

# Combined Fault Tree Analysis and Bayesian Network for Reliability Assessment of Marine Internal Combustion Engine

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## Abstract

This paper investigates the reliability of internal marine combustion engines using an integrated approach that combines Fault Tree Analysis (FTA) and Bayesian Networks (BN). FTA provides a structured, top-down method for identifying critical failure modes and their root causes, while BN introduces flexibility in probabilistic reasoning, enabling dynamic updates based on new evidence. This dual methodology overcomes the limitations of static FTA models, offering a comprehensive framework for system reliability analysis. Critical failures, including External Leakage (ELU), Failure to Start (FTS), and Overheating (OHE), were identified as key risks. By incorporating redundancy into high-risk components such as pumps and batteries, the likelihood of these failures was significantly reduced. For instance, redundant pumps reduced the probability of ELU by 31.88%, while additional batteries decreased the occurrence of FTS by 36.45%. The results underscore the practical benefits of combining FTA and BN for enhancing system reliability, particularly in maritime applications where operational safety and efficiency are critical. This research provides valuable insights for maintenance planning and highlights the importance of redundancy in critical systems, especially as the industry transitions toward more autonomous vessels.

**Keywords** Fault tree analysis; Bayesian network; Reliability; Redundancy; Internal combustion engine

## 1 Introduction

The reliability of ship machinery is essential to ensure safe and efficient maritime operations. Reliable machinery reduces downtime, minimizes the risk of accidents, and ensures that vessels meet their performance and safety standards. Reliability tools like Fault Tree Analysis (FTA), Event Tree Analysis (ETA), and Reliability Block Diagrams (RBD) assess failure risks by analysing both quantitative and qualitative machinery data. Methods such as

Failure Mode, Effects, and Criticality Analysis (FMECA) and Fuzzy Multi-Criteria Decision-Making Approaches (FCDMA) have been applied to identify critical components and support maintenance decisions (Daya and Lazakis, 2023a). Other tools, including Bayesian belief networks, Monte Carlo simulations, and Markov chains, are used to model maintenance planning for complex systems with stochastic failures (Daya and Lazakis, 2023b).

System reliability analysis has long supported maintenance planning, evolving from simple machine breakdowns to condition monitoring and predictive analysis (Lazakis et al., 2016). Advances in reliability analysis have shaped modern maintenance strategies, helping prioritize actions based on how component failures affect equipment availability (Iheukwumere-Esotu and Yunusa-Kaltungo, 2021). In industries where human safety and environmental protection are paramount, risk and criticality play a central role in maintenance planning (DE Jonge et al., 2017). The adoption of new technologies, such as onboard diagnostics, intelligent sensors, and Internet of Things (IoT), allows ship operators to implement remote monitoring and digital twin technologies. These innovations enable real-time condition monitoring, reduce crew levels, lower maintenance costs, and improve environmentally friendly operations.

Aided by rapid development of various technologies such as artificial intelligence, robotics, sensors, and advanced

## Article Highlights

- FTA and BN are integrated for comprehensive reliability assessment.
- ELU, FTS, and OHE are identified as the main critical failure contributors.
- Redundancy implementation significantly reduces the probability of critical failure occurrences.
- Redundant design lowers failure risks by up to 42.78% across subsystems.

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control systems to navigate, communicate, and make decisions Maritime Autonomous Surface Ships (MASS) have become an important research topic (Jovanović et al., 2024). Compared with conventional ships, MASS have high embodied intelligence and smart technologies that offer advantages such as lower crew expenses, reduced chance of human error, and so on (Antão and Guedes Soares, 2019; Goerlandt, 2020; Utne et al., 2019).

It is still unknown whether MASS can operate safely without human intervention (Burmeister et al., 2014; Papadimitriou et al., 2020). Although smart technologies will be included in MASS in the future, there are still significant concerns for the system's reliability due to removing humans from ship operations. It is not clearly defined yet how the failures are managed as quickly as possible without human interaction (Karatuğ et al., 2022).

### 1.1 Maintenance of marine systems

Maintenance is one of the crucial factors in sustaining efficient and uninterrupted cruises performed by marine vessels (Pintelon and Parodi-Herz, 2008). It enables the operation of the systems or equipment at the desired level and improves their condition in case of failures. Performing an influential maintenance process throughout the system can significantly contribute to the management from the perspective of the reduction of damages caused by failures, saving from production and operation costs, safety hazards for seafarers, and protection of the environment (Barata et al., 2002; Lazakis and Ölçer, 2016). Moreover, it allows for increasing reliability, availability, and operational efficiency of the systems and equipment (Karatuğ and Arslanoğlu, 2022).

Maintenance activities of the ship machinery systems are mostly made by the marine operators onboard or a specialized third-party company. In the maritime industry, maintenance has evolved by corrective (CM), preventive (PM), and predictive (PrM) (Cullum et al., 2018). Current practices onboard rely on a planned maintenance system. In this regard, maintenance management plans of a ship are performed according to maintenance schedules created based on the experience of experts in the technical department, requirements of legal or class, and recommendations of manufacturers. Although this approach is the most frequent strategy used within the shipping industry, thanks to recent technological developments, it has been noticed that it has some drawbacks such as loss from the useful life of the equipment and more maintenance costs (Tan et al., 2020).

Maintenance of ship machinery systems is complicated since various systems and equipment are linked. The correlation between the subsystems can cause huge fault damage to the system (Kowalski et al., 2017). Islam et al. (2018) developed a Bayesian network (BN) model to assess human error probability (HEP) during maintenance activi-

ties, emphasizing both internal (e. g., training, fatigue) and external factors (e. g., weather, ship motion). This study provided a framework to dynamically update human error probabilities based on real-time data, offering a significant advancement in risk management strategies. Islam et al. (2019) further explored the reliability of fuel oil systems in marine propulsion engines, identifying critical failure-prone components such as fuel injectors and high-pressure pipes. The study collected failure data through structured surveys and statistical analyses, highlighting the inadequacies in traditional maintenance schedules and advocating for condition-based approaches to mitigate risks. Furthermore, the challenges in maintaining overall engine reliability were examined by Anantharaman et al. (2019). They identified key subsystems, including lubricating oil and cooling water systems, as frequent sources of failure. Their research underlined the need for enhanced data collection and analysis to develop robust reliability assessment models. These models would enable better maintenance planning and reduce engine-related accidents.

### 1.2 Maintenance and MASS

In term of maintenance of the MASS, Karatuğ et al. (2022) proposed that different types of maintenance strategies need to be adopted in the future based on the autonomy level and crew present onboard. Accordingly, it is seen that the combination of the predictive and preventive approaches is promising for the MASS due to achieve advantages from both strategies. Hence, the reliability level of ship machinery systems can be sustained at high levels.

Eriksen et al. (2021) developed a reliability-centered maintenance strategy for unmanned ships and practiced it along the main engine freshwater cooling system. They found that a redundant system design reduces risks within the system on unmanned ships but it is still challenging. Daya and Lazakis (2023b) analysed the reliability and availability of four diesel generators by combining dynamic FTA, Bayesian Belief Network (BBN), and FMECA. They found that the lubricating system has the highest reliability while the cooling system has the lowest. Moreover, they built on a smart maintenance framework integrated with Artificial Neural Networks (ANN) by improving their analysis (Daya and Lazakis, 2024). In Lazakis et al. (2018), an intelligent maintenance strategy was proposed for predicting the upcoming values of all main engine cylinder exhaust gas temperatures. As a base for the strategy, reliability tools such as FTA and Failure Mode Effect Analysis (FMEA) were used to determine critical parameters.

Some reliability analyses were performed for the systems belonging to the ship engine room such as the cooling water system (Allal et al., 2017) and lubricating oil system (Allal et al., 2018). The reliability levels of the systems were revealed in two different scenarios which are conventional system design and system design with redundancy.

