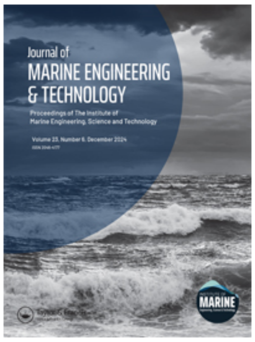

Journal of Marine Engineering & Technology

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/tmar20

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JOURNAL OF MARINE ENGINEERING & TECHNOLOGY
https://doi.org/10.1080/20464177.2024.2423425

A probabilistic assessment of ship blackout incident with Fault Tree Analysis into (FTA) Bayesian Network (BN)

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ABSTRACT
Blackouts in maritime activities can cause propulsion loss and dangerous maritime conditions. Bayesian risk analysis is applied to ship blackout incidents in this study to improve understanding and reduce risks. Using Fault Tree Analysis (FTA), a Bayesian Network (BN) model incorporates fuel quality, lubricating oil quality, sensor error, injector error, and mechanical defects to estimate blackout probability. The model analyses how hazards and their interactions affect this situation using probabilistic inference. Sensitivity analysis identifies variables that affect blackout probabilities and prioritises risk mitigation solutions. Based on prior and posterior probabilities, 'Automatic Voltage Regulator Failure' (0.03 prior, 0.17 posterior), 'Rotor Mechanical Fault' (0.03 prior, 0.15 posterior), and 'High Cooling Water Temperature' (0.03 prior, 0.13 posterior) are the top three blackout causes. Other significant variables include 'Switchboard Line Failure,' 'Faulty Fuel Pump,' 'Rotor Open Circuit,' and 'Temperature Sensor Failure' in relative amounts. Bayesian risk analysis can identify and minimise marine blackout concerns, giving decision-makers a comprehensive framework for informed decision-making and proactive risk management. This research emphasises blackout accidents' importance, improving maritime transportation safety and reliability.

ARTICLE HISTORY
Received 18 August 2024
Accepted 27 October 2024

KEYWORDS
Bayesian Network (BN); blackout; Fault Tree Analysis (FTA); maritime safety; risk analysis

1. Introduction

In terms of volume, the marine industry transports over 90% of global commerce commodities, whereas these goods comprise 70% of the world trade value (Hulme, 2021). In addition to cargo ships, improvements in the cruise ship business also indicate major expansion in the overall marine industry (Pallis & Vaggelas, 2019). Modern ships need advanced propulsion and power generation technologies to support their operations and assure their sustainability. There are technological distinctions across ship types, as well as variations in the type and capacity of electrically powered equipment (Bolbot, Theotokatos, Boulougouris, et al., 2021a). This greatly influences the precautionary scenarios in the case that electrical energy cannot be supplied.

The most prevalent safety threats for ships include loss of propulsion and drift at sea, fire, collision/contact/allision, sinking, grounding, pipeline defects, the spreading of viruses on board, and poor sanitation (Ibrion et al., 2021). Among them, the failure of the propulsion system was assessed to be the most probable to lead to an accident (Montewka et al., 2014). Unexpected events like as changes in main engine load, mechanical damage, auxiliary system problems, and extreme weather might increase the likelihood of a propulsion system failure. Furthermore, the dimensions of the results are impacted by the incidence of these defects in any manoeuvre condition. When describing ship manoeuvres, three distinct manoeuvring zones can be identified: canal crossing, port arrival and departure, and manoeuvres in the port (Gucma, 2019). These regions are prone to groundings, collisions with other vessels or coastal structures, and collisions with floating navigational buoys. It is a combination of internal and external factors, including deteriorating environmental conditions, rudder failure, and main engine or generator failure.

Tanker vessels carry several dangerous commodities such as nonylphenol, ethanol, sulfuric acid, nitric acid, xylenes, methanol, and ammonia (Sormunen et al., 2015). Chemical cargo transportation inherently involves various risks such as poisoning, chemical burns, suffocation, and heat burns (Aydin et al., 2021). Tanker ships carry out various chemical cargo operations such as loading, unloading, stacking, transfer, tank cleaning, and inert gas. Therefore, failure of any of these operations causes extremely serious environmental and human damage. In this context, International Maritime Organization (IMO), an international authority and supervisor, has adopted the stated purpose, 'IMO is the global standard-setting authority for the safety, security and environmental performance of international shipping' (IMO, 2023). The initial International Maritime Convention, known as the International Convention for the Safety of Life at Sea (SOLAS) Convention, was established in London in 1914. On November 2, 1973, IMO adopted the International Convention for the Prevention of Pollution from Ships Convention (MARPOL). Due to several tanker disasters in 1976-1977, the MARPOL 1978 Protocol was enacted (Kacmaz et al., 2016). The occurrence of catastrophic accidents forms the basis of the current legislation regulating the protection of life, property, and the marine environment. The compliance of ships with regulations such as the International Maritime Dangerous Goods (IMDG) code, the International Bulk Chemical (IBC) code, and the International Code of the Construction

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and Equipment of Ships Carrying Liquefied Gases in Bulk (IGC code) under SOLAS Chapter VII (Carriage of Dangerous Goods) is assessed, for instance, within the context of various stipulations (Rukavina, 2020). In addition, these rules are revised and reorganised in considering current conditions. Transporting liquid and gas commodities via tanker ships necessitates adherence to regulations and the use of a skilled crew. Aside from that, any mistake, whether deliberate or inadvertent, might have devastating impacts. Hence, tanker ship operations, particularly in the port area, must be uninterrupted and errorless. Thus, in this study, the root causes of possible blackouts on tanker ships and their effects on the top event (TE) are investigated.

The interruption of electrical energy for whatever reason (blackout) can cause not just an accident, but also human deaths and severe environmental contamination during and after the accident (Antão & Guedes Soares, 2008). This has a negative effect on the ship operator's finances as well as the company's reputation. The definition of shipboard power outage is the stoppage of main and/or auxiliary systems due to a malfunction in the ship's service electrical energy production system (Payvand & Hosseini, 2022). Loss of propulsion and essential auxiliary systems that have become fully inoperable is a critical safety concern that can lead to disaster. Possible causes of a malfunction in the ship's power generation system include fire, prime mover error, fuel system contamination, damaged panel, short circuit, defective power management system, or faulty transmission line (Akhter Hossain et al., 2013; Yuksel & Koseoglu, 2022). Furthermore, the emergence of hidden faults attributable to the design of an electrical system may occur (Islam et al., 2013).

Typically, onboard generators provide the energy required for the auxiliary systems of modern ships (Al-Falahi et al., 2018; Yuksel & Koseoglu, 2023). Like the main engines present aboard most ships, these engines have internal combustion and utilise fossil fuel energy. The loss of electrical power during ship navigation and manoeuvres initially disrupts the operation of auxiliary systems (Geertsma et al., 2017). Subsequently, because of failures in other systems that support the main engine, it will cease to function as well (Jaleel et al., 2016). In this scenario, the propulsion and steering systems will be inoperable, leading in contact/collision, drifting, and stranding, which will cause human, property, and ecological damage. Furthermore, with the recent rise in commercial vessel numbers, the frequency of accidents and resulting damage will grow, even if the probability of a 'Blackout' remains unchanged. Table 1 contains incidents of blackout failures and details on resulting accidents.

Table 1. Sample blackout incidents that cause ship accidents.

Date	Ship name	Ship type	Incident
11-01-2019	DC Orisant	Dredger	The vessel suddenly suffered a blackout. At that moment, no alarm had been activated on the bridge. There were various alarms in the control room and a fire was observed in the main switchboard. The fire was restricted to the main switchboard.
30-10-2018	Regal Star	Ro-Ro	The incident, when water entered the fuel pipes resulting in a blackout, led to the vessel's engines stopping and the unit being stranded in the Baltic Sea. The ship lost control near the Remmargrund lighthouse due to strong winds, causing it to collide with the lighthouse before being halted by anchors.
11-03-2018	Bulk India	Bulk carrier	The ship lost control of steering and propulsion when the main engine was accelerated to full speed and the auxiliary diesel generator engines shut down due to a malfunction in the cooling water temperature controller, causing the cooling water to overheat.
12-01-2018	Fantastic	Ro-Pax	The ship experienced a power outage while leaving the port of Barcelona. This caused the main engines to fail, causing the bridge crew to lose control of the ship and collide with the cruise ship Viking Star.
05-02-2014	Luno	General cargo ship	The pilot had been informed about a propulsion engine failure and he noticed that a blackout had also occurred. Then the ship control was lost, consequently grounding and complete loss of the ship Luno on the breakwater of the outer harbour of Bayonne, France.
03-12-2012	LNG Aries	LNG tanker	The ship docked at Keihin Port to unload LNG. It experienced a power outage, which caused the main turbine (main engine) to stop working and resulted in a loss of control.
29-07-2011	B Oceania	Bulk carrier	The ship experienced a total loss of power, leading to a collision with another ship and significant damage to its hull. This occurred in the Malacca Strait, Malaysia.
16-03-2011	Clonlee	Container vessel	Upon entering the Port of Tyne, England, the ship had an electrical outage. The ship's engineers could not promptly regain power, causing the vessel to run aground on Little Haven Beach at a speed of approximately 6–7 knots.
29-06-2008	Moondance	Ro-Ro	While the ship was shifted from a berth at the Port of Warrenpoint in Northern Ireland to a ferry connection, a power outage caused it to stop on the south-west shore of Carlingford Lough.

Modern automation technologies are regularly used to prevent interruptions on board. Automated Power Management Systems monitor the status of energy production and distribution systems in power plants. They control generator operations, synchronise generators, and perform load sharing and load reduction to meet increasing power demands (Al-Falahi et al., 2018). Also, a system that can rapidly identify the type of problems that cause system failures and provide suitable corrective procedures to prevent shutdowns is preferred (Rukavina, 2020). Due to the originality of each ship's design and configuration, although the number of generators, maximum and lowest power consumption varies, the necessity to strengthen the system's safety, security, and performance stays constant (Shen et al., 2011). The power management system (PMS) is responsible for initiating and stopping backup generators based on changes in power demand, detecting and replacing faulty components, allocating power to functioning components, issuing early warnings in specific fault scenarios, and overseeing maintenance tasks for the power generation system.

At the same time, restrictions are in effect to reduce carbon dioxide (CO_2), sulphur oxide (SOx), and nitrogen oxide (NOx) emissions from newly constructed and existing ships. In addition, ships must be equipped with modern technology infrastructure and comply with all safety measures of the relevant system. The Energy Efficiency Design Index (EEDI) was substituted by the Energy Efficiency Existing Ship Index (EEXI) on 17 June 2021 to decrease carbon emissions from current marine vessels (Ivanova, 2021; Yuksel, 2023). EEXI determines the energy efficiency of a marine vessel depending on its navigation distance and cargo capacity (Rutherford et al., 2020; Bayraktar & Yuksel, 2023). SOLAS Chapter II-1 focuses on the construction of ships, covering aspects such as structure, subdivision, stability, machinery, and electrical installations. Part D specifically deals with electrical installations, with Regulation 41 addressing the main source of electrical power and lighting systems. Guideline regarding machinery and electrical installation regulations for passenger and freight ships. In this scope, ecologically friendly, cost-effective, and safe solutions enhance the competitiveness of maritime transport businesses and promote their respect for nature and the environment (Bolbot et al., 2020). Hence, it becomes essential that diverse systems and subsystems communicate effectively with one another. This is accomplished with the assistance of national institutions and organisations, under the international authority of the IMO.

The size and intended use of the ship have a major impact on its energy production system capacity (Michalopoulos et al., 2022). The type of propulsion engine (diesel or electric) remains a significant component in deciding the scope of the propulsion system (Jeong et al., 2018). Although electric power station supplies the auxiliary systems with at least two generators in conventional diesel-mechanical propulsion systems, the dependence on electric energy is greater in diesel-electric propulsion systems, which have become more popular and have a growing market share (Kozak & Zawirski, 2011). The fact that not only the auxiliary systems but also the main electric motor that will drive the propeller are powered by the generator emphasises once more the need of eliminating shutdowns in energy generation (Jaleel et al., 2016).

