacuation on offshore installations in a harsh environment. Appl. Ocean Res. 79, 1–6.
Wang, Y., Wang, K., Wang, T., Li, X.Y., Khan, F., Yang, Z., Wang, J., 2021. Reliability analysis of evacuation on offshore platforms: a dynamic Bayesian network model. Process Saf. Environ. Prot. 150, 179–193.
Rahman MS. Risk management of offshore logistics support operations in remote harsh environments. Doctoral dissertation, Memorial University of Newfoundland; 2020.s.
Chen, G., 2025. Vulnerability assessment of offshore platform emergency response system based on cloud model. J. Loss Prev. Process Ind. 88, 105842.
Li, X., Zhu, Y., Abbassi, R., Chen, G., 2022. A probabilistic framework for risk management and emergency decision-making of marine oil spill accidents. Process Saf. Environ. Prot. 162, 932–943.
Liu, K., Cai, B., Wu, Q., Chen, M., Yang, C., Khan, J.A., Liu, Y., 2023. Risk identification and assessment methods of offshore platform equipment and operations. Process Saf. Environ. Prot. 177, 1415–1430.
Surbled, A., 2024. Seawater heat exchangers' monitoring and inspection, corrosion management of seawater cooling systems. Elsevier 163–224.
Gong, Y., Ma, F.Q., Xue, Y., Jiao, C.S., Yang, Z.G., 2019. Failure analysis on leaked titanium tubes of seawater heat exchangers in recirculating cooling water system of coastal nuclear power plant. Eng. Fail. Anal. 101, 172–179.
Zhang, H., Otahuhu, B., 2008. Power Station condenser in-leakage analysis and condensate monitoring system: a thesis presented in partial fulfilment of the requirements for the degree of Master of Engineering in Electronics Engineering at Massey University, Wellington. Massey University, New Zealand.
IMO (2008). Resolution MSC.255(84), Adoption of the Code of The International Standards and Recommended Practices for A Safety Investigation into A Marine Casualty or Marine Incident (Casualty Investigation Code). International Maritime Organization (IMO), London.
Goerlandt, F., Khakzad, N., Reniers, G., 2017. Validity and validation of safety-related quantitative risk analysis: a review. Saf. Sci. 99, 127–139.
Wang, H., Liu, Z., Wang, X., Graham, T., Wang, J., 2021. An analysis of factors affecting the severity of marine accidents. Reliab. Eng. Syst. Saf. 210, 107513.
Liu, S., McGree, J., Ge, Z., Xie, Y., 2015. Computational and statistical methods for analysing big data with applications. Academic Press.
Hänninen, M., Banda, O.A.V., Kujala, P., 2014. Bayesian network model of maritime safety management. Expert Syst. Appl. 41 (17), 7837–7846.
Loughney S, Wang J. Bayesian network modelling of an offshore electrical generation system for applications within an asset integrity case for normally unattended offshore installations. Proceedings of the Institution of Mechanical Engineers, Part M: Journal of Engineering for the Maritime Environment 2017;1475090217704787.
Uğurlu, Ö., 2025. Real-time intelligent maritime accident prediction and prevention system for narrow waterways. Autonomous Transp. Res. 1 (1), 84–96.
Uğurlu, Ö., Yıldız, S., Loughney, S., Wang, J., Kuntchulia, S., Sharabidze, I., 2020. Analyzing collision, grounding, and sinking accidents occurring in the Black Sea utilizing HFACS and Bayesian networks. Risk Anal. 40 (12), 2610–2638.
Zadeh, L.A., 1965. Fuzzy sets. Inf. Control 8 (3), 338–353.
Klir G, Yuan B. Fuzzy sets and fuzzy logic. Prentice Hall New Jersey;1995.
Sarıalioğlu, S., Uğurlu, Ö., Aydın, M., Vardar, B., Wang, J., 2020. A hybrid model for human-factor analysis of engine-room fires on ships: HFACS-PV&FFTA. Ocean Eng. 217, 107992.
Lin, C.T., Wang, M.J.J., 1997. Hybrid fault tree analysis using fuzzy sets. Reliab. Eng. Syst. Saf. 58 (3), 205–213.
Hsu, H., Chen, C., 1994. Fuzzy hierarchical weight analysis model for multicriteria decision problem. J. Chinese Institute of Industrial Eng. 11 (3), 126–136.
Ma, L., Ma, X., Wang, T., Chen, L., Lan, H., 2024. On the development and measurement of human factors complex network for maritime accidents: a case of ship groundings. Ocean & Coastal Manage. 248, 106954.
Buckley, J.J., 2006. Fuzzy probability and statistics. Springer.
Kaushik, M., Kumar, M., 2023. An integrated approach of intuitionistic fuzzy fault tree and Bayesian network analysis applicable to risk analysis of ship mooring operations. Ocean Eng. 269, 113411.
Gudder, S., 1998. Fuzzy probability theory. Demonstration Mathematica 31 (1), 235–254.
Zhao, R., Govind, R., 1991. Defuzzification of fuzzy intervals. Fuzzy Set. Syst. 43 (1), 45–55.

Arun, N., Mohan, B., 2017. Modeling, stability analysis, and computational aspects of some simplest nonlinear fuzzy two-term controllers derived via center of area/gravity defuzzification. ISA Trans. 70, 16–29.
Vahidnia, M.H., Alesheikh, A.A., Alimohammadi, A., 2009. Hospital site selection using fuzzy AHP and its derivatives. J. Environ. Manage. 90 (10), 3048–3056.