The analyses present major recommendations regarding autonomous ships. Gao et al. (2021) modelled the overall reliability of unmanned surface vessels to identify the critical subsystems and components. In this regard, importance measures and sensitivity analyses were performed using the Dynamic Bayesian Network (DBN). Liang et al. (2017) proposed a framework for the maintenance of ship machinery systems to evaluate reliability by merging the BN and the Monte Carlo simulation method.

Han et al. (2024) proposed a maintenance model related to ship machinery systems of the MASS based on the DBN. The model is applied to cooling systems and it is found that planned maintenance costs may be decreased by redundancy and enhanced detection facilities. Abee et al. performed some reliability analysis regarding the MASS. In Abaei et al. (2021) analysis, it was aimed to enhance system reliability based on the model using a Multinomial Process Tree method. In the other paper Abaei et al. (2022), the effect of redundancy on unmanned ships was demonstrated by estimating the availability of unmanned ships using the Random Process Tree and Probabilistic Bayesian Network. BahooToroodi et al. (2022) established a probabilistic model to estimate the reliability of different degrees of autonomous ship machinery systems with a methodology that includes the Markov Chain method, Monte Carlo simulation, and Bayesian Interface.

### 1.3 Reliability analysis of marine systems

FTA has been widely applied in the maritime industry to assess and improve the reliability and safety of various ship systems and operations. Its structured approach helps identify potential failure points and assess the risk of undesired events in complex maritime environments. FTA is used to evaluate the reliability of critical shipboard machinery, such as propulsion systems, engines, and power generation systems. By modeling potential failures in machinery components (e.g., pumps, compressors, and control units), it helps identify weak points that could lead to system failure (Laskowski, 2015; Lazakis et al., 2018). It supports maintenance planning by estimating the likelihood of machinery breakdowns, helping to minimize downtime and improve operational efficiency (Basurko and Uriondo, 2015; Meneghetti and De Zan, 2016). FTA is applied to assess the dependability of navigation systems, including radar, GPS, and electronic chart display and information systems (ECDIS). By mapping potential failures in these systems, FTA can help improve ship navigational safety and reduce the risk of accidents like groundings or collisions (Fan et al., 2022; Yan et al., 2020). However, traditional FTA does not incorporate time-dependent failures or sequence dependencies, leading to static assessments. The introduction of dynamic fault tree analysis (DFTA) overcomes these limitations by integrating time-sequential analysis and repair mechanisms (Akyuz et al., 2020; Guan

et al., 2016).

ETA, an inductive method, complements FTA by analyzing the outcomes of initiating events. It is particularly suited for assessing cascading failures and decision pathways in risk management scenarios. However, ETA often relies heavily on accurate probability data and can be limited in modeling interdependencies among system components (Akyuz et al., 2020; Hosseini et al., 2020). FMECA extends FMEA by introducing a criticality assessment to prioritize risks based on their severity and probability. This tool is particularly valuable in preventive maintenance and identifying high-risk components. However, it is labor-intensive and subjective, as its effectiveness heavily depends on expert judgment (Zaman et al., 2014). RBD provides a graphical approach to assess system reliability by visualizing the interdependencies among components in terms of serial or parallel arrangements. While it offers a straightforward mechanism for modular analysis, it often oversimplifies the actual interrelations in dynamic or redundant systems, which can lead to inaccuracies in complex scenarios (Jakkula et al., 2021).

Integrative approaches that combine these methods are increasingly prevalent in maritime risk analysis. For instance, combining FTA with fuzzy logic has been applied to account for uncertainties in expert judgments, particularly in maritime scenarios like cargo liquefaction (Akyuz et al., 2020). Similarly, integrating RBD and BN has shown promise in providing a more comprehensive analysis of system reliability under dynamic conditions (Laskowski, 2015).

BNs in maritime applications are utilized for risk assessment and management (Zhou and Yuen, 2024), allowing for the identification of potential hazards (Bai et al., 2023) and their impacts on maritime operations (Basnet et al., 2023; Iaiani et al., 2023). They assist in fault diagnosis by analyzing sensor data to determine the most likely causes of equipment failures, enhancing maintenance strategies (Cheliotis et al., 2022). Additionally, BN optimize navigation and route planning by evaluating various factors such as weather conditions and vessel performance to improve safety and efficiency (Li et al., 2023; Zhang et al., 2024). Furthermore, BN are applied for investigating reliability and safety of autonomous shipping (Guo and Utne, 2022; Johansen and Utne, 2022; Lee et al., 2023; Maidana et al., 2023; Yang et al., 2023).

### 1.4 Aim and contributions of the paper

Based on the literature review presented in Sections above, knowledge gaps are identified as follows:

- Although the impact of redundancy is evaluated within a couple of papers, there is still a lack of knowledge on the examination of reliability corresponding to systems related to the ship's main engine as a whole.
- To the best of the authors' knowledge, there are no stud-

ies that address specific failures of ship main engine and their connection with specific equipment. However, these aspects are very important since the goal to increase ship autonomy appears simultaneously with target of increase of ship reliability, so it is important to understand what are the weak points of main engine.

The aim of this paper is to utilize FTA and BN to assess reliability of ship main engine.

The contributions of this paper are summarized as follows:

- Identification of critical failures and failure mechanisms of ship main engine.
- Identification of weak points of ship main engine.
- Evaluation of the impact of redundancy on the overall reliability of a ship's main engine.

In addition, the results of the analysis are essential for the relevant literature and the maritime sector to provide general ideas regarding the possible failures of the ship's main engine and its reliable operation within the more autonomous ship design. The proposed methodology is able to guide future redundancy and maintenance planning for more reliable ship operations.

## 2 Methodology

Methodology for system reliability assessment, integrating FTA and BN, is illustrated in Figure 1. The process begins with selecting the system, defining its boundaries, specifying subsystems and components, identifying failure modes, and obtaining reliability data. These inputs are utilized to construct an FTA, which organizes primary events, intermediate events, and a top event through the application of Boolean gates and associated occurrence probabilities. Subsequently, the FTA structure is mapped into BN, wherein primary events are represented as root nodes, intermediate events as intermediate nodes, and the top event as a leaf node. The probabilities derived from the FTA are

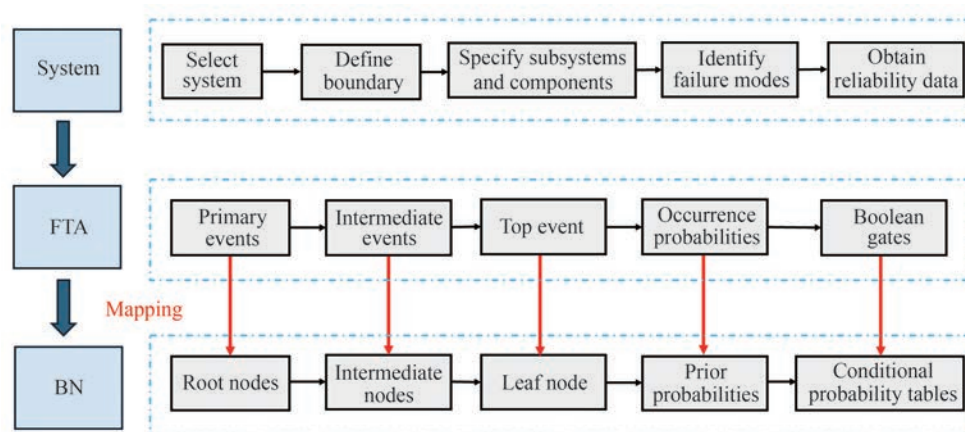
incorporated into the BN as prior probabilities and conditional probability tables, facilitating a dynamic and probabilistic analysis of system reliability and interdependencies.