2. Literature review, research gap, and objectives

Blackout prevention on marine vessels and associated risks have been investigated in several studies. Hansen and Ådnanes, (2009) presented several strategies to prevent blackouts, including load limiting through PMS, event-based load reduction, frequency-based load control, and advanced methods for monitoring the status of the power plant. Grzeczka et al. (2017) used the recording and analysis of voltage and excitation current fluctuations in parallel synchronous generators to determine the threshold at which their parallel operation could lead to power failure. Jayasinghe et al. (2018) asserted an innovative approach based on Model Predictive Control to overcome the load fluctuation challenge and improve power quality. The proposed approach uses a battery energy storage system to handle load variations and regulate the frequency of the ship's power system. Bolbot et al. (2019) executed an analysis utilising the Combinatorial Approach to Safety Analysis method, Fault Trees (FTs) are generated with the blackouts as the known event, the frequency of blackouts is estimated, and is executed. Furthermore, extreme conditions, such as rapid changes, caused frequency sags or swells for auxiliary engines, which led to blackouts. Moreover, variations in service loads may cause frequency variances that result in severe power quality difficulties. Ibrion et al. (2021) used a systems approach research and analysis called Causal Analysis based on Systems Theoretic Accident Model and Processes to systematically learn from the blackout failures of Viking Sky and help reduce failures in the cruise ship industry. Bolbot et al., (2021b) undertook an additional investigation to execute a comprehensive safety assessment for the Diesel-Electric Propulsion (DEP) system of a cruise ship, with particular attention given to blackout incidents. Payvand & Hosseini (2022) performed a study to reduce power outages on ships and prevent possible damage, the electromechanical model of the entire system is created, and the frequency is constantly changed by adding a frequency controller. Direct torque control is used to analyse the main controller of the drive system. The frequency controller is designed to have minimal impact on the standard operation of the drive and only helps reduce variations in situations where diesel generators are not very responsive. Breedlove et al. (2023) introduced an optimisation framework for dynamically positioned vessels, benchmarking the associated risks, including the occurrence of blackouts. Bolbot et al. (2024) investigated cybersecurity risks associated with inland waterway ships using dual-fuel (DF) engines for propulsion, with a particular focus on analysing blackout-related risks.

Risk analysis in ship engine rooms (ER) has been addressed in numerous studies, focusing on various aspects and equipment using different methodologies. Saatçioğlu et al. (2017) categorised overall risks in the ER through a decision-tree (DT) approach. Başhan et al. (2020) employed a hybrid method, combining the neutrosophic analytic hierarchy process (AHP) with the trapezoidal fuzzy technique for order preference by similarity to ideal solutions (TOPSIS), to identify and rank common ER risks. Sarıalioğlu et al. (2020) analysed ER fires and human factors using fuzzy Fault Tree Analysis (FTA) combined with the Human Factors Analysis and Classification System. Yüksel et al. (2021) utilised Bayesian Networks (BNs) to assess pipeline failure-related risks in ER accidents. Li et al. (2022) developed a fuzzy-FTA-based risk analysis method, incorporating expert evaluations to assess fire risks in the ship's power system during ER fires. Sezer et al. (2022) evaluated the risks associated with ballast water systems on tanker ships, which pose threats to ship safety, the marine environment, and cargo, using a combination of Dempster-Shafer evidence theory and Failure Mode Effects and Criticality Analysis (FMECA). Gürgen et al. (2023) applied FTA to assess risks affecting a ship's steering capability, while Göksu et al. (2023) used BNs to investigate the causes of failures in the steering gear system. Ceylan (2023) used Failure Mode Effects Analysis (FMEA) to identify risks associated with the ship's air compressor system, and in another study, fuzzy FMEA was applied to evaluate risks related to turbocharger fouling (Ceylan, 2024). Ceylan et al. (2023) also applied FMEA to assess the impact of sea chest fouling on ER equipment. Karatuğ et al. (2024) implemented a rule-based FMEA to evaluate the risks of scrubber usage in maritime transportation. Ma et al. (2024) examined ER fire risks using an integrated bowtie and fuzzy BN approach, while Liu et al. (2024) conducted a quantitative risk assessment of ER fire risks caused by fuel leakage. Ceylan & Celik (2024) executed a risk analysis based on the analytical network process (ANP) method on the marine boilers to enhance the system safety.

The literature review in this study is divided into two sections: blackout prevention and risk assessment in the ER. The first section reveals that blackout prevention research primarily focuses on modelling and optimising electrical system behaviour, determining blackout frequency, estimating failures, and assessing the safety of newer systems such as DF and DEP. The second section highlights risk analysis studies related to ER fires, ER risk categorisation, steering gear, air compressors, ER pipelines, marine boilers, and sea chest fouling. Commonly used methodologies include FMEA, FTA, and BNs, while methods like ANP, AHP, DT, and TOPSIS are also applied.

The review identifies a gap in the literature regarding the investigation of blackout risk probabilities in commercial marine vessels using BNs. They are essential for modelling uncertain systems, integrating prior data, managing uncertainty, conducting scenario and sensitivity analyses, supporting decision-making, and producing comprehensible results. These qualities make BNs versatile and applicable across various sectors, including finance, engineering, health, and environmental risk assessments.

As a result, this study aims to model ship blackouts using a hybrid FTA-BN approach to predict key factors influencing power outages and assess their probability. The hybrid FTA-BN method enhances risk analysis by integrating uncertainty management, scenario analysis, and probabilistic evaluation, offering a more robust prediction of factors influencing power outages. This novel approach provides valuable insights for improving vessel safety and reliability. Factors such as the ship's age, maintenance history, structural integrity, environmental conditions (e.g. weather and sea state), and human errors are excluded. The study focuses on evaluating the likelihood of power outages due to mechanical and electronic system failures, assessing the severity of the main factors involved.

3. Materials and methods

The study proposes an FTA and BN combined risk analysis framework using the fuzzy methodology for the determination of blackout occurrence on board which is one of the most crucial incidents, especially during cargo operations and navigation. Figure 1 illustrates the used methodology framework in the fuzzy FTA and BN integrated approach.

There are two distinct parts to the article's methodology: qualitative and quantitative procedures. Determining the study statement, defining variables, and establishing FTA and BN were components of the qualitative methodology. The qualitative analysis involved reviewing academic articles, accident reports, expert opinions, technical notes, and expert commentary to identify key processes contributing to the 'Blackout' event. In the quantitative part of the research, expert opinions were collected, and previous probabilities of the root causes were found. These opinions were then brought together by considering the weight coefficients of the experts. The defuzzification method converted probabilities into quantifiable values, and FTA calculated the highest probability of the event 'Blackout'. Later, the mapping technique was used to transition from BN to FTA. To calculate the posterior probabilities for the BN, the backward analysis method was used to modify the prior probabilities. Sensitivity analysis is used to determine which nodes have the most significant impact on target nodes.

FTA and BN were combined by converting the graphical structure of the FTA into a BN to represent causal relationships between system events. The FTA, consisting of events and logic gates (AND, OR), was transformed into BN nodes and arcs, reflecting dependencies between events. The expert-assigned probabilities were initially processed within the FTA structure before being transferred to the BN. This step ensured that the probabilities aligned with the FTA's event logic and structure, facilitating a smoother conversion into the BN's probabilistic framework. While this method simplifies the causal structure, it increases computational complexity due to the larger number of nodes. Probabilities were assigned to basic events in the BN, with conditional probabilities calculated for intermediate and final events. This process, supported by algorithms and tables, has been extensively studied.

3.1. Power management systems in ships

The conventional PMS monitors the total amount of power required by the ship's equipment and optimises the use of available resources (Herdzik, 2012). The system operates by autonomously controlling

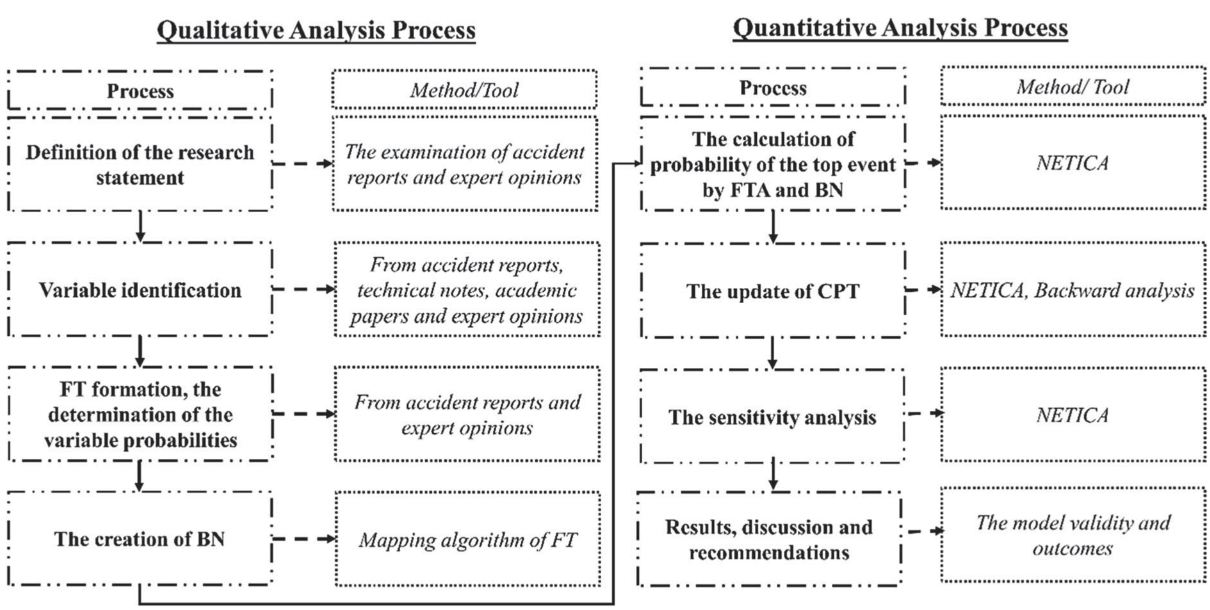

Figure 1. The structure of the methodology framework.

the load change of the generator sets, which are activated and deactivated based on the pre-set and the load. The total power capacity of the generator sets should be such that if they are all operating together and one generator set fails, the remaining generator sets must be able to sustain the load of the malfunctioning generator set (Evangelos & Agapios, 2013). For the rest of the generators in the circuit, it is crucial that there is no frequency fluctuation, deficiency, or excess, i.e. that the circuit breaker is not activated (Radan et al., 2008). During the design phase, optimising the equipment that ships will have, determining equal or unequal generators, and sharing the burden are crucial factors to consider (Xie et al., 2022).

The loss of all electrical power aboard the ship is referred to as a 'blackout' rather than an ordinary system failure (Grzeczka et al., 2017). With it, all the systems finally collapse. Certain systems fail due to the 'partial blackout' issue, which is not as serious as it sounds (Rødseth et al., 2006). Thus, it is an emergency of the second degree. Designers construct systems that monitor and alert on a variety of diagnostic symptoms to minimise the potential that a ship's offshore or onshore mission will be suspended for whatever reason (Islam et al., 2013).

Parallel and synchronous generator systems are the fundamental operating condition of marine power supplies. A safe and cost-effective electrical system is a prerequisite for navigation and an essential element of continuity (Jeong et al., 2018). Besides balancing the load on generator sets, separating active and reactive powers is also an important issue. The control interface continuously monitors and analyses data such as active/reactive power, voltage, current, frequency, and power factor (Jaleel et al., 2016). Since each ship is composed of large and small microsystems, ship electrical systems are also divided into low-voltage and high-voltage categories. Low-voltage three-phase 400 V/50Hz-60 Hz distribution networks are used to power standard industrial equipment that is resistant to the marine environment and typically feeds auxiliary machinery (Al-Falahi et al., 2018). Due to the higher power demands of the propulsion machinery, high-voltage distribution lines such as 3-11 kV are required (Herdzik, 2010). This increases the complexity of ships with electric propulsion systems and necessitates the maintenance of a continuous power supply. This makes the installation of systems with integrated and sophisticated decision-making mechanisms a requirement, as opposed to a basic power management system (Valkeejärvi, 2006).

As with any other system, power generation systems will eventually fail. Nonetheless, several technical procedures are required to mitigate the potential consequences of the malfunction (Yang et al., 2014). When designing a reliable and practical power system, regular and predictive maintenance practices should be considered first (Jimenez et al., 2020). Quantitative and qualitative risk assessment methodologies aimed at analysing potential failure scenarios and their underlying causes are the second. In a power system comprised of conventional internal combustion engines, the oil/water temperature and pressure, exhaust gas pressure, machine rotation speed (rpm), output voltage, and other parameters must not exceed the specified limit values (Jaleel et al., 2016). Otherwise, everyone can claim that a problem exists. Although every control parameter has its value, they also influence one another. In this regard, a risk assessment and expert advice are required. The failure of a system valve or filter, as well as the wear or collapse of mechanical structural components, are examples of these issues (Yang et al., 2014). In this study, the FTA into BN method is accustomed to analysing the components of the electrical power generation system, the effects of these parts on each other, and the defect occurrence.

As mentioned previously, the power management system's functions are described in greater detail below (Shen et al., 2011).