Animah, I., 2024. Application of Bayesian network in the maritime industry: comprehensive literature review. Ocean Eng. 302, 117610.
Rajakarunakaran, S., Kumar, A.M., Prabhu, V.A., 2015. Applications of fuzzy faulty tree analysis and expert elicitation for evaluation of risks in LPG refuelling station. J. Loss Prev. Process Ind. 33, 109–123.
Laskowski, R., Smyk, A., Rusowicz, A., Grzebielec, A., 2020. A useful formulas to describe the performance of a steam condenser in off-design conditions. Energy 204, 117910.
Vidojkovic, S., Onjia, A., Matovic, B., Grahovac, N., Maksimovic, V., Nastasovic, A., 2013. Extensive feedwater quality control and monitoring concept for preventing chemistry-related failures of boiler tubes in a subcritical thermal power plant. Appl. Therm. Eng. 59 (1–2), 683–694.
Khalid, S., Song, J., Raouf, I., Kim, H.S., 2023. Advances in fault detection and diagnosis for thermal power plants: a review of intelligent techniques. Mathematics 11 (8), 1767.
Yasmal, A., Kaya, G.K., Oktay, E., Çölmekci, C., Uzunlar, E., 2023. Data driven leak detection in a real heat exchanger in an oil refinery. Comput. Aided Chemical Engi. Elsevier 3091–3096.
Kannan, P., Amirthagadeswaran, K., Christopher, T., Nageswara, R.B., 2013. Failures of high-temperature critical components in combined cycle power plants. J. Fail. Anal. Prev. 13, 409–419.
Choi, J., Yun, J.I., 2025. Optimization of water chemistry to mitigate corrosion products in nuclear power plants using big data and multiple linear regression in machine learning. Prog. Nucl. Energy 183, 105685.
EPRI. Electric Power Research Institute. https://www.epri.com; 2025 [accessed 31 July 2025].
Du, Z., Liu, Z., Zhou, Q., Zhao, Y., Sun, Z., Li, L., 2024. Research on process safety of offshore wind turbines installation: a theoretical model and empirical evidence. Process Saf. Environ. Prot. 181, 493–501.
Oliveira Pinto, S., Rosa Santos, P., Taveira, P.F., 2019. Electricity supply to offshore oil and gas platforms from renewable ocean wave energy: overview and case study analysis. Energ. Conver. Manage. 186, 556–569.
Walnum, H.T., Nekså, P., Nord, L.O., Andresen, T., 2013. Modelling and simulation of CO2 (carbon dioxide) bottoming cycles for offshore oil and gas installations at design and off-design conditions. Energy 59, 513–520.
Al-Ballam, S., Karami, H., Devegowda, D., 2022. A ded reliability analysis of ESP failures in oil production wells. J. Energy and Power Technol. 4 (4), 1–29.
Hao K, Khatib AR, Herbert N, Shah N. Case study: Integrating the power management system of an existing oil production field, 2016 Petroleum and Chemical Industry Technical Conference (PCIC). IEEE;2016. pp. 1-9.
Pelenev DN, Abramovich BN, Turysheva AV, Babyr KV. Organization of selective protection against single-phase ground faults in autonomous power supply networks of oil production facilities, 2019 IEEE Conference of Russian Young Researchers in Electrical and Electronic Engineering (EIConRus). IEEE;2019. pp. 1025-1028.
Li, X., Yang, C., Wang, Y., Hou, S., Wu, Y.J., 2021. Failure analysis and protection suggestions of a leakage condenser tubes in thermal power plants. J. Phys.: Conference Series. IOP Publishing, 012126.
Oñoro, J., 2024. Failure analysis of aluminum brass condenser tubes due to dezincification. J. Fail. Anal. Prev. 24 (1), 172–178.
Xu, N., Ding, N., Zaïri, F., Liu, L., Guo, W., Wu, X., Ma, H., Xu, H., Wu, C.M.L., 2022. Leakage failure of a stainless steel spiral plate condenser. Eng. Fail. Anal. 132, 105921.
Arena, S., Florian, E., Zennaro, I., Orrù, P.F., Sgarbossa, F., 2022. A novel decision support system for managing predictive maintenance strategies based on machine learning approaches. Saf. Sci. 146, 105529.
Yildiz, S., Uğurlu, Ö., Wang, J., Loughney, S., 2021. Application of the HFACS-PV approach for identification of human and organizational factors (HOFs) influencing marine accidents. Reliab. Eng. Syst. Saf. 208, 107395.
Yıldız, S., Uğurlu, Ö., Wang, X., Loughney, S., Wang, J., 2024. Dynamic accident network model for predicting marine accidents in narrow waterways under variable conditions: a Case Study of the Istanbul Strait. J. Marine Sci. Eng. 12 (12), 2305.
Arunthavanathan, R., Khan, F., Ahmed, S., Imtiaz, S., 2021. A deep learning model for process fault prognosis. Process Saf. Environ. Prot. 154, 467–479.
Yilin, W., Ming, Z., Zikai, D., Mengli, L., Long, L., 2025. Failure analysis of condenser copper tubes in a data center cooling system. Eng. Fail. Anal., 110442
Rao, T.S., 2015. Biofouling in industrial water systems. In: Mineral Scales and Deposits. Elsevier, pp. 123–140.
Sattari, F., Macciotta, R., Kurian, D., Lefsrud, L., 2021. Application of Bayesian network and artificial intelligence to reduce accident/incident rates in oil & gas companies. Saf. Sci. 133, 104981.