### 2.1 Fault tree analysis

FTA is a widely adopted method for modeling the dependability of large systems. It is a deductive approach that uses Boolean logic to graphically represent the combinations of equipment failures, human errors, and external factors that contribute to specific system failures. By using a fault tree diagram, the causes of an event can be identified, and, with known failure rates, the probability of the undesired event (top event) can be calculated for both qualitative and quantitative analysis. FTA assumes all events are binary (either functioning or not), that events are statistically independent, and that their relationships can be modeled using logical AND and OR gates. More complex gates are created through combinations of these basic gates. The different pages may be linked together by transfer gate. Although FTA effectively represents the causes of system failures and accounts for multiple simultaneous faults, it does not capture the sequential order of component failures leading to a system failure. FTA diagrams used in this paper are illustrated on Figure 1.

### 2.2 Bayesian networks

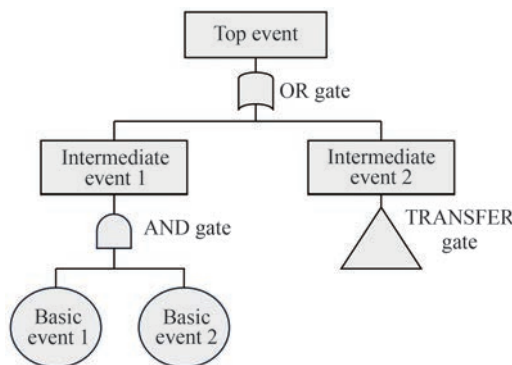
A BN is a directed acyclic graph (DAG), which means it does not contain any cycles, ensuring that one cannot return to a previous position. The network consists of nodes and directed arcs, also known as edges. Each node represents a specific state or condition, while an arc indicates a direct influence between nodes. The directed nature of the arcs allows them to represent cause-and-effect relationships. In the context of system reliability modeling, the nodes of the BN represent the states of different items, and the arcs illustrate how these states influence one another. A BN describes how one node directly affects other nodes.



**Figure 1** Methodology

Typically, the nodes (and variables) in a BN are not independent, so it is necessary to use conditional probabilities. This influence is represented by a conditional probability table (CPT). CPT is a crucial component of a BN that quantifies the relationships between nodes. Each node in the BN can have a CPT that describes the probabilities of the node’s possible states given the states of its parent nodes (Rausand, 2004).

In a Bayesian model, the nodes represent random variables, while the arcs indicate the relationships or dependencies between them. Each node can include descriptions of the variables through probability distribution functions, probability tables, or deterministic equations from parent nodes. Specifically, prior probability tables are used for root nodes, conditional probability tables apply to parent nodes. The links between nodes signify the influence or causal relationships among the variables. The primary goal of Bayesian networks is to determine the probability distribution of a set of variables based on prior knowledge of certain variables and observations of others. Figure 2 illustrates BN with two variables *A* and *B*. Both variables have two states respectively (*a*1 and *a*2); (*b*1 and *b*2). The a priori probability of node *A* is given by  $P(A = a1)$  and  $P(A = a2)$ .



**Figure 2** FTA diagrams used in this paper

A Conditional Probability Table (CPT) will be associated with node *B*, that is to say  $P(B|A)$ . It is defined as the matrix (1):

$$P(B|A) = \begin{bmatrix} P(B = b1|A = a1) & P(B = b1|A = a2) \\ P(B = b2|A = a1) & P(B = b2|A = a2) \end{bmatrix} \quad (1)$$

This probability is computed by the Bayes Theorem which gives the name of BNs written as:

$$P(A|B) = \frac{P(A, B)}{P(B)} = \frac{P(B)P(B, A)}{P(B)} \quad (2)$$

The semantics of Bayesian networks allows assessing also the joint probability as (3):

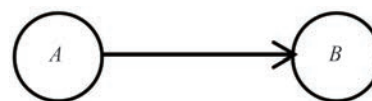
$$P(X_1, X_2, \dots, X_n) = \prod_i^n (X_i | pa(X_i)) \quad (3)$$

where  $(X_1, X_2, \dots, X_n)$  are the variables and  $pa(X_i)$  are the parents.

Knowledge represented by BNs can be obtained from experience feedback, observations, expert’s judgements, manufacturer’s documents. BNs allow merging data from different sources and of diverse nature in one model.

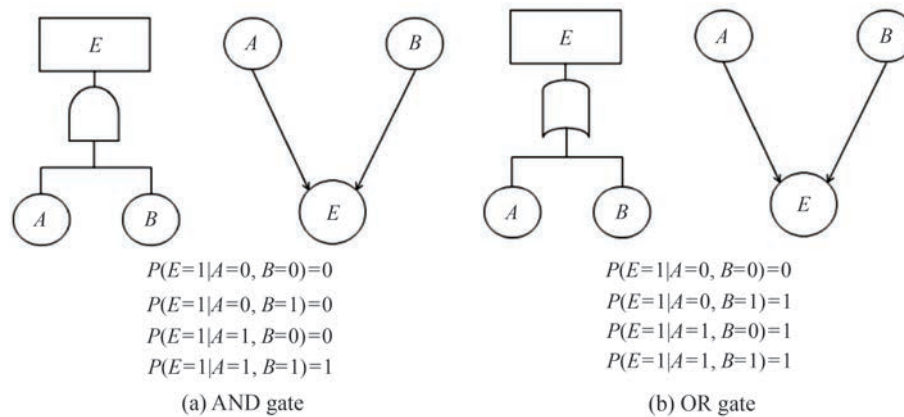
### 2.3 Converting an FTA into a BN

While it is possible to construct a BN directly from system analysis, converting a FTA into a BN leverages the familiarity that most analysts have with FTs to create an initial version of the BN for the system in question. This conversion process is straightforward, and any analyses conducted using FTAs can also be executed using BN inference (Jones et al., 2010). However, as previously noted, BNs provide additional benefits, such as the ability to incorporate local dependencies, multistate variables, and uncertainties, along with dependencies among elements that can be added to the BN post-conversion. Figure 3 illustrates the simplified process of transforming FTAs into BNs. The first step in converting a FTA into a BN is to create a corresponding node for each event and base element (primary event/component) in the FTA. If a base element appears multiple times in the FTA, only one node should be created in the BN. The second step involves connecting the nodes in the same manner as the gates in the FTA. The third step is to construct a conditional probability table (CPT) for each node based on the logic gates in the FTA. In Figure 4, the CPT is assigned to nodes connected by AND and OR gates, which represent deterministic relationships; thus, the entries are either 0 or 1, with 1 indicating a failure and 0 indicating operational status.



**Figure 3** Example of Bayesian network

Mapping FTA in BN to perform risk assessment analysis has been carried out for various problems. Sakar et al. (2021) analyse grounding accident risks by applying a combined FTA and BN model, contributing to the literature by using this dynamic risk assessment methodology to evaluate the relationships and impacts of contributing factors. Sokukcu and Sakar (2022) conducted a probabilistic risk analysis of collision incidents by integrating FTA with BN analysis, enhanced by fuzzy theory to address uncertainty and simulate risks through probability updating and sensitivity analysis. A BN model is utilized to overcome the limitations of FTA, including issues with conditional depen-



**Figure 4** Converting an FTA into a BN (Martins et al., 2014)

dependencies and its rigidity, in the analysis of pilot transfer accidents (Sakar and Sokukcu, 2023). Roozbahani and Ghanian (2024) demonstrated that the integrated approach effectively addresses limitations of FTA and BN models, offering valuable advantages to decision-makers in water supply and resource management by incorporating social, political, environmental, technical, and economic factors, and serving as a flexible tool for various water transfer projects.