- Energy savings encompass decreases in specific fuel consumption, engine consumption of fuel, and total ship fuel consumption.
- Auxiliary generators automatically start, stop, or go into standby mode depending on the power needed. Limit available excess power as much as possible for safety purposes. Consistent comparison of overall load generated with load-dependent automatic start/stop thresholds. When available power becomes insufficient due to increased load or generator failure, the PMS will automatically switch to the next backup generator set in line. When the load drops to the point where other generators will not be overloaded, the backup generator will stop and disconnect.
- Automatic load sharing involves connecting a second generator to the control panel as the load increases. After synchronisation, the PMS allocates the generators' workload efficiently.
- Load shedding occurs when a sudden loss or increase in load on one generator causes other generators to overload. PMS instantly shuts down non-essential loads to protect essential systems.
- The generators are automatically synced to maintain the necessary speed, voltage, and phase due to automatic synchronisation and system restoration. The system adheres to a particular process for restarting and reconfiguring the power system following a power outage. This entails initiating and coordinating generator sets and activating loads in a particular order.
- The PMS includes a monitoring system for the load profile, an active and reactive load-sharing monitoring system to detect load-sharing faults, and graphical data to monitor fuel usage and engine efficiency. Some PMS monitoring systems have a feature that analyses past data to help in decision-making about operating and maintaining equipment and ship power system components.
- The PMS may oversee the transfer of load between the shaft and the auxiliary engine, as well as the transmission of power from the shore to the auxiliary engine in the cold ironing system.

The adoption of a safe management strategy is founded on real-cause statistics derived from the analysis of operational data (Oltedal, 2010) Thus, it is possible to determine where most of the effort should be focused to accomplish the greatest effect. In this way, undesirable behaviours in emergencies can be prevented (Antão & Guedes Soares, 2008). One of the difficulties encountered on ships is the absence of reporting (Kimera & Nangolo, 2020). Perfectly filled reports are another crucial aspect of creating a database of events and taking effective action that should be recognised. The primary causes of power failure on ships, as presented by (Hansen and Ådnanes, 2009) are as follows, in order of importance:

- Human mistake,
- Protection system,
- Failure/lack of maintenance,
- Projecting and commissioning,
- Lack of procedure,

is expressed as.

Due to the aforementioned causes, Fuel System Failures may occur, including leakage in the circuit transporting fuel to the cylinder, poor fuel quality, clogged filters, and carbon coating of the fuel injector; Mechanical Problems including wear/deformation in piston and crankshaft bearings, piston ring and piston wear, and cylinder liner cracks; Cooling System malfunctions, including thermocouple failure, leakage in cooling water and/or oil, and excessively high lubricating oil temperature; or Intake-Exhaust System malfunctions, such as the inability to accept intake air and exhaust gas, are a few of the issues encountered with conventional on-board electrical power generation systems (Başhan & Demirel, 2018). Faulty electrical and electronic circuits, as well as blown fuses, are among the most frequent causes of failure in modern systems (Akhter Hossain et al., 2013).

3.2. Definition of fuzzy-based approach

Fuzzy sets were developed by (Zadeh, 1965) as a means of addressing absences of precise data. To designate the membership of each element in the fuzzy set, a specific rank is assigned to that element. Although there may be instances of ambiguity regarding an element's membership, it is generally possible to forecast the affiliation of each element within a cluster in practical situations. Concern regarding membership degrees is unexplainable within fuzzy set theory (Dubois et al., 2005).

In situations involving the definition of an object's degree of membership in a set, fuzzy set theory is frequently applied. The level of complexity of systems encountered in many practical situations may deter specialists from precisely determining an object's degree of membership in the set. The inclusion of expert judgment uncertainty in fuzzy sets may result in data loss due to their membership function-only nature. Faulty numbers and membership functions constitute the foundation of fuzzy set theory. Fuzzy numbers, which are defined by a membership function that spans from 0 to 1, are employed to represent the uncertainties of experts. The function $\mu A(x)$ value indicates x's membership degree in set A (Kabir & Papadopoulos, 2018). The study utilised the membership function depicted in Eq. (1).

$$\mu_{A'}(x) = \begin{cases} 0, & x < a_1 \\ \dfrac{x-a_1}{a_2-a_1}, & a_1 \leq x \leq a_2 \\ 1, & a_2 \leq x \leq a_3 \\ \dfrac{x-a_4}{a_3-a_4}, & a_3 \leq x \leq a_4 \\ 0, & x < a_4 \end{cases} \quad (1)$$

3.3. Fault Tree Analysis definition

FTA is a common technique for examining mishaps in complex systems. Using system failure as a starting point, potential causes can be found and grouped into branches or tip nodes of the FT model. The nodes that cannot be further divided are known as intermediate events (IEs), whereas basic events (BEs) are the indivisible nodes. In the FT model, the specified accident scenario is represented by the TE. A tree diagram can be used to depict the cause-and-effect relationship, and different logic gates are utilised to represent various causative ties in accidents. The FTA will assess all contributing elements, including potential hazards, in addition to the fundamental causes of accidents (Uğurlu et al., 2015). Therefore, there is a strong base upon which the risk analysis depends.

Finding minimal cut sets (MCSs) and minimal path sets (MPSs) is done in the qualitative part of FTA using the Boolean algebra reduction technique. A system's danger level is proportional to the number of MCSs, which stand for accident modes. Alternatively, MPSs demonstrate how well the system keeps users safe. Quantitative FTA begins with calculating the failure probability of BEs, then moves on to TE for risk assessment. Comprehensive accident causation analysis and the identification of MCSs and MPSs are its primary uses. The quantitative step involves determining the most likely outcome and assigning probabilistic values to each of the basic components. The logic gates link all the events in FT; they are basically AND and OR gates (Hamza & Abdallah, 2015). Eq. (2) can be

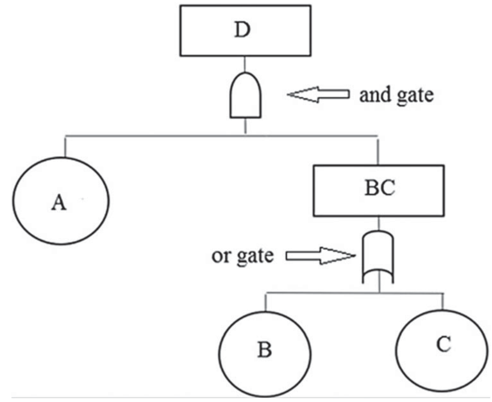

Figure 2. A basic FT network (Kang et al., 2019).

used to determine the AND gate's probability:

$$P = \prod_{i=1}^{n} P_i \quad (2)$$

The output of an OR gate is generated if any of the following conditions are met by Eq. (3):

$$P = 1 - \prod_{i=1}^{n} (1 - P_i) \quad (3)$$

An example of FT is shown in Figure 2. An intermediate event is the 'BC' event, while the top-level events in this diagram are the 'A', 'B', and 'C' events, which represent the basic operations. Since the 'D' TE can only take place if both the 'A' and 'BC' conditions are satisfied, the 'AND' gate is employed. Since the 'BC' intermediate event can only take place if either the 'B' or the 'C' BEs take place, the 'OR' gate is used (Kang et al., 2019).

3.3.1. Evaluation of the basic event's failure probability (FP) by experts

Using a fuzzy model, this study determines the probability of a BE occurring. Since there is a lack of operational data (Lavasani et al., 2015), when it comes to risk assessment in the marine industry, effective solutions often depend on the judgment of experts. A typical approach (Clemen & Winkler, 1999) involves selecting multiple experts with diverse experiences and combining their distinct opinions into a single conclusion. Regarding the computation of the variables' probabilities, (Lavasani et al., 2015) and (Shan et al., 2017) relied on contrasting expert judgments. Expert weight coefficients were established in consideration of the variations in qualifications and pertinent experiences among the experts. Subsequently, the probabilities of the variables were computed by the impact exerted by each expert. To derive probability values in numerical format, it is necessary to transform linguistic expressions into ambiguous numbers.

Because each person evaluates the possible outcomes from a unique perspective, it is essential to combine their assessments using professional weight coefficients. Aggregation techniques based on fuzzy set theory are used to integrate expert opinions when there are several of them (Hsu & Chen, 1996). The developed Similarity Agreement Method (SAM) formulations are among the most widely applied techniques for heterogeneous groups of experts.

The research employs the similarity aggregation method to integrate the linguistic viewpoints of an ensemble of specialists. Assume that each expert $E_k = (k = 1, 2, \ldots, M)$ utilises a specific collection of linguistic terms to articulate their opinions regarding an event to accomplish this goal. They are subsequently converted into nebulous numerals that are associated with them. The stages of SAM are described below.

3.3.2. Aggregation process

This procedure was designed to compile the expert opinions provided through the five phases listed below (Sokukcu & Sakar, 2022):

1. Calculating the degree of consensus between two experts $S(\widetilde{A}, \widetilde{B})$, Eq. (4).

$$S(\widetilde{A},\widetilde{B}) = 1 - \frac{1}{J}\sum_{i=1}^{J}|a_i - b_i| \tag{4}$$

J is a parameter of the membership function; a_i and b_i are also parameters of the membership function.

2. Using Eq. (5), it can be determined the average degree of accord (AA) among an expert's opinions $(AA(E_u))$.

$$AA(E_u) = \frac{1}{J-1}\sum_{v=1,u\neq v}^{J} S(\widetilde{R_u},\widetilde{R_v}) \tag{5}$$

3. Eq. (6) shows how to figure out the $(RA(E_u))$ degree $(RA(E_u))$ of all experts.

$$E_u(u = 1, 2, \ldots, j)\ as\ RA(E_u) = \frac{AA(E_u)}{\sum_{u=1}^{J} AA(E_u)} \tag{6}$$

4. Estimation of the coefficient degree of expert opinion $(CC(E_u))$, Eq. (7).

$$CC(E_u) = \beta W(E_u) + (1-\beta)RA(E_u) \tag{7}$$

where W is each expert's weight and β is the relaxation factor $(0 \leq \beta \leq 1)$.

5. Finally, Eq. (8) shows how to figure out the $\widetilde{R_{AG}}$ result, which is the sum of all the experts' views.

$$\widetilde{R_{AG}} = CC(E_1)\otimes\widetilde{R_2}\oplus CC(E_2)\otimes\widetilde{R_2}\oplus\ldots\oplus CC(E_m)\otimes\widetilde{R_m} \tag{8}$$

where $\widetilde{R_{AG}}$ is a fuzzy set, defuzzification algorithms are required to convert it into a fuzzy possibility score (FPS) is a single numerical value, which signifies the probability of the fundamental occurrences.

3.3.3. Calculating the FP for top and basic events

Finally, the FPS of all BEs must be converted to their FP or $P(X_i)$ values, which can range between 0 and 1. Eq. (9) represents the FP as defined by (Onisawa, 1988).

$$P(x) = \begin{cases} \dfrac{1}{10^k} & for\ FPS \neq 0 \\ 0 & for\ FPS = 0 \end{cases} \quad k = 2.301\left(\frac{1-FPS}{FPS}\right)^{\frac{1}{3}} \tag{9}$$

3.4. Definition of Bayesian Network

One probabilistic way to reasoning under uncertainty is BNs, which are also called Bayesian belief networks. Many areas, especially those dealing with dependability and safety, have successfully used it (Peng et al., 2010). Figure 3 shows that in a BN, the arcs go from the parent nodes (A, B) to the child node (C). A conditional probability table (CPT) is provided with each node in the BN to show the cause-and-effect relationship between them.

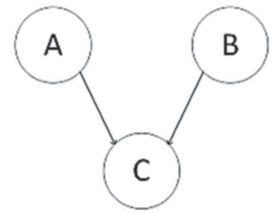

Figure 3. A typical BN (Baksh et al., 2018).

As shown in Eq. (10), BNs show the joint probability distribution $P(X)$ of variables for all BNs. This is based on conditional independence and the chain rule.

$$P(X) = \prod_{i=1}^{n} p\left(\frac{X_i}{parents(X_i)}\right) \tag{10}$$

Eq. (11) shows that BNs can use Bayes' theorem to update the posterior probability/posterior probability of any event in the context of new information as M evidence.

$$P(X/M) = \frac{P(X,M)}{P(M)} = \frac{P(X,M)}{\sum_x (X,M)} \tag{11}$$

3.5. Combining FTA with BN

Complex modern machines and installations can have devastating impacts on output when they break down; building BNs graphically is difficult and time-consuming (Jun & Kim, 2017). From the FT, it is possible to deduce the causal relationship between components. FT construction facilitates BN construction. Utilising the enormous quantity of available data, this stage permits the derivation of the graphical structure of the BN, which represents the causal relationship between the various events of the studied system.

To construct a BN from an FT, the graphical representation of the FT must be converted to a BN, as shown in Figure 4. The FT is composed fundamentally of events and logic gates (AND, OR). However, the BN is composed of two fundamental components: nodes, which symbolise events, and arcs, which symbolise the interdependencies among events and cause-and-effect connections.