### 3 Case study

Reliability data can generally be obtained from: field, testing, manufacturers, generic reliability databases, expert judgment, reliability prediction models, research reports and papers (Rausand, 2004). In this paper, reliability data is obtained from The Offshore and Onshore Reliability Data (OREDA) (OREDA, 2015). OREDA is generic reliability database commercially available as handbooks and computerized database. OREDA is often claimed to be the highest quality source of reliability data available and has been a model for other databases (Rausand, 2004). OREDA classifies failure modes in three categories:

1. Critical—A failure that causes immediate and complete loss of a system's capability of providing its output.
2. Degraded—A failure that is not critical, but that prevents the system from providing its output within specifications. Such a failure would usually, but not necessarily, be gradual or partial, and may develop into a critical failure in time.
3. Incipient—A failure that does not immediately cause loss of a system's capability of providing its output, but which, if not attended to, could result in a critical or degraded failure in the near future.

In this paper, the combustion engine is analysed. The boundary definition applies to combustion engines (diesel/gas) driving equipment such as compressors, generators and pumps. The combustion engines are further subdivided

into Subunits and Maintainable Items. Included within the boundary is the starting system and auxiliaries related to the engine, as shown in Figure 5.

Combustion engine is divided into six subsystems: starting system, engine, lubrications system, cooling system, control and monitoring system, and miscellaneous, which are further subdivide into equipment units and subunits. The failure rate function expresses how likely it is that an item that has survived up to time  $t$ , will fail during next unit of time. The life of the technical item can generally be split into three different phases: early failure phase, useful phase, and wear-out phase, Figure 6.

It is assumed that failure rate remains constant in useful phase. The main part of the failure events in OREDA (2015) come from the useful life phase, where failure rate is constant.

According to, these failure modes are identified for combustion engine:

1. AIR—Abnormal instrument reading,
2. BRD—Breakdown,
3. External leakage—Fuel—ELF,
4. External leakage—Utility medium—ELU,
5. Erratic output—ERO,
6. Fail to start on demand—FTS,
7. High output—HIO,
8. Internal leakage—INL,
9. Low output—LOO,
10. Noise—NOI,
11. Overheating—OHE,
12. Other—OTH,
13. Parameter deviation—PDE,
14. Plugged/Choked—PLU,
15. Minor in-service problems—SER,
16. Structural deficiency—STD,
17. Fail to stop on demand—STP,
18. Unknown—UNK,
19. Spurious stop—UST,
20. Vibration—VIB.

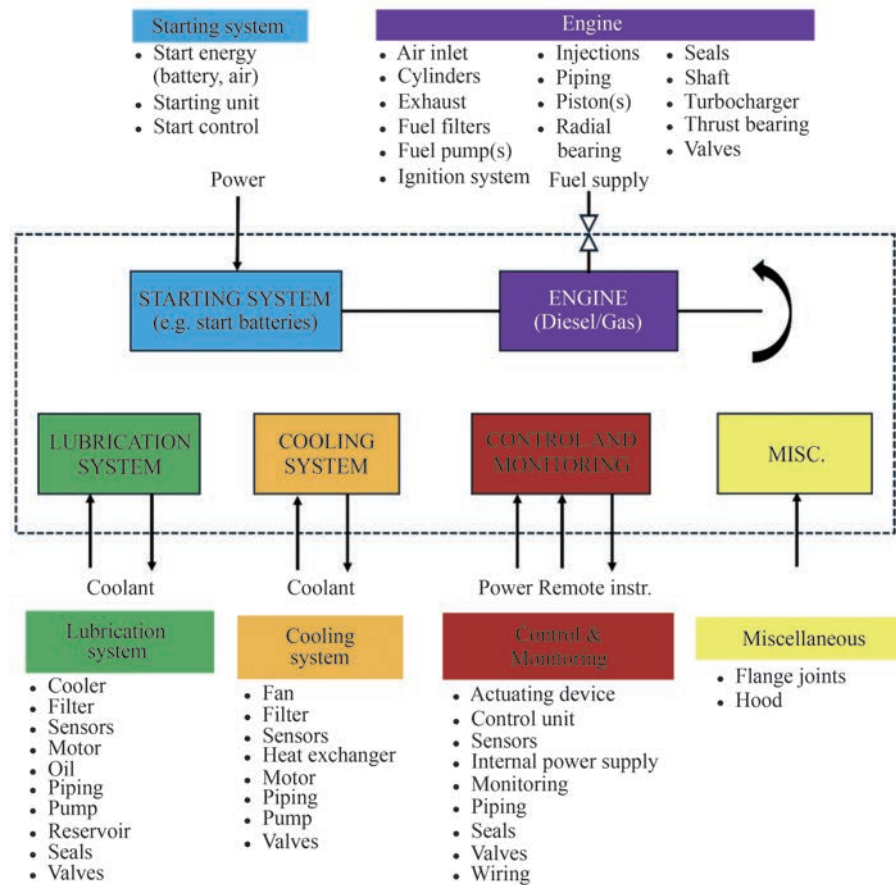


Figure 5 Boundary definition of ship engine

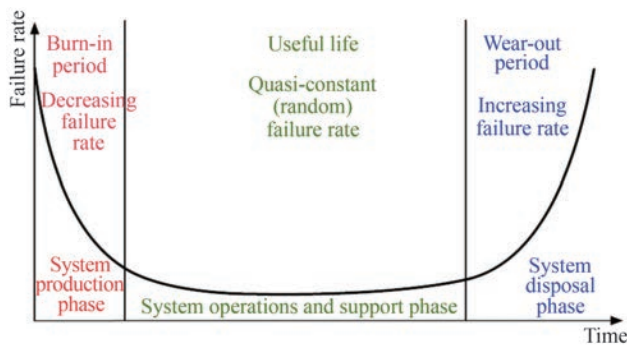


Figure 6 Bath-tub shape of the failure rate

### 4 Results

In the FTA construction, the following assumptions were considered:

- The components present binary failure modes (works/fails),
- Relationship between events and causes are represented through logical AND and OR gates,
- Failures are statistically independent.

Considering failure modes and failure mechanisms FTA

of critical failure is constructed and shown on Figures 7–11. Occurrence probabilities are obtained from OREDA (2015) and assigned to each primary event, as given in Table 1.

Using the algorithm described in Section 2.3, the BN is constructed for the critical failure, as illustrated in Figure 12. Once developed, BN is analysed using Netica (Netica Applications, 7.01).

The prior probability of the leaf node in the BN is calculated to be  $P(CF) = 0.345$ . It is worth noting that during predictive analysis when calculating the scenario occurrence probability (deductive reasoning), the BN provides similar results to those of the traditional FT as long as primary events are independent of each other. However, one of the unique characteristics of BN is its ability to use abductive reasoning, which is aimed at updating the probability of the primary events given the occurrence of the accident precursors. Table 2 provides prior and posterior occurrences for all events. The prior probability refers to the probability of an event or hypothesis before any new evidence or data is considered. The posterior probability is the updated probability of an event or hypothesis after taking into account new evidence. prior probabilities represent initial beliefs, and posterior probabilities reflect updated beliefs after evidence is incorporated. Six failure events can lead to critical failure: ELU, FTS, STP, HIO, OHE,

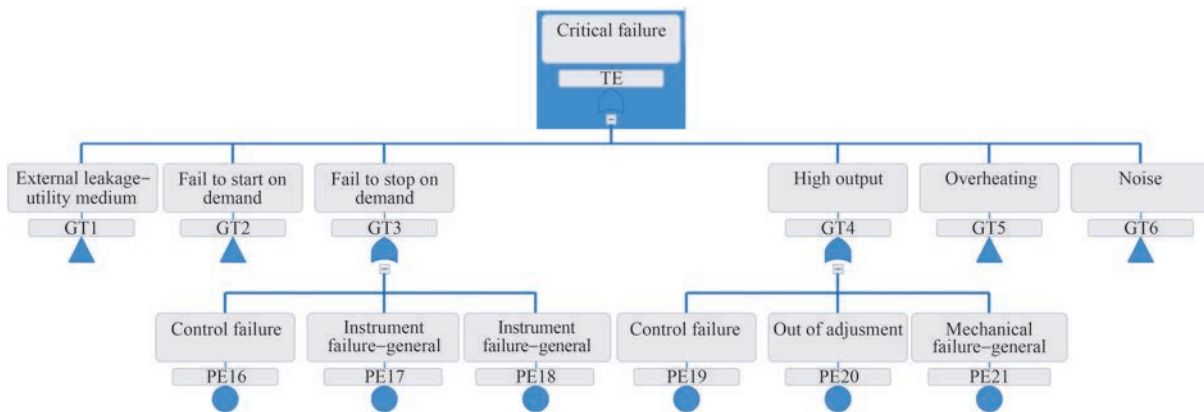


Figure 7 FTA representing critical failure

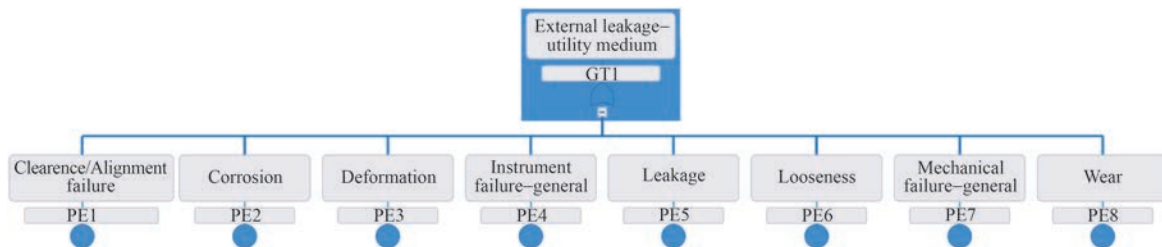


Figure 8 FTA representing critical failure, GT1

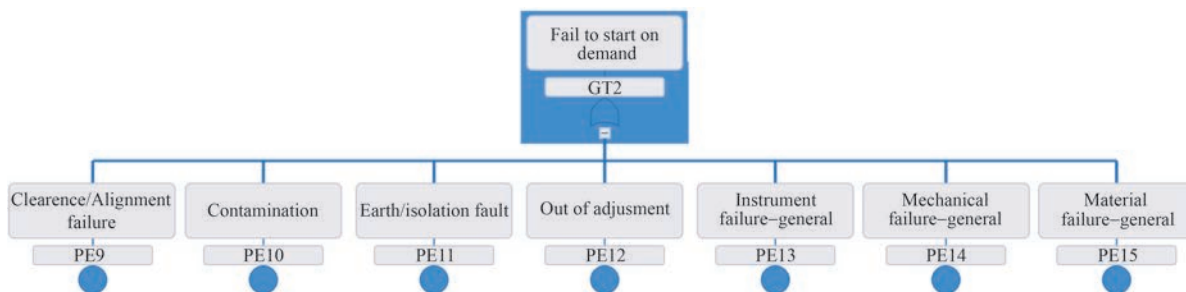


Figure 9 FTA representing critical failure, GT2

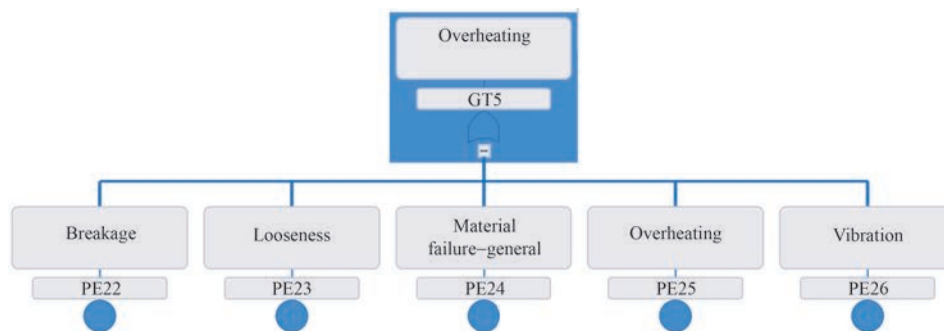
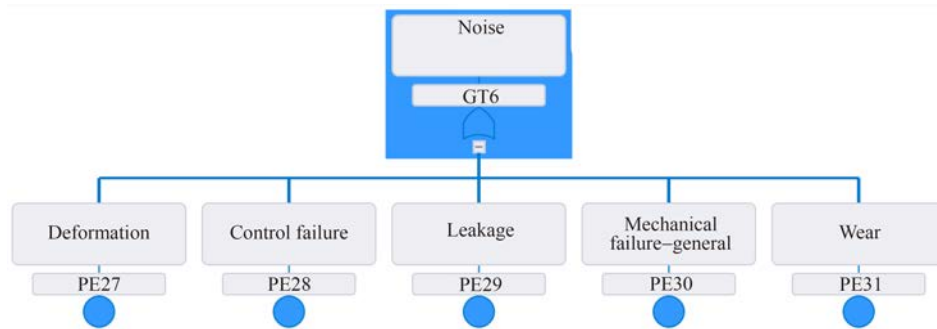


Figure 10 FTA representing critical failure, GT5

and NOI. It is shown that failure mode ELU and FTS have the greatest impact on the occurrence of critical failure. Leakage and general mechanical failure contribute the most to ELU occurrence.

Figure 13 represents FTA constructed for failure mode

ELU (External leakage–Utility medium) with regards to failure mechanism and maintainable item. Occurrence probabilities obtained from OREDA are assigned to each primary event in Table 3. Piping and pumps have the greatest failure rate.



**Figure 11** FTA representing critical failure, GT6

**Table 1** Different events related to critical failure and their occurrence probabilities–FTA

Number	Component	Symbol	Probability
1	Clearance/Alignment failure	CAF	0.0134
2	Corrosion	COR	0.0067
3	Deformation	DEF	0.0067
4	Instrument failure-general	IFG	0.0067
5	Leakage	LE	0.0872
6	Looseness	LO	0.0201
7	Mechanical failure-general	MCG	0.0470
8	Wear	W	0.0680
9	<b>External leakage-utility medium</b>	<b>ELU</b>	<b>OR-gate</b>
10	Clearance/Alignment failure	CAF	0.0067
11	Contamination	CON	0.0067
12	Earth/isolation fault	EIF	0.0067
13	Out of adjustment	OOA	0.0134
14	Instrument failure-general	IFG	0.0067
15	Mechanical failure-general	MCG	0.0134
16	Material failure-general	MFG	0.0134
17	<b>Fail to start on demand</b>	<b>FTS</b>	<b>OR-gate</b>
18	Control failure	CF	0.0067
19	Instrument failure-general	IFG	0.0067
20	Mechanical failure-general	MCG	0.0067
21	<b>Fail to stop on demand</b>	<b>STP</b>	<b>OR-gate</b>
22	Control failure	CF	0.0067
23	Out of adjustment	OOA	0.0067
24	Mechanical failure-general	MCG	0.0067
25	<b>High output</b>	<b>HIO</b>	<b>OR-gate</b>
26	Breakage	BR	0.0067
27	Looseness	LO	0.0067
28	Material failure-general	MFG	0.0067
29	Overheating	OHEI	0.0134
30	Vibration	V	0.0067
31	<b>Overheating</b>	<b>OHE</b>	<b>OR-gate</b>
31	Deformation	DEF	0.0067
32	Control failure	CF	0.0067
33	Leakage	LE	0.0134
34	Mechanical failure-general	MCG	0.0201
35	Wear	W	0.0067
36	<b>Noise</b>	<b>NOI</b>	<b>OR-gate</b>