A BN can be generated from an FT by converting the logical gates into network nodes; nevertheless, this process introduces complexity into the calculation due to the increased number of network nodes. The method employed in this work consists of transforming the various types of FT events into nodes in the associated BNs (Bobbio et al., 2001), with the logic gates not participating in the graphical structure of the networks.

The subsequent step in constructing a BN from an FT is the quantification of probabilities. Assigning a priori probabilities to node roots for the occurrence of fundamental events (primaries) of the FT constitutes this stage. Nevertheless, the estimation of associated probabilities for induced events (intermediate) and ultimate events (dreaded) is dependent on the computation of conditional probabilities (Medkour et al., 2017). Furthermore, considerable research has been devoted to the conversion of FTs to BNs. The algorithm for converting an FT to a BN is illustrated in Figure 5, while Table 2 contains the CPT of the child node.

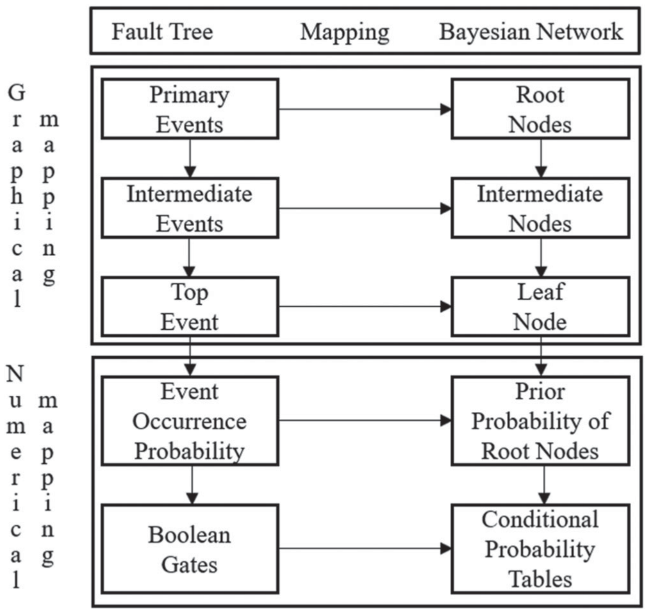

Figure 4. Mapping FT to BN (Atehnjia et al., 2018).

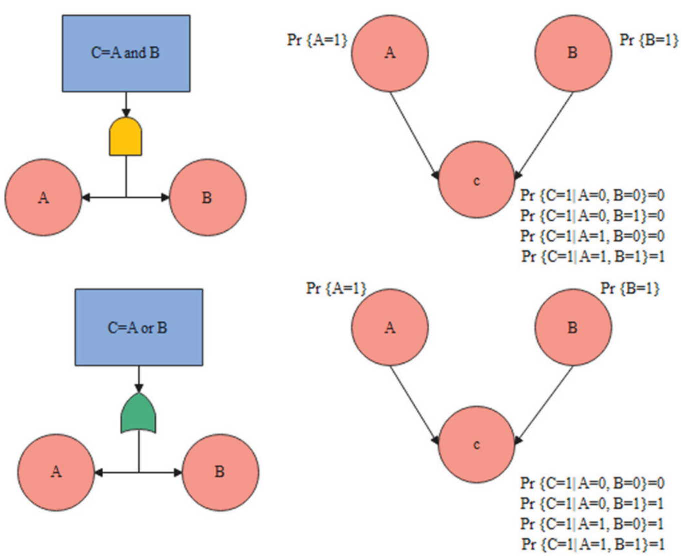

Figure 5. The BN and FT gate illustrations (Bobbio et al., 2001).

Table 2. Conditional probabilities for the node C (Sokukcu & Sakar, 2022).

CPT for C 'OR' gate				
B	0			1
A	0	1	0	1
0	1	0	0	0
1	0	1	1	1
CPT for C 'AND' gate				
B	0		1	
A	0	1	0	1
0	1	1	1	0
1	0	0	0	1

4. Failure modelling of the blackout case

4.1. Fault tree modelling

The literature on marine engine failures does not involve many studies, especially the research concerning the blackout risks has not been sufficient alone to determine the subfactors. Because of this, the causes of accidents are determined by consulting industry publications, accident records, and expert comments. The Marine Systematic Cause Analysis Technique, developed by Det Norske Veritas, is used to classify the variables that lead to collisions.

Marine specialists' opinions were considered when arranging the variables in the FT structure. Before the expert interviews, a thorough discussion of the FT technique's primary implementation approaches was held with maritime specialists The top event, the 'blackout', can be broken down into two primary categories: prime mover failures and synchronisation unit failures. The 'OR' logical gate, which has been applied in all links between the events, is used to aggregate sixteen IEs among the seventeen BEs that make up the root causes. Table 7 enumerates every potential malfunction that could result in a blackout. Figure 6 depicts the blackout failure FT.

4.2. Estimation of the probabilities of nodes' (basic events)

The nodes' failure probability was computed using experts' opinions because of unreliable data and uncertainty in the blackout risk assessment. These experts employ linguistic variables to determine the likelihood that fundamental events will fail (Shan et al., 2017). A multitude of linguistic variables may be applied to ascertain the verbal variables. Seven linguistic factors were employed in this study to calculate the probability of the root cause. Because humans can process between five and nine evaluations at a time, the human brain has a short-term storage capacity of seven ± two pieces, which is why the table with seven variables was chosen (Huang et al., 2001). This was achieved through the implementation of the numerical approximation method developed by (Chen and Hwang, 1992) for linguistic variables to be converted to imprecise numbers. Within this paradigm, each linguistic variable was specified as a trapezoidal fuzzy number in Table 3.

Of all the specialists who had participated in marine diesel generator operations on vessels of various types and tonnages as duty engineers, six were selected to render the verdict for the primary event. The influence of experts within homogeneous organisations is diminished in comparison to those within heterogeneous groups. The weights of experts may be computed by their credentials and professional backgrounds (Lavasani et al., 2015). Expert weighting scores, decision weights, and profiles are displayed in Tables 4 and 5, respectively.

The viewpoints of marine specialists were compiled utilising the SAM method and Eqs. (4) – (8). As illustrated in Table 6, the computation of expert opinion aggregation concerning the fundamental cause of 'Switchboard line failure' is performed. An identical combination computation was performed for each root cause. The relaxation factor, denoted as β, is established at 0.5 in the comprehensive computation of subjective BEs to ensure that all experts are regarded equally. Table 6 presents the results obtained by each BE after the aggregate computations.

Following the aggregation, the centre-of-area (COA) defuzzification method – described in Eq. (9) – was used to construct the defuzzied alternatives for each subjective node. Using Eq. (10), which converted the implications of the experts' linguistic assessments into failure probability values, the failure probability values for each node were determined. Specific results on defuzzification and probability values are shown in Table 7. It also provides expert verbal explanations for every one of the BEs, or underlyingcauses.

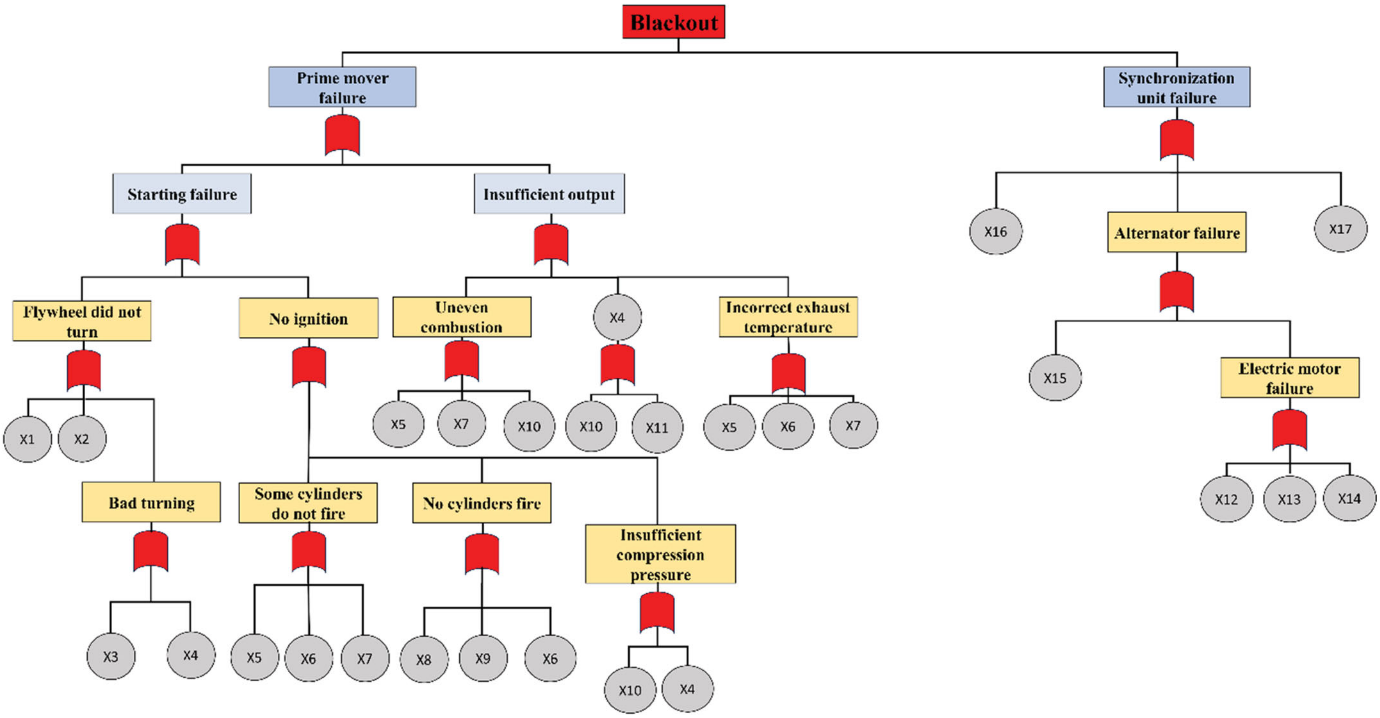

Figure 6. FT diagram.

Table 3. Description of fuzzy scale.

Linguistic terms	Fuzzy sets
Very low (VL)	(0.0, 0.0, 0.1, 0.2)
Low (L)	(0.1, 0.2, 0.2, 0.3)
Mildly low (ML)	(0.2, 0.3, 0.4, 0.5)
Medium (M)	(0.4, 0.5, 0.5, 0.6)
Mildly high (MH)	(0.5, 0.6, 0.7, 0.8)
High (H)	(0.7, 0.8, 0.8, 0.9)
Very high (VH)	(0.8, 0.9, 1.0, 1.0)

Table 4. Weight criteria values of different experts.

Constitution	Classification	Score
Professional position	Academician-Chief Engineer	5
	Technical Manager (Chief Engineer)	4
	Chief Engineer	3
	1st Engineer	2
	Watchkeeping Engineer	1
Maritime experience including sea and shore	$\geq$ 16	5
	11–15	4
	6–10	3
	3–5	2
	$\leq$ 2	1
Educational level	Ph.D.	5
	Master	4
	Bachelor	3
	Vocational High School	2
	School Level	1

5. Determining the blackout quantitative risk via Bayesian Network

This section used the BN to conduct a probabilistic relationship study between the intermediate nodes responsible for blackout incidents on ships and the root causes of these nodes. The network structure displays 'Starting failure' and 'Insufficient output' nodes under the variable 'Prime move failure'. The 'Synchronous unit failure' variable on ships includes nodes for 'Automatic voltage regulator failure', 'Switchboard line failure', and 'Alternator failure'. Factors influencing these main factors are linked to intermediary elements, originating from the root causes.

5.1. Information transfer from a fault tree to a Bayesian Network

The NETICA model consists of 32 nodes; the 40 connections between nodes symbolise the relationships between them. The conversion from the FT diagram to the BN architecture was accomplished using the mapping methodology outlined in the 'Materials and Methods' section. In the BN framework, events in the FT framework were converted into nodes and logical gates in the FT framework were used to find the conditional probabilities in the BN. Expert opinion and a logical 'OR' gate were used to create CPTs for the BN topology. The OR gate represents the deterministic relationship between the parent node and the child node.

The BN structure, as generated by the NETICA software, is illustrated in Figure 7. The BN was analysed with NETICA after the prior probabilities in Table 7 were applied, and the FTA computed the probability. FTA and BN are used to compute the same failure probability for 'Blackout' incidents due to the integration procedure that derives the conditional probabilities of BN from the FT.

5.2. Adjustment of ambiguous causal connections

FT's logical gate symbolises deterministic causal relationships. Table 8 displays the CPT for the node labelled 'No cylinders fire'. If any parent node is in the 'Yes' state, the condition 'No cylinders fire' will occur. The 'No cylinders fire' node is dependent on all parent nodes being in a 'No' state for it to also be in a 'No' state. When all parent nodes have a state of 'No' in Table 8, it is ascertained that the target node is non-existent. However, the status of the No Cylinders Fire node could still be 'Yes'.

Table 5. Profiles of experts and computed decision weights.

No of Expert	Title	Maritime exp. (years)	Educational level	Weighting factor	Weighting score
E1	Chief Engineer	12	Bachelor	$3+4+3=10$	$10/66=0.152$
E2	1st Engineer	7	Bachelor	$2+3+3=8$	$8/66=0.121$
E3	Chief Engineer	9	Master	$3+3+4=10$	$10/66=0.152$
E4	Tech. Man. (C/Eng.)	22	Bachelor	$4+5+3=12$	$12/66=0.182$
E5	Tech. Man. (C/Eng.)	19	Vocational High School	$4+5+2=11$	$11/66=0.167$
E6	Academician (C/Eng.)	27	Ph.D.	$5+5+5=15$	$15/66=0.227$

Table 6. Calculation of aggregation for the root node 'Switchboard line failure'.

S (E12)	1	S (E26)	0.85	AA (E1)	0.910	AA (E4)	0.850
S (E13)	1	S (E34)	0.85	AA (E2)	0.910	AA (E5)	0.790
S (E14)	0.85	S (E35)	0.85	AA (E3)	0.910	AA (E6)	0.850
S (E15)	0.85	S (E36)	0.85				
S (E16)	0.85	S (E45)	0.7	CC (E1)	0.163	CC (E4)	0.172
S (E23)	1	S (E46)	1	CC (E2)	0.148	CC (E5)	0.159
S (E24)	0.85	S (E56)	0.7	CC (E3)	0.163	CC (E6)	0.195
S (E25)	0.85						
				RA (E1)	0.174	RA (E4)	0.163
Weight of Expert 1		0.152		RA (E2)	0.174	RA (E5)	0.151
Weight of Expert 2		0.121		RA (E3)	0.174	RA (E6)	0.163
Weight of expert 3		0.152					
Weight of expert 4		0.182					
Weight of expert 5		0.167					
Weight of expert 6		0.227					
$\widetilde{a}R_{AG}$ Aggregation		0.5576		0.6576	0.7049	0.8049	
Defuzzification (COA) occurrence likelihood of solenoid fuse failure is 0.68126							

The occurrence of 'No cylinders fire' is uncertain when the conditions 'Cooling water temperature is low' and 'Poor fuel quality' are met in specific combinations. Thus, the conditional probability tables of certain nodes in the network topology were revised based on the research (Li et al., 2016). Table 9 displays the revised CPTs for 'No cylinders fire'. The revised data in CPT were acquired through expert opinions. The CPTs for the nodes 'Insufficient compression pressure', 'Insufficient output' and 'Uneven combustion' in the network topology have been revised similarly.

The blackout possibility stayed at 16.3% in the calculation, and the conditional probabilities were not changed. This is very close to what was found in the FTA. This is mostly due to the rigorous application of FT logic gates while constructing CPTs for nodes in BNs. The revised approach resulted in a risk assessment of 19.5% for a 'Blackout' occurrence, highlighting the potential riskiness of the actions and the rapid escalation of this risk percentage without proper precautions. Decreasing the likelihood of risk is contingent upon understanding the potential risks and implementing risk mitigation strategies.

5.3. Probability updating

After constructing the BN through the utilisation of FTA, the probability can be revised by incorporating evidence into the network. The input for revising probabilities using the backward inference method within the BN structure is the fundamental event probabilities. Through probability updating, the posterior probability of fundamental events is derived. Probability updating aids in determining the most likely important root causes that lead to evidence

Table 7. Probabilities of occurrence based on expert opinions and fuzzy set theory.

		Expert Judgments											
	Root node Title	1	2	3	4	5	6	Aggregated Fuzzy Numbers				FPs	FPr
X1	Insufficient Start Air	ML	L	L	VL	VL	VL	0.061	0.106	0.176	0.276	0.18586	0.00017
X2	Defective air starter	ML	L	ML	VL	VL	VL	0.077	0.122	0.208	0.308	0.18065	0.00016
X3	L/O Viscosity	L	MH	ML	MH	H	MH	0.430	0.530	0.599	0.699	0.56447	0.00775
X4	Mechanical damage	MH	MH	ML	MH	H	MH	0.490	0.590	0.674	0.774	0.63168	0.01196
X5	Faulty fuel pump	VH	MH	MH	H	ML	MH	0.536	0.636	0.718	0.803	0.67228	0.01546
X6	Central fuel control system fault	M	VL	L	ML	L	M	0.209	0.296	0.327	0.427	0.31575	0.00105
X7	Faulty injection	L	VL	L	ML	VL	ML	0.106	0.175	0.243	0.343	0.21793	0.00030
X8	Cooling water temperature is low	VL	L	VL	VL	VL	L	0.033	0.067	0.133	0.233	0.11965	0.00003
X9	Poor fuel quality	L	MH	M	ML	L	M	0.281	0.381	0.413	0.513	0.39709	0.00227
X10	Low air intake pressure	L	MH	ML	VL	VL	M	0.193	0.259	0.323	0.423	0.30092	0.00090
X11	Cooling water temperature is high	VH	H	VH	M	H	MH	0.644	0.744	0.796	0864	0.76037	0.02717
X12	Rotor open circuit	VH	H	VH	M	L	MH	0.555	0.655	0.708	0.776	0.67190	0.01542
X13	Temperature sensor failure	MH	H	H	M	H	M	0.559	0.659	0.675	0.775	0.66688	0.01494
X14	Rotor mechanical fault	VH	VH	VH	ML	MH	H	0.641	0.741	0.821	0.873	0.76699	0.02839
X15	Heat exchanger failure	ML	L	L	ML	H	M	0.280	0.380	0.415	0.515	0.39760	0.00228
X16	Automatic voltage regulator failure	VH	MH	H	VH	MH	H	0.672	0.772	0.836	0.902	0.79387	0.03404
X17	Switchboard line failure	MH	MH	MH	H	M	H	0.558	0.658	0.705	0.805	0.68126	0.01636

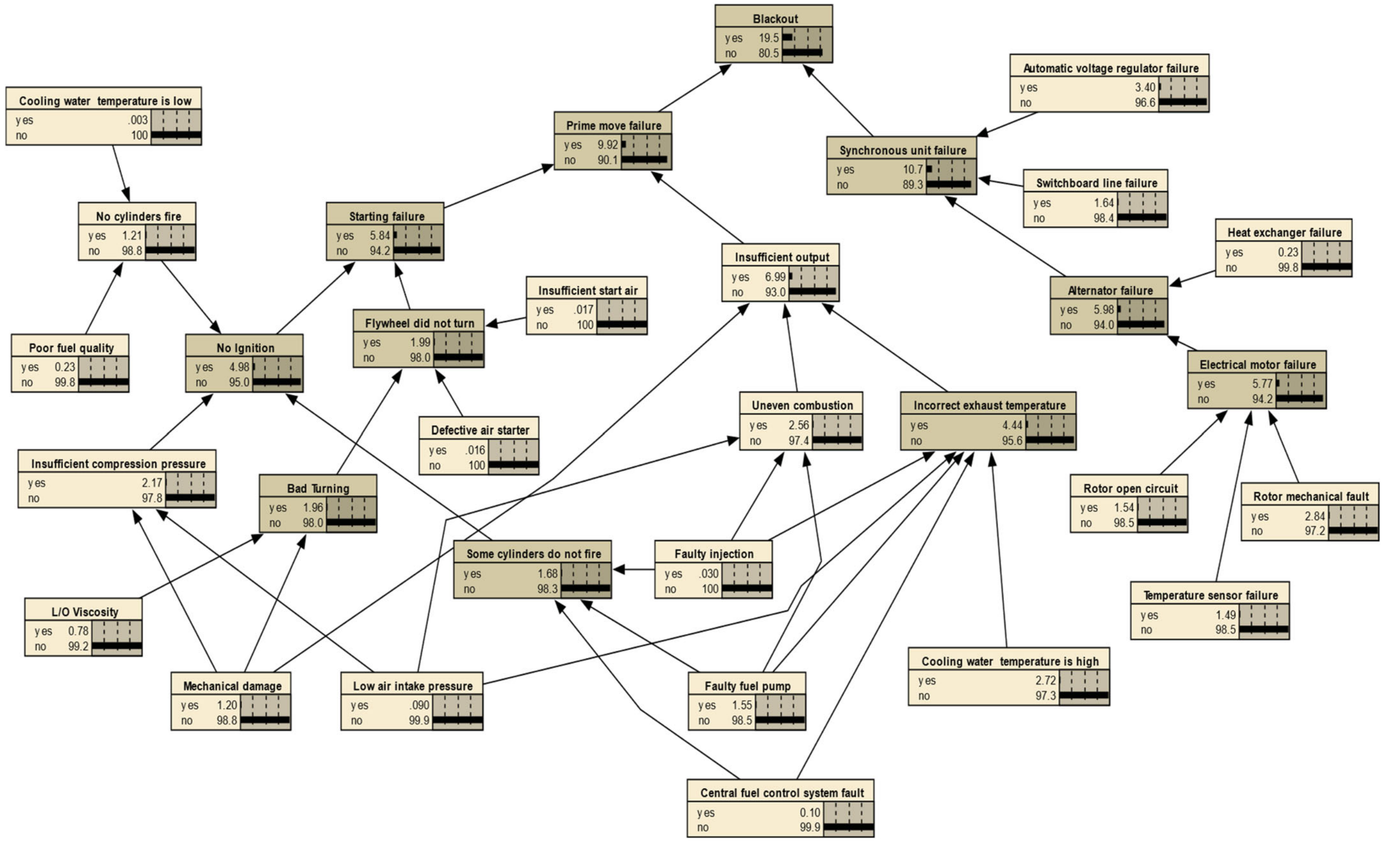

Figure 7. BN model mapping from FTA.

Table 8. CPT corresponding to OR gate 'No Cylinders Fire' node.

Cooling water temperature is low		Yes		No	
Poor fuel quality		Yes	No	Yes	No
No cylinders fire	Yes	1	1	1	0
	No	0	0	0	1

Table 9. Revised CPT for 'No Cylinders Fire' node.

Cooling water temperature is low		Yes		No	
Poor fuel quality		Yes	No	Yes	No
No cylinders fire	Yes	0.99	0.96	0.92	0.01
	No	0.01	0.04	0.08	0.99

(Bobbio et al., 2001). The primary evidence for updating probabilities is often knowledge of the TE. This study utilised the top event, Blackout, as evidence to establish the posterior probabilities P(Xi/blackout) of the BEs. Table 10 displays the prior and posterior probability values of critical situations in the event of a blackout.

Some basic variables experience a substantial increase when comparing the updated probabilities to the prior probabilities. Figure 8 displays the rates of change for BEs prior and posterior events. High rates of prior and posterior change indicate that these variables are very responsive to the top event. Factors with high likelihood changes are variables that significantly influence the incidence of blackouts.

Figure 8 illustrates that the basic factors contributing to ship blackout are X16 (Automatic voltage regulator failure), X14 (Rotor mechanical fault), and X11 (Cooling water temperature is high). X17, X12, X13, and X5 have very similar impacts on blackout. Greater focus should be given to these key elements to avoid a blackout that could endanger the ship during its navigation or operations.

Table 10. The fundamental incident and its prior and posterior probabilities.