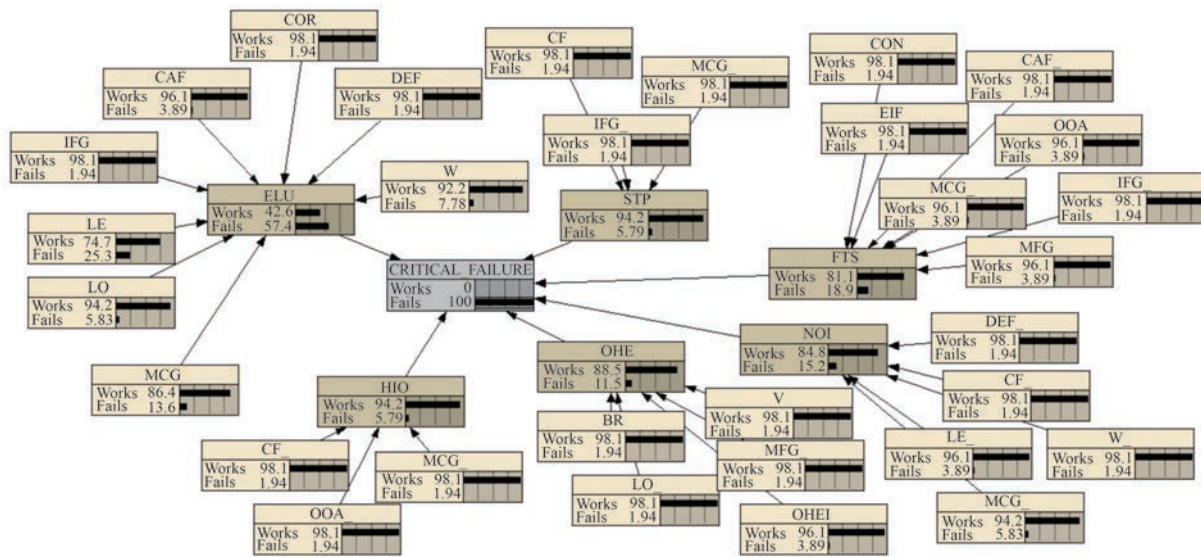


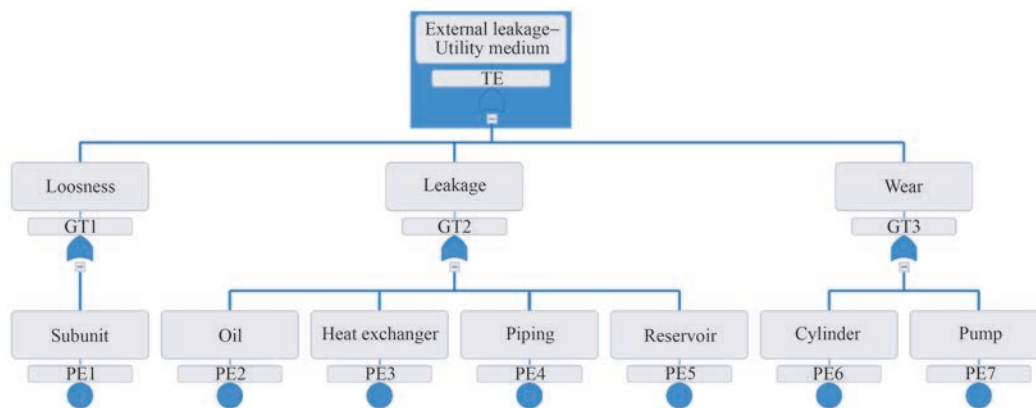
Figure 12 BN representing critical failure

Table 2 Comparison between prior and posterior probabilities—critical failure

Number	Component	Symbol	Probability	
			Prior	Posterior
1	Clearance/Alignment failure	CAF	0.0134	0.0389
2	Corrosion	COR	0.0067	0.0194
3	Deformation	DEF	0.0067	0.0194
4	Instrument failure—general	IFG	0.0067	0.0194
5	Leakage	LE	0.0872	0.2530
6	Looseness	LO	0.0201	0.0583
7	Mechanical failure—general	MCG	0.0470	0.1360
8	Wear	W	0.0680	0.0778
9	<b>External leakage—utility medium</b>	<b>ELU</b>	0.1980	0.5740
10	Clearance/Alignment failure	CAF	0.0067	0.0194
11	Contamination	CON	0.0067	0.0194
12	Earth/isolation fault	EIF	0.0067	0.0194
13	Out of adjusment	OOA	0.0134	0.0389
14	Instrument failure—general	IFG	0.0067	0.0194
15	Mechanical failure—general	MCG	0.0134	0.0389
16	Material failure—general	MFG	0.0134	0.0389
17	<b>Fail to start on demand</b>	<b>FTS</b>	0.0651	0.1890
18	Control failure	CF	0.0067	0.0194
19	Instrument failure—general	IFG	0.0067	0.0194
20	Mechanical failure—general	MCG	0.0067	0.0194
21	<b>Fail to stop on demand</b>	<b>STP</b>	0.0200	0.0579
22	Control failure	CF	0.0067	0.0194
23	Out of adjusment	OOA	0.0067	0.0194
24	Mechanical failure—general	MCG	0.0067	0.0194

**Table 2** Comparison between prior and posterior probabilities—critical failure (continued)

Number	Component	Symbol	Probability	
			Prior	Posterior
25	<b>High output</b>	<b>HIO</b>	0.0200	0.0579
26	Breakage	BR	0.0067	0.0194
27	Looseness	LO	0.0067	0.0194
28	Material failure—general	MFG	0.0067	0.0194
29	Overheating	OHEI	0.0134	0.0389
30	Vibration	V	0.0067	0.0194
31	<b>Overheating</b>	<b>OHE</b>	0.0396	0.1150
31	Deformation	DEF	0.0067	0.0194
32	Control failure	CF	0.0067	0.0194
33	Leakage	LE	0.0134	0.0389
34	Mechanical failure—general	MCG	0.0201	0.0583
35	Wear	W	0.0067	0.0194
36	<b>Noise</b>	<b>NOI</b>	0.0525	0.1520
37	<b>Critical failure</b>	<b>CF</b>	0.3450	1.0000



**Figure 13** External leakage–Utility medium, FTA

**Table 3** Different events related to ELU and their occurrence probabilities

Number	Component	Symbol	Probability
1	Subunit	SU	0.0201
2	Looseness	Lo	OR-gate
3	Oil	O	0.0134
4	Heat exchanger	HE	0.0134
5	Piping	PI	0.0201
6	Reservoir	R	0.0067
7	Leakage	LE	OR-gate
8	Cylinder	C	0.0134
9	Pump	P	0.0134
10	Wear	W	OR-gate

Redundancy can be defined as provision of more than one means or parallel paths in as tructure for performing a given function such that all means must fail before causing system failure (Rausand, 2004). Redundant parallel pump and piping is added for reliability analysis in Figure 14.

BN are constructed and anayis is performed. Figure 15 represents BN for ELU and Figure 16 represents BN for ELU with redundancy. Prior and posterior probabilities for each event are given in Table 4. By adding one redundant pump and piping, probability of ELU occurrence is decreased by 31.88%.

Figure 17 represents FTA constructed for failure mode FTS (Fail to start on demand) with regards to failure mechanism and maintainble item. Occurrence probabilities obtained from OREDA are assigned to each primary event in Table 5.