Symbol	Description	Prior Probability	Posterior Probability
X1	Insufficient start air	0.00017	0.00087
X2	Defective air starter	0.00016	0.00082
X3	L/O Viscosity	0.00775	0.03968
X4	Mechanical damage	0.01196	0.06124
X5	Faulty fuel pump	0.01546	0.07916
X6	Central fuel control system fault	0.00105	0.00538
X7	Faulty injection	0.00030	0.00015
X8	Cooling water temperature is low	0.00003	0.00015
X9	Poor fuel quality	0.00227	0.01087
X10	Low air intake pressure	0.00090	0.00460
X11	Cooling water temperature is high	0.02717	0.12865
X12	Rotor open circuit	0.01542	0.07898
X13	Temperature sensor failure	0.01494	0.07650
X14	Rotor mechanical fault	0.02839	0.14537
X15	Heat exchanger failure	0.00228	0.01168
X16	Automatic voltage regulator failure	0.03404	0.17430
X17	Switchboard line failure	0.01636	0.08377

The numerical results from FTA-BN analysis, especially the probability updates, offer valuable guidance for practical, real-time applications in maritime operations. By identifying critical failure events, such as X16, X14, and X11 these findings can directly inform preventive maintenance strategies, optimise resource allocation, and enhance ship design. The prominence of electrical system failures over mechanical issues, as reflected in the high probabilities of X16 and X14, underscores the need to prioritise the maintenance of electrical components, particularly in critical systems like generators. Additionally, the high likelihood of cooling water temperature issues

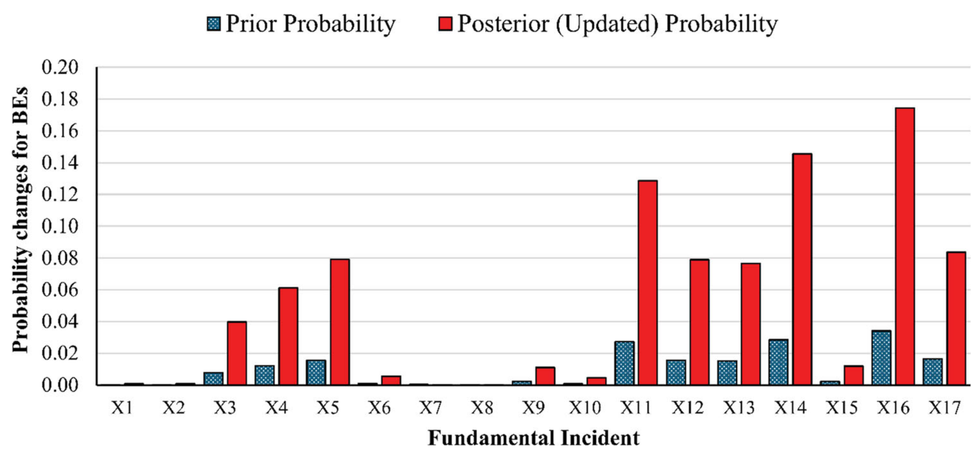

Figure 8. Probability changes of BE.

(X11) highlights the importance of maintaining the cooling systems of generators, especially during operations in hot climates or while docked in port.

These insights enable maritime operators to focus on key areas for system checks, ensure that operational protocols are adjusted based on real-world risks, and prepare crews more effectively for emergencies. This proactive approach to maintenance and operational planning can significantly reduce the risk of blackouts, improving overall reliability. Moreover, the findings can inform and refine maritime safety protocols and regulatory standards, shifting the focus toward preventive measures. This not only enhances operational safety but also ensures more efficient and reliable maritime operations in the long term.

5.4. Sensitivity analysis

To evaluate the model, sensitivity analysis was performed. The utilisation of the sensitivity analysis method aids in identifying the variables that have the greatest impact on the achievement of the target node. By implementing measures to decrease specific variables, the likelihood of the target node will correspondingly diminish.

The BN topology shows that the causes of outages are categorised under the nodes 'Prime move failure' and 'Synchronous unit failure'. Two nodes were selected as target nodes for the study. NETICA software's sensitivity analysis tool was used to understand how important the factors affecting these nodes are in terms of their risks. The NETICA tool uses the 'sensitivity to findings' feature to measure the relationship between each node in the network structure and the target node through 'mutual information'. A high mutual information value indicates the most significant impact on the target node (Marcot, 2012). When the 'Prime move failure' variable is chosen in NETICA, the impacts of other nodes on that node are displayed in descending order. Table 11 displays the outcomes of the sensitivity analysis conducted using the 'substandard act' selection.

The 'Alternator failure' node has the node with the greatest mutual information per node related to the 'Synchronous unit failure' target node in Table 12, followed by its child node, 'Electrical motor failure'. Additionally, 'Automatic voltage regulator', 'Rotor mechanical fault' and 'Switchboard line failure' are three more significant nodes within the category of 'Synchronous unit failure'.

Table 11. Sensitivity analysis for 'Prime move failure' node.

Nodes	Mutual Information	Percentage
Prime move failure	0.46647	100
Insufficient output	0.27853	59.7
Starting failure	0.22408	48
No Ignition	0.18632	39.9
Incorrect exhaust temper	0.14136	30.3
Uneven combustion	0.08252	17.7
Cooling water temperature is high	0.07635	16.4
Insufficient compression	0.07584	16.3
The flywheel did not turn	0.06929	14.9
Bad Turning	0.06812	14.6
Some cylinders do not fi	0.05794	12.4
Faulty fuel pump	0.05320	11.4
No cylinders fire	0.04132	8.86
Mechanical damage	0.04085	8.76
L/O Viscosity	0.02624	5.63
Poor fuel quality	0.00621	1.33
Central fuel control sys	0.00351	0.752
Low air intake pressure	0.00299	0.641
Faulty injection	0.00100	0.215
Insufficient start air	0.00057	0.122
Defective air starter	0.00053	0.114
Cooling water temperature is low	0.00009	0.0192

Table 12. Sensitivity analysis result of 'Synchronous unit failure' node.

Nodes	Mutual Information	Percentage
Synchronous unit failure	0.48980	100
Alternator failure	0.22116	45.2
Electrical motor failure	0.21193	43.3
Automatic voltage regulator	0.11789	24.1
Rotor mechanical fault	0.09709	19.8
Switchboard line failure	0.05454	11.1
Rotor open circuit	0.05131	10.5
Temperature sensor failure	0.04966	10.1
Heat exchanger failure	0.00739	1.51

5.5. Model validation

Validation is a critical phase in the BN modelling process as it provides a reliable level of confidence in the model's outputs (Jones et al., 2010). Modest adjustments to the parameters of a realistic network should not cause inconsistencies in the impacted nodes, according to Cai et al. (2013). The research employed the three-axiom model that was formulated by (Jones et al., 2010).

(1) Every parentnode's initial probability should be able to be detected with just a small modification, and this should lead to a proportional change in the child nodes' posterior probabilities.
(2) The probabilities of the child nodes should be systematically impacted by changes in the starting probability of each parent node.

Table 13. Verification of axiom I and II.

	Parent node		Child node	
	Poor fuel quality		No cylinders fire	
0.20 increase	Yes	0.43	Yes	1.39
0.10 increase		0.33		1.30
Prior Probability		0.23		1.21
0.10 decrease		0.13		1.12
0.20 decrease		0.03		1.03

(3) A single parent node shouldn't have a greater impact on child nodes with multiple parent nodes than the total effect of all parent nodes combined.

Axioms I and II were validated, as seen in Table 13. The node 'Poor fuel quality' is the superior node to 'No cylinders fire'. Per axiom I, a 0.10 increase in the prior probability of 'Poor fuel quality' results in a 0.09 rise in 'Poor fuel quality'. A 0.10 increase in the initial probability of the parent node results in a 0.09 increase in the initial probability of the child node, as stated in axiom II. The axioms are consistently observed as alterations in the parent node impact the posterior probability of the child node directly.

'Cooling water temperature is low' and 'Poor fuel quality' are the parent nodes of the child node 'No cylinders fire' in axiom III. This verification evaluated the impact that the parent nodes had on their child. When the probability of 'Poor fuel quality' is 100%, the possibility of 'No cylinders fire' increases to 92%. If the probability of 'Cooling water temperature is low' is 100%, then the likelihood of 'No cylinders fire' increases to 96%. Table 14 demonstrates that with 99% certainty, increasing the probabilities of both parent nodes simultaneously will increase the predicted probability for 'No cylinders fire' in comparison to modifying the probabilities of the two parent nodes separately. When the identical axiom is applied to multiple nodes, the results are identical to those in the preceding scenario.

5.6. Propagation analysis

A benefit of BNs is that modifications to evidence in nodes influence the network. This is referred to as 'propagation analysis' by (Fenton and Neil, 2012). The functionality was shown using the accident reports of the 'Clonlee' container vessel and the 'Bulk India' bulk carrier ship as case studies.

The main factors that led to the Clonlee accident were the malfunctions of the switchboard line and the automatic voltage regulator. When the variables responsible for the grounding accident at Clonlee are marked as 'Yes' in the BN structure, the likelihood of a blackout incidence in the network is shown to reach 100%, as illustrated in Figure 9.

The other case in this study was the Bulk India ship, where the main reason for the blackout incident was identified as 'Cooling

Table 14. Verification of Axiom III.

	Prior Probability		Individual effect of Poor fuel quality		Individual effect of Cooling water temperature is low		Poor fuel quality and Mechanical damage (combined effect)	
No cylinders fire	Yes	No	Yes	No	Yes	No	Yes	No
100% positive	1.21	98.8	92	8	96	3.99	99	1
100% negative			1.0	99	1.20	98.9	0.99	99.1

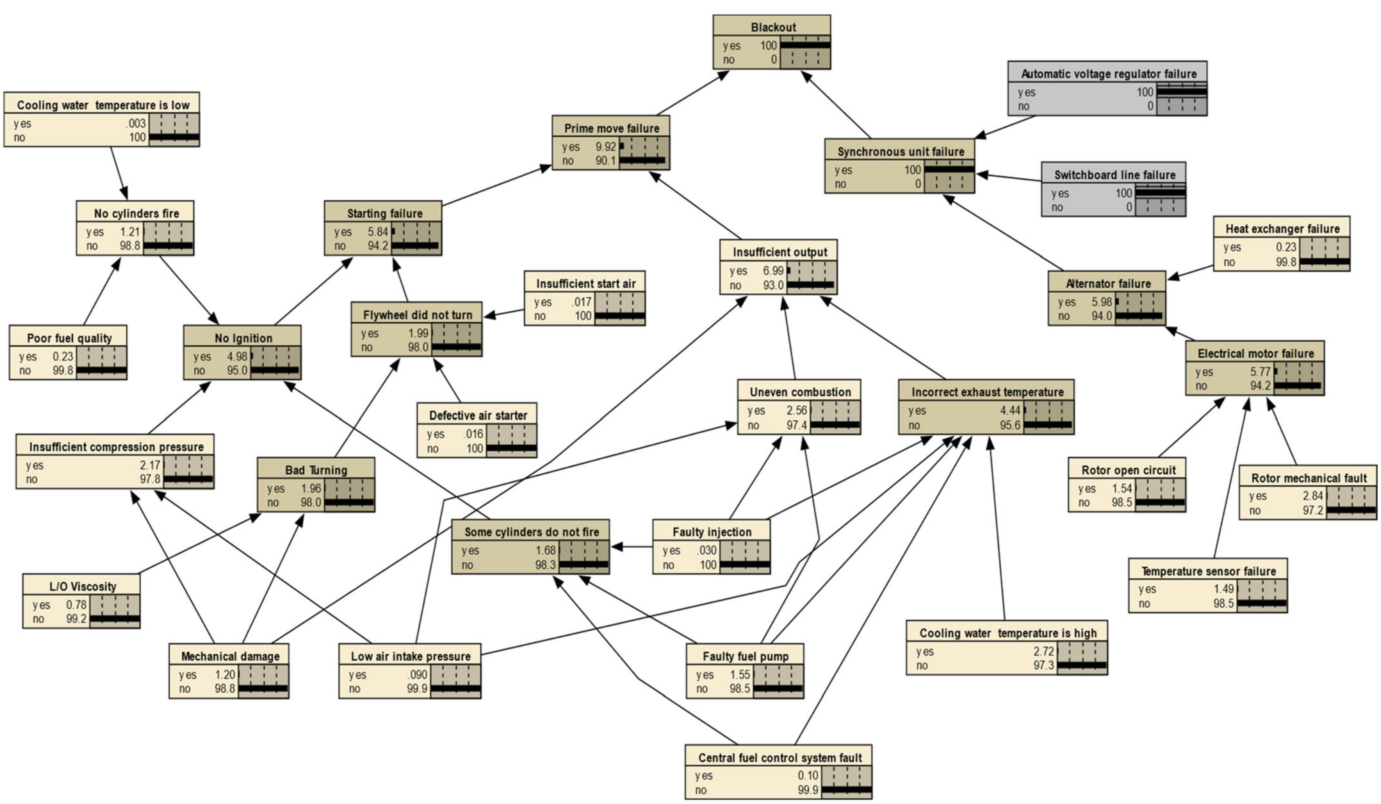

Figure 9. The BN model for the Clonlee vessel.

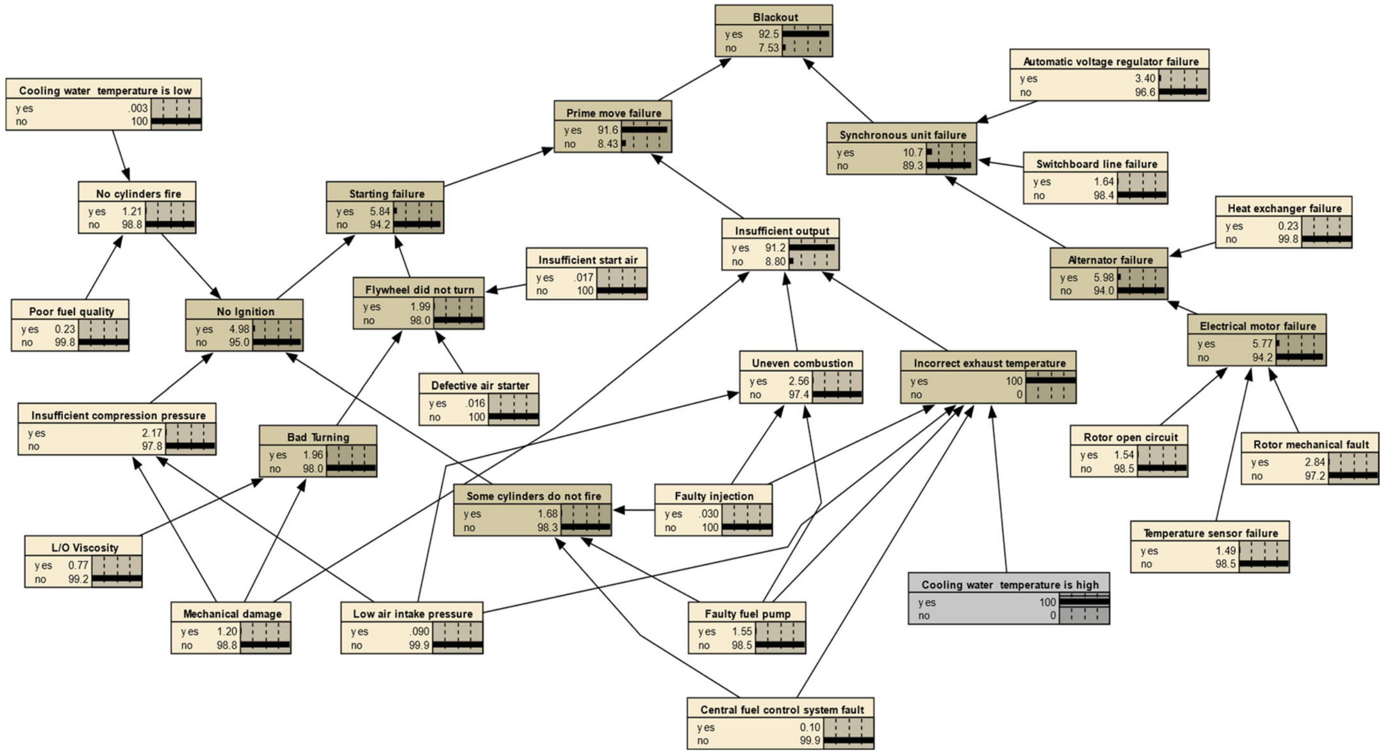

Figure 10. The BN model for the Bulk India ship.

water temperature is high'. When the variable is inputted as 'Yes' in the BN structure, the likelihood of blackout increases to 92.5%, indicating that the accident is certain, as depicted in Figure 10.

6. Conclusion

The study highlights the significance of blackouts in ship operations and emphasises their potential to result in power loss at sea and related hazardous scenarios. The significance of thoroughly addressing and comprehending this issue is emphasised. Presented is a systematic strategy utilising Bayesian risk analysis to comprehend the main factors that contribute to blackout incidents. This method uses numerical expressions to quantify uncertainty levels and interactions among different risk variables.

The onboard energy generation system has a 19.5% probability of encountering a 'blackout' due to its nature. If such a system is on the ship, it indicates that you are dealing with a system that is prone to malfunctioning. Nevertheless, this percentage does not imply that around 20 out of every 100 ships in operation will encounter a 'blackout' occurrence. This potential is minimised by the energy production system's monitoring system in the ship's engine room and bridge control area, as well as the constant physical control of the system by operators. Ships can maintain operational reliability by averting blackouts through immediate interventions. The accident was considerably prevented under real-life circumstances due to the presence of crew working in shifts aboard the ship and the implementation of regular monitoring and maintenance procedures.

The FTA-BN approach considers the complex nature of blackout events and the diverse factors that can influence their probability. FTA enhances model reliability by methodically identifying potential causes that may cause a blackout. This structured approach has led to a comprehensive understanding of the causal linkages among various risk variables. The nodes 'Automatic voltage regulator failure', 'Rotor mechanical fault', and 'Cooling water temperature is high' are the top three causes of blackout when assessed based on prior and posterior probabilities. Following these, 'Switchboard line failure', 'Faulty fuel pump', 'Rotor open circuit', and 'Temperature sensor failure' are identified as nodes that lead to occurrences at very similar amplitudes. The significance of components involved in an incident indicates that they should be prioritised based on their potential during maintenance, repair, and operation. This aids operators and ship owners in enhancing the reliability of their ships. This aligns precisely with the industry's expectations for safe and reliable transportation.

Conducting sensitivity analysis for risk prioritisation helps pinpoint important variables that strongly influence the probability of a blackout. This process aids in ranking risk mitigation strategies, enabling decision-makers to efficiently allocate resources to tackle the most crucial risk factors. The study offers a comprehensive structure for decision-makers to make well-informed decisions and effectively handle risks. Enhancing safety protocols, highlighting the significance of blackout events, and implementing a systematic strategy can enhance safety and reliability in maritime transportation.

The limitations of the study include the following:

- The initial priorities were based on expert opinions and accident data, which may introduce bias or subjectivity.
- Human error was not examined separately in the network, potentially inflating the failure probability. In other words, expert judgments inherently included human error-related risks when determining the initial priorities.
- Regional factors, such as sea water temperature or salinity, which can affect generator cooling, were not incorporated into the analysis.

The findings presented here may benefit researchers exploring related topics, as well as engineers involved in the design, implementation, and operational phases of ship electrification systems. Future studies could focus more extensively on human errors contributing to blackout-related incidents. Moreover, supplementary risk assessments could examine other critical events, including the impacts of blackouts and their connections to system failures.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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References

Akhter Hossain M, Kelly SJ, Ahmed MF, Roa MJ. 2013. Cause and effect of catastrophic failure of shipboard and offshore vessel/platform power sources. Industry Applications Society 60th Annual Petroleum and Chemical Industry Conference. p. 1–8.

Al-Falahi MDA, Tarasiuk T, Jayasinghe SG, Jin Z, Enshaei H, Guerrero JM. 2018. Ac ship microgrids: control and power management optimization. Energies. *11*(6):1458. doi:10.3390/en11061458.

Antão P, Guedes Soares C. 2008. Causal factors in accidents of high-speed craft and conventional ocean-going vessels. Reliab Eng Syst Saf. *93*(9):1292–1304. doi:10.1016/j.ress.2007.07.010.

Atehnjia DN, Zaili Y, Wang J. 2018. Application of fault tree – Bayesian Network for graving dock gate failure analysis. Int J Adv Sci Res Eng. *4*(1):27–37. doi:10.7324/ijasre.2018.32576.

Aydin M, Camliyurt G, Akyuz E, Arslan O. 2021. Analyzing human error contributions to maritime environmental risk in oil/chemical tanker ship. Hum Ecol Risk Assess: Int J. *27*(7):1838–1859. doi:10.1080/10807039.2021.1910011.

Baksh AA, Abbassi R, Garaniya V, Khan F. 2018. Marine transportation risk assessment using Bayesian Network: application to Arctic waters. Ocean Eng. *159*(April):422–436. doi:10.1016/j.oceaneng.2018.04.024.

Başhan V, Demirel H. 2018. Evaluation of critical operational faults of marine diesel generator engines by using DEMATEL method. J ETA Mar Sci. *6*(2):119–128. doi:10.5505/jems.2018.24865.

Başhan V, Demirel H, Gul M. 2020. A novel risk evaluation approach for frequently encountered risks in ship engine rooms. Brodogradnja. *71*(2):31–54. doi:10.21278/BROD71203.

Bayraktar M, Yuksel O. 2023. A scenario-based assessment of the energy efficiency existing ship index (EEXI) and carbon intensity indicator (CII) regulations. Ocean Eng. *278*:114295. doi:10.1016/j.oceaneng.2023.114295.

Bobbio A, Portinale L, Minichino M, Ciancamerla E. 2001. Improving the analysis of dependable systems by mapping Fault Trees into Bayesian Networks. Reliab Eng Syst Saf. *71*:249–260. doi:10.1016/S0951-8320(00)00077-6.

Bolbot V, Theotokatos G, Boulougouris E, Psarros G, Hamann R. 2021a. A combinatorial safety analysis of cruise ship diesel–electric propulsion plant blackout. Safety. *7*(2):38. doi:10.3390/safety7020038.

Bolbot V, Theotokatos G, Hamann R, Psarros G, Boulougouris E. 2021b. Dynamic blackout probability monitoring system for cruise ship power plants. Energies. *14*(20):6598. doi:10.3390/en14206598.

Bolbot V, Trivyza N, Theotokatos G, Boulougouris E, Rentizelas A, Vassalos D. 2019. Cruise ship optimal power plants design identification and quantitative safety assessment. Environ Pollut. 55–63.

Bolbot V, Trivyza NL, Theotokatos G, Boulougouris E, Rentizelas A, Vassalos D. 2020. Cruise ships power plant optimisation and comparative analysis. Energy. *196*. doi:10.1016/j.energy.2020.117061.

Bolbot V, Xiang L, Brunou P, Kiviharju M, Ding Y, Banda OV. 2024. Cybersecurity risk assessment of a marine dual-fuel engine on inland waterways ship. Proc Inst Mech Eng Part M: J Eng Marit Environ. doi:10.1177/14750902241265173/ASSET/IMAGES/LARGE/10.1177_14750902241265173-FIG6.JPEG.

Breedlove TR, Nguyen PQ, Hensley M. 2023. Energy optimization for dynamically positioned vessels through closed bus operations. Proceedings of the Annual Offshore Technology Conference, 2023-*May*.

Cai B, Liu Y, Zhang Y, Fan Q, Yu S. 2013. Dynamic Bayesian networks based performance evaluation of subsea blowout preventers in presence of imperfect repair. Expert Syst Appl. 40(18):7544–7554.

Ceylan BO. 2023. Shipboard compressor system risk analysis by using rule-based fuzzy FMEA for preventing major marine accidents. Ocean Eng. *272*:113888. doi:10.1016/j.oceaneng.2023.113888.

Ceylan BO. 2024. Marine diesel engine turbocharger fouling phenomenon risk assessment application by using fuzzy FMEA method. Proc Inst Mech Eng Part M: J Eng Marit Environ. *238*(3):514–530. doi:10.1177/14750902231208848.

Ceylan BO, Celik MS. 2024. Operational risk assessment of marine boiler plant for on-board systems safety. Appl Ocean Res. *144*:103914. doi:10.1016/j.apor.2024.103914.

Ceylan BO, Karatuğ Ç, Ejder E, Uyanık T, Arslanoğlu Y. 2023. Risk assessment of sea chest fouling on the ship machinery systems by using both FMEA method and ERS process. Aust J Marit Ocean Aff. *15*(4):414–433. doi:10.1080/18366503.2022.2104494.

Chen S-J, Hwang C-L. 1992. Lecture notes in economics and mathematical systems. Fuzzy Multiple Attribute Decis Making: Methods Appl. 289–486. doi:10.1007/978-3-642-46768-4_5.

Clemen RT, Winkler RL. 1999. 'Combining probability distributions from experts in risk analysis'. Risk Anal. *20*(2):155–156. doi:10.1111/0272-4332.202015.

Dubois D, Gottwald S, Hajek P, Kacprzyk J, Prade H. 2005. Terminological difficulties in fuzzy set theory – the case of "Intuitionistic Fuzzy Sets". Fuzzy Sets Syst. *156*(3):485–491. doi:10.1016/j.fss.2005.06.001.

Evangelos M, Agapios P. 2013. Availability assessment of diesel generator system of a ship: a case study. Int J Performability Eng. *9*(5):561–567.

Fenton N, Neil M. 2012. Risk assessment and decision analysis with Bayesian Networks. In: Fenton N, Neil M, editors. Risk assessment and decision analysis with Bayesian Networks. Boca Raton, FL: CRC Press; p. 177–179.

Geertsma RD, Negenborn RR, Visser K, Hopman JJ. 2017. Design and control of hybrid power and propulsion systems for smart ships: a review of developments. Appl Energy. *194*:30–54. doi:10.1016/j.apenergy.2017.02.060.

Göksu B, Yüksel O, Şakar C. 2023. Risk assessment of the ship steering gear failures using fuzzy-Bayesian Networks. Ocean Eng. *274*:114064. doi:10.1016/j.oceaneng.2023.114064.

Grzeczka G, Piłat T, Polak A. 2017. The parameters of excitation current of ship synchronous generator as the diagnostic symptoms of the propelling IC engine. J Marine Eng Technol. *16*(4):344–348. doi:10.1080/20464177.2017.1381063.

Gucma S. 2019. Conditions of safe ship operation in seaports – optimization of port waterway parameters. Pol Marit Res. *26*(3):22–29. doi:10.2478/pomr-2019-0042.