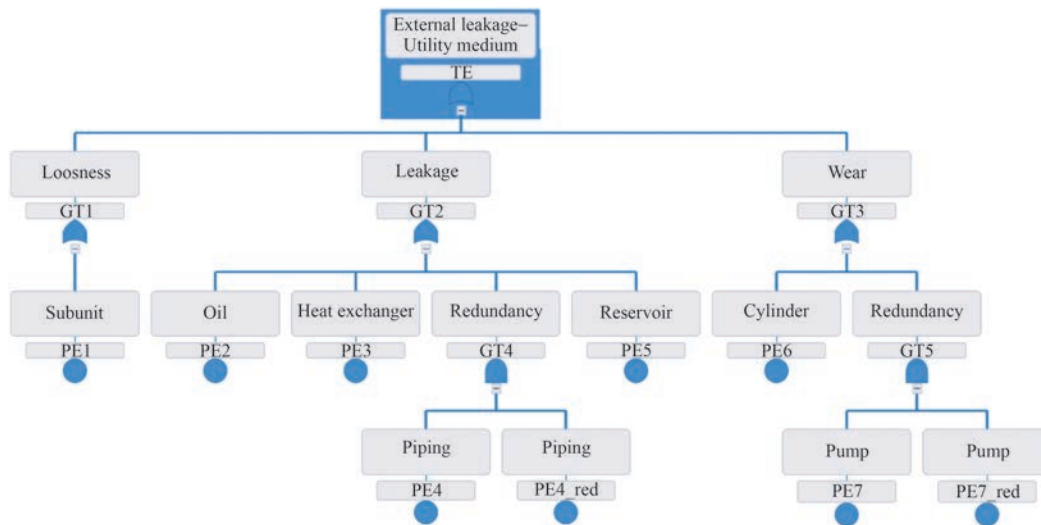


Figure 14 External leakage-Utility medium, FTA, redundancy

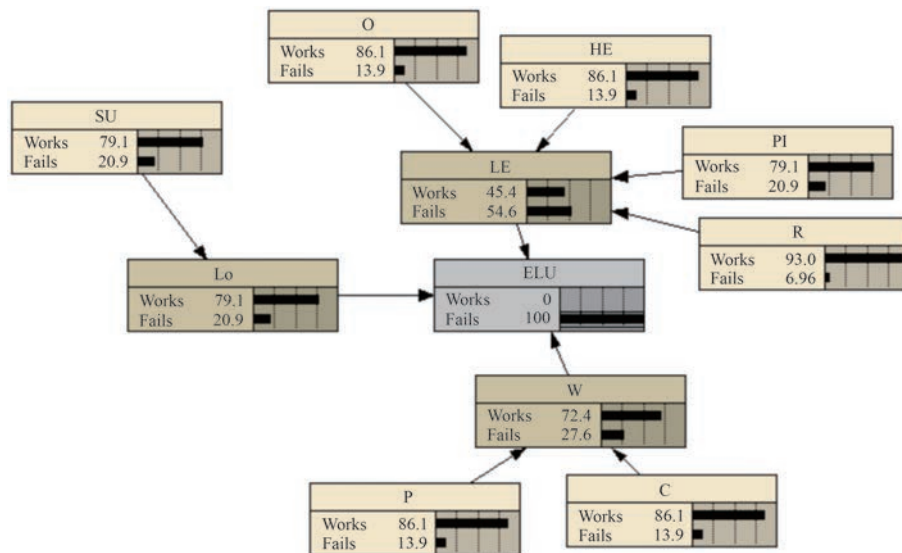


Figure 15 BN representing ELU

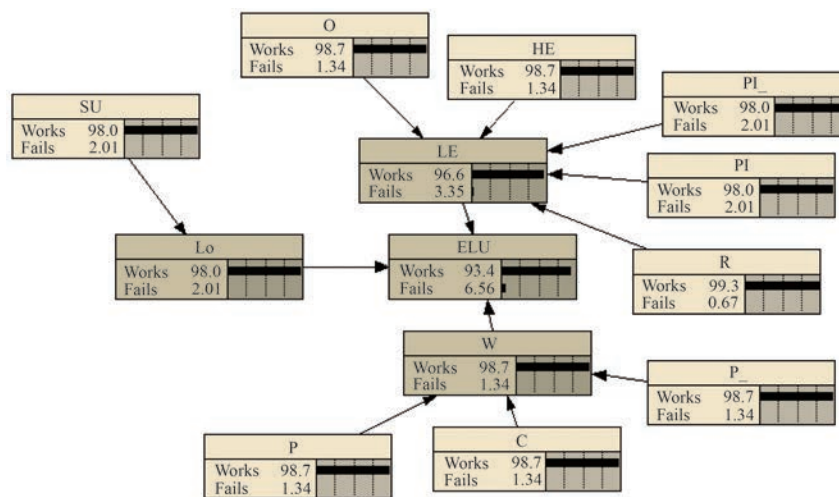
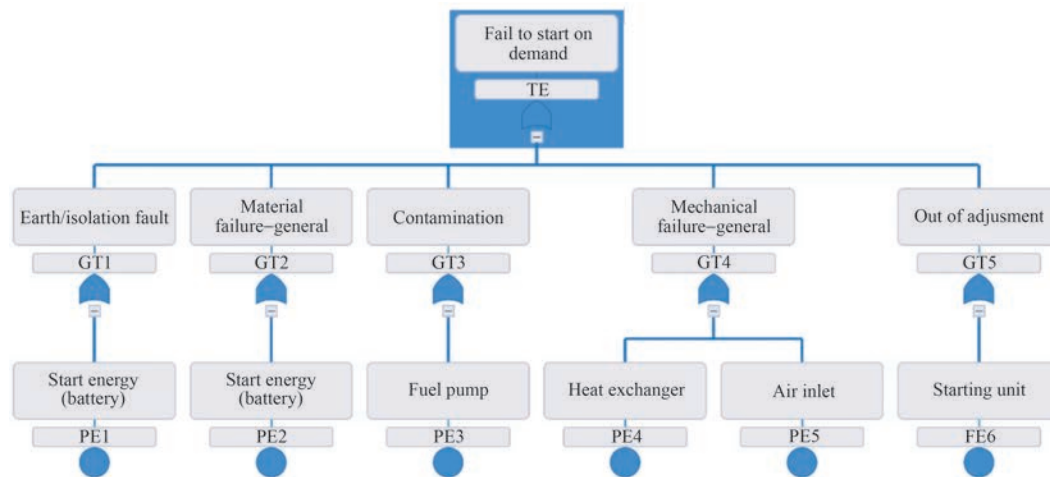


Figure 16 BN representing ELU redundancy

**Table 4** Prior and posterior probabilities of different events related to ELU

Number	Component	Symbol	First modelling		Redundancy	
			Prior	Posterior	Prior	Posterior
1	Subunit	SU	0.0201	0.2090	0.0201	0.3060
2	Looseness	Lo	0.0201	0.2090	0.0201	0.3060
3	Oil	O	0.0134	0.1390	0.0134	0.2040
4	Heat exchanger	HE	0.0134	0.1390	0.0134	0.2040
5	Piping	PI	0.0201	0.2090	0.0201	0.0257
6	Piping	PI	–	–	0.0201	0.0257
7	Reservoir	R	0.0067	0.0696	0.0067	0.1020
8	Leakage	LE	0.0526	0.5460	0.0529	0.5110
9	Cylinder	C	0.0134	0.1390	0.0134	0.2020
10	Pump	P	0.0134	0.1390	0.0134	0.0134
11	Pump	P	–	–	0.0134	0.0160
12	Wear	W	0.0266	0.2760	0.0134	0.2040
13	External leakage–Utility medium	ELU	0.0963	1	0.0656	1



**Figure 17** Fail to start on demand, FTA

**Table 5** Different events related to FTS and their occurrence probabilities

Number	Component	Symbol	Probability
1	Start energy (battery)	SE	0.0067
2	Earth/isolation fault	EIF	OR-gate
3	Start energy (battery)	SE	0.0134
4	Material failure-general	MFG	OR-gate
5	Fuel pump	FP	0.0067
6	Contamination	CON	OR-gate
7	Heat exchanger	HE	0.0067
8	Air inlet	AI	0.0067
9	Mechanical failure-general	MCG	OR-gate
10	Starting unit	STU	0.0134
11	Out of adjustment	OOA	OR-gate

Redundant start energy (battery) is added for reliability analysis in Figure 18.

BN are constructed and analysis is performed. Figure 19 represents BN for FTS and Figure 20 represents BN for FTS with redundancy. Prior and posterior probabilities for each event are given in Table 6. By adding one battery, probability of FTS occurrence is decreased by 36.45%.