Gürgen S, Yazır D, Konur O. 2023. Fuzzy Fault Tree Analysis for loss of ship steering ability. Ocean Eng. *279*:114419. doi:10.1016/j.oceaneng.2023.114419.

Hamza Z, Abdallah T. 2015. Mapping Fault Tree into Bayesian Network in safety analysis of process system. 2015 4th International Conference on Electrical Engineering, ICEE 2015. p. 1–5.

Hansen JF, Ådnanes AK. 2009. Blackout prevention & recovery. Dynamic Positioning Conference.

Herdzik J. 2010. Problems of propulsion arrangement choice of multi-mode ship. J KONES Powertrain Transport. *17*(2):129–135.

Herdzik J. 2012. Challenges of ship propulsion systems during DP operations. J KONES Powertrain Transport. 19(2).

Hsu HM, Chen CT. 1996. Aggregation of fuzzy opinions under group decision making. Fuzzy Sets Syst. *79*(3):279–285. doi:10.1016/0165-0114(95)00185-9.

Huang D, Chen T, Wang MJJ. 2001. A fuzzy set approach for event tree analysis. Fuzzy Sets Syst. *118*(1):153–165. doi:10.1016/S0165-0114(98)00288-7.

Hulme PE. 2021. Unwelcome exchange: international trade as a direct and indirect driver of biological invasions worldwide. One Earth. *4*(5):666–679. doi:10.1016/j.oneear.2021.04.015.

Ibrion M, Paltrinieri N, Nejad AR. 2021. Learning from failures in cruise ship industry: the blackout of Viking Sky in Hustadvika, Norway. Eng Fail Anal. *125*. doi:10.1016/j.engfailanal.2021.105355.

IMO. 2023. *Introduction to IMO*. https://www.imo.org/en/About/Pages/Default.aspx.

Islam M, Garg K, Patel P, Shah S. 2013. Protection system design ship and offshore vessels - An overview. Industry Applications Society 60th Annual Petroleum and Chemical Industry Conference. p. 1–7.

Ivanova G. 2021. Analysis of the specifics in calculating the index of existing marine energy efficiency EEXI in force since 2023. 2021 13th Electrical Engineering Faculty Conference, BulEF 2021. p. 1–4.

Jaleel AHA, Devassy G, Vincent MC, Rose N, Raphel R, Sreechithra CM. 2016. Power management system in vessel. Proceedings of 2016 Online International Conference on Green Engineering and Technologies, IC-GET 2016.

Jayasinghe SDG, Nayanasiri DR, Tashakori A, Alahakoon S, Fernando N, Vilathgamuwa DM. 2018. MPC and energy storage based frequency regulation strategy for hybrid electric ships. IEEE International Symposium on Industrial Electronics, 2018-June. p. 929–936.

Jeong B, Oguz E, Wang H, Zhou P. 2018. Multi-criteria decision-making for marine propulsion: hybrid, diesel electric and diesel mechanical systems from cost-environment-risk perspectives. Appl Energy. *230*(April):1065–1081. doi:10.1016/j.apenergy.2018.09.074.

Jimenez VJ, Bouhmala N, Gausdal AH. 2020. Developing a predictive maintenance model for vessel machinery. J Ocean Eng Sci. *5*(4):358–386. doi:10.1016/j.joes.2020.03.003.

Jones B, Jenkinson I, Yang Z, Wang J. 2010. The use of Bayesian Network modelling for maintenance planning in a manufacturing industry. Reliab Eng Syst Saf. *95*(3):267–277. doi:10.1016/j.ress.2009.10.007.

Jun HB, Kim D. 2017. A Bayesian Network-based approach for fault analysis. Expert Syst Appl. *81*:332–348. doi:10.1016/j.eswa.2017.03.056.

Kabir S, Papadopoulos Y. 2018. A review of applications of fuzzy sets to safety and reliability engineering. Int J Approx Reason. *100*:29–55. doi:10.1016/j.ijar.2018.05.005.

Kacmaz E, Kara G, Yıldız M. 2016. Evaluation of marine pollution caused by tanker ships and preventing under focus of the international regulations. The Second Global Conference on Innovation in Marine Technology and the Future of Maritime Transportation, October. p. 318–325.

Kang J, Sun L, Guedes Soares C. 2019. Fault Tree Analysis of floating offshore wind turbines. Renewable Energy. *133*:1455–1467. doi:10.1016/j.renene.2018.08.097.

Karatuğ Ç, Ceylan BO, Arslanoğlu Y. 2024. A risk assessment of scrubber use for marine transport by rule-based fuzzy FMEA. Proc Inst Mech Eng Part M: J Eng Marit Environ. *238*(1):114–125. doi:10.1177/14750902231166030.

Kimera D, Nangolo FN. 2020. Maintenance practices and parameters for marine mechanical systems: a review. J Qual Maint Eng. *26*(3):459–488. doi:10.1108/JQME-03-2019-0026.

Kozak M, Zawirski K. 2011. A concept of induction squirrel cage generator application in ship electric network. 2011 IEEE International Symposium on Industrial Electronics. p. 483–488.

Lavasani SM, Ramzali N, Sabzalipour F, Akyuz E. 2015. Utilisation of Fuzzy Fault Tree Analysis (FFTA) for quantified risk analysis of leakage in abandoned oil and natural-gas wells. Ocean Eng. *108*:729–737. doi:10.1016/j.oceaneng.2015.09.008.

Li C, Zhang H, Zhang Y, Kang J. 2022. Fire risk assessment of a ship's power system under the conditions of an engine room fire. J Mar Sci Eng. 10(11):1658. doi:10.3390/jmse10111658.

Li X, Chen G, Zhu H. 2016. Quantitative risk analysis on leakage failure of submarine oil and gas pipelines using Bayesian Network. Process Saf Environ Prot. *103*:163–173. doi:10.1016/j.psep.2016.06.006.

Liu J, Chen H, Li D, Wang Z, Wang J. 2024. Quantitative risk assessment of a spill fire caused by the continuously leaked fuel in a sealed ship engine room. Ocean Eng. *303*:117664. doi:10.1016/j.oceaneng.2024.117664.

Ma L, Ma X, Chen L. 2024. Risk evolution from causes to consequences of engine room fires on ships by mapping bow-tie into fuzzy Bayesian network. J Mar Eng Technol. 423–438. doi:10.1080/20464177.2024.2353955.

Marcot BG. 2012. Metrics for evaluating performance and uncertainty of Bayesian network models. Ecol Modell. *230*:50–62. doi:10.1016/j.ecolmodel.2012.01.013.

Medkour M, Khochmane L, Bouzaouit A, Bennis O. 2017. Transformation of fault trees into Bayesian networks methodology for fault diagnosis. Mechanics. *23*(6):891–899. doi:10.5755/j01.mech.23.6.17281.

Michalopoulos P, Tsekouras GJ, Kanellos FD, Prousalidis JM. 2022. Optimal selection of the diesel generators supplying a ship electric power system. Appl Sci. *12*(20). doi:10.3390/app122010463.

Montewka J, Ehlers S, Goerlandt F, Hinz T, Tabri K, Kujala P. 2014. A framework for risk assessment for maritime transportation systems – a case study for open sea collisions involving RoPax vessels. Reliab Eng Syst Saf. *124*:142–157. doi:10.1016/j.ress.2013.11.014.

Oltedal H. 2010. The use of safety management systems within the Norwegian tanker industry – do they really improve safety?. Reliab Risk Safety: Theory Appl. *1*:2355–2362. doi:10.1201/9780203859759.ch324.

Onisawa T. 1988. An approach to human reliability in man-machine systems using error possibility. Fuzzy Sets Syst. *27*(2):87–103. doi:10.1016/0165-0114(88)90140-6.

Pallis AA, Vaggelas GK. 2019. Cruise shipping and green ports: a strategic challenge. In: Bergqvist, R, Monios, J, editors. *Green ports inland and seaside sustainable transportation strategies*. Elsevier; p. 255–273.

Payvand B, Hosseini SMH. 2022. A new method for mitigating frequency fluctuations in ships with electrical propulsion. ISA Trans. *125*:707–713. doi:10.1016/j.isatra.2019.02.013.

Peng Y, Zhang S, Pan R. 2010. Bayesian network reasoning with uncertain evidences. Int J Uncertain Fuzziness Knowl-Based Syst. *18*(5):539–564. doi:10.1142/S0218488510006696.

Radan D, Sørensen AJ, Ådnanes AK, Johansen TA. 2008. Reducing power load fluctuations on ships using power redistribution control. Mar Technol SNAME News. *45*(3):162–174. doi:10.5957/mt1.2008.45.3.162.

Rødseth ØJ, Knight M, Storari R, Foss H, Tinderholt AR. 2006. Alarm management on merchant ships. Proceedings of World Maritime Technology Conference/ICMES 06; London.

Rukavina B. 2020. Some issues about legal regulation regarding handling dangerous goods in maritime traffic. Pomorstvo. *34*(2):302–308. doi:10.31217/p.34.2.11.

Rutherford D, Mao X, Comer B. 2020. Potential CO2 reductions under the Energy Efficiency Existing Ship Index. In: Rutherford D, Mao X, Comer B, editors. International council on clean transportation. Washington, DC: International Council on Clean Transportation (ICCT); p. 1–18.

Saatçıoğlu ÖY, Göksu B, Yüksel O, Gülmez Y. 2017. Ship engine room casualty analysis by using decision tree method. J ETA Mar Sci. *5*(1):59–68. doi:10.5505/jems.2017.27146.

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. doi:10.1016/j.oceaneng.2020.107992.

Sezer SI, Ceylan BO, Akyuz E, Arslan O. 2022. D-S evidence based FMECA approach to assess potential risks in ballast water system (BWS) on-board tanker ship. J Ocean Eng Sci. doi:10.1016/j.joes.2022.06.040.

Shan X, Liu K, Sun PL. 2017. Risk analysis on leakage failure of natural gas pipelines by Fuzzy Bayesian Network with a Bow-Tie model. Sci Program. doi:10.1155/2017/3639524.

Shen Q, Ramachandran B, Srivastava SK, Andrus M, Cartes DA. 2011. Power and energy management in integrated power system. 2011 IEEE Electric Ship Technologies Symposium, ESTS 2011. p. 414–419.

Sokukcu M, Sakar C. 2022. Risk analysis of collision accidents during underway STS berthing maneuver through integrating Fault Tree Analysis (FTA) into Bayesian network (BN). Appl Ocean Res. *126*(January):103290. doi:10.1016/j.apor.2022.103290.

Sormunen OVE, Goerlandt F, Häkkinen J, Posti A, Hänninen M, Montewka J, Ståhlberg K, Kujala P. 2015. Uncertainty in maritime risk analysis: extended case study on chemical tanker collisions. Proc Inst Mech Eng Part M: J Eng Mar Environ. *229*(3):303–320. doi:10.1177/1475090213515640.

Uğurlu Ö, Köse E, Yıldırım U, Yüksekyıldız E. 2015. Marine accident analysis for collision and grounding in oil tanker using FTA method. Mar Policy Manage. *42*(2):163–185. doi:10.1080/03088839.2013.856524.

Valkeejärvi K. 2006. The ship's electrical network, engine control and automation. *Koninklijke Gallois Genootschap Magazine*.

Xie P, Guerrero JM, Tan S, Bazmohammadi N, Vasquez JC, Mehrzadi M, Al-Turki Y. 2022. Optimization-based power and energy management system in shipboard microgrid: a review. IEEE Syst J. *16*(1):578–590. doi:10.1109/JSYST.2020.3047673.

Yang L, Chen W, Zhao X. 2014. Effect of steam-exhaust operation of secondary coolant circuit on ship reactor blackout accident. Ann Nucl Energy. *63*:38–45. doi:10.1016/j.anucene.2013.07.033.

Yuksel O. 2023. A comprehensive feasibility analysis of dual-fuel engines and solid oxide fuel cells on a tanker ship considering environmental, economic, and regulation aspects. Sustainable Prod Consumption. *42*:106–124. doi:10.1016/j.spc.2023.09.012.

Yuksel O, Koseoglu B. 2022. Regression modelling estimation of marine diesel generator fuel consumption and emissions. Trans Mar Sci. *11*(1):79–94. doi:10.7225/toms.v11.n01.w08.

Yuksel O, Koseoglu B. 2023. Numerical simulation of the hybrid ship power distribution system and an analysis of its emission reduction potential. Ships Offsh Struct. *18*(1):78–94. doi:10.1080/17445302.2022.2028435.

Yüksel OŞCGB. 2021. Determination of the ship engine room pipeline failure risk rating with Fuzzy-Bayesian Network. Nav Eng J. *133*(4):139–156.

Zadeh LA. 1965. Fuzzy sets. Inf Control. *8*(3):338–353. doi:10.1016/S0019-9958(65)90241-X.