Figure 21 represents FTA constructed for failure mode OHE (Overheating) with regards to failure mechanism and maintainable item. Occurrence probabilities obtained from OREDA are assigned to each primary event in Table 7.

Redundant pump is added for reliability analysis in Figure 22.

BN are constructed and analysis is performed. Figure 23 represents BN for OHE and Figure 24 represents BN for OHE with redundancy. Prior and posterior probabilities for each event are given in Table 8. By adding one redundant

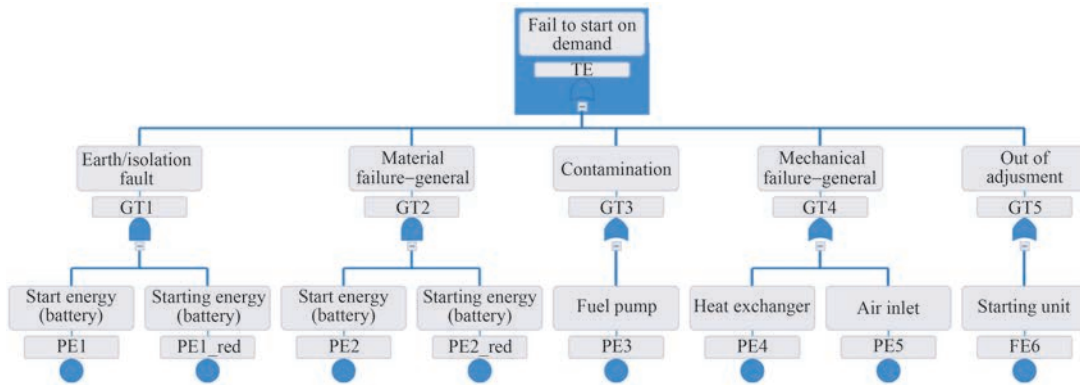


Figure 18 Fail to start on demand, FTA, redundancy

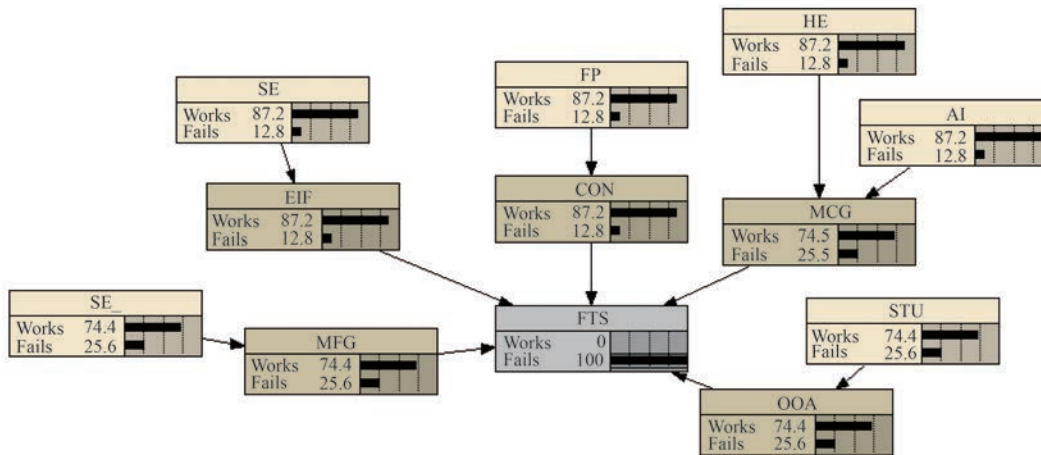


Figure 19 BN representing FTS

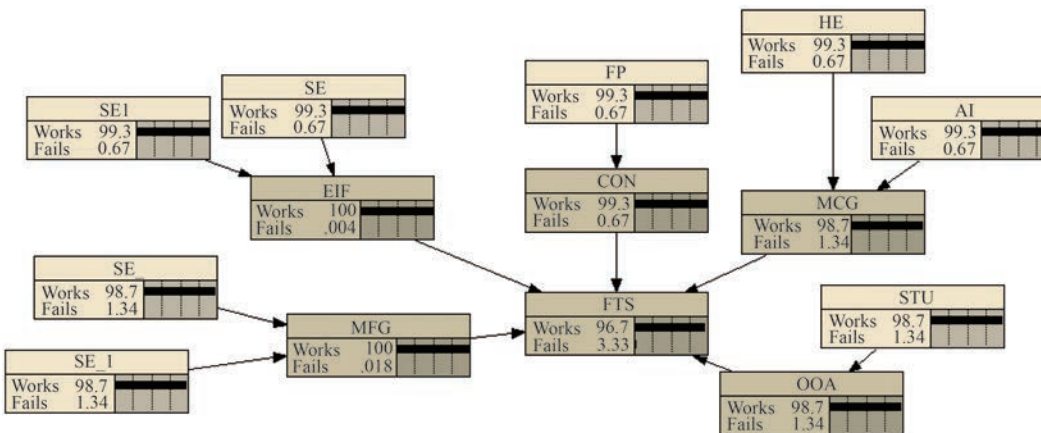


Figure 20 BN representing FTS redundancy

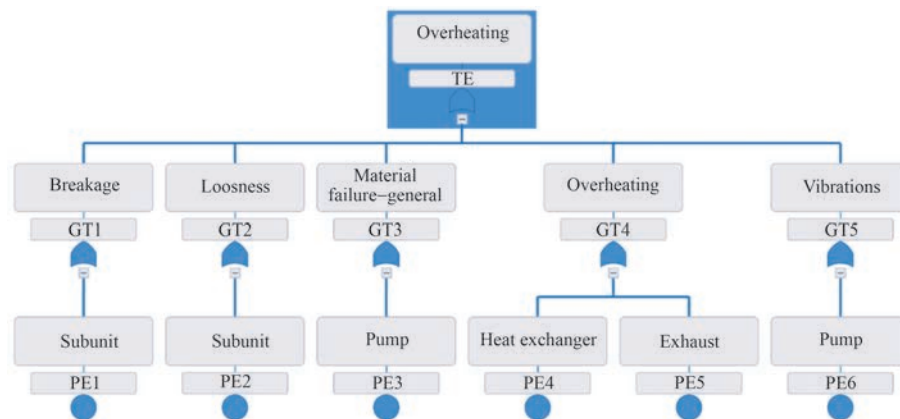
pump, probability of OHE occurrence is decreased by 42.78%.

The results underscore the effectiveness of combining FTA and BN for reliability analysis. Redundancy proves to be a critical strategy for mitigating risks, especially for high-impact failure modes like ELU, FTS, and OHE. These findings provide valuable guidance for designing

more reliable marine systems, emphasizing the need for targeted interventions in critical subsystems. This is especially important for future ship designs with higher autonomy degree. Their human-free nature is a crucial challenge since it is impossible to intervene in any failure during the cruise immediately. In this regard, the proposed methodology can guide redundancy planning of the ship main engine

**Table 6** Prior and posterior probabilities of different events related to FTS

Number	Component	Symbol	First modelling		Redundancy	
			Prior	Posterior	Prior	Posterior
1	Start energy (battery)	SE	0.0067	0.128	0.00670	0.0080
2	Start energy (battery)	SE	–	–	0.00670	0.0080
3	Earth/isolation failure	EIF	0.0067	0.128	0.00004	0.0013
4	Start energy (battery)	SE	0.0134	0.256	0.01340	0.0185
5	Start energy (battery)	SE	–	–	0.01340	0.0185
6	Material failure–general	MFG	0.0134	0.256	0.00018	0.0054
7	Fuel pump	FP	0.0067	0.128	0.00670	0.2010
8	Contamination	CON	0.0067	0.128	0.00670	0.2010
9	Heat exchanger	HE	0.0067	0.128	0.00670	0.2010
10	Air inlet	AI	0.0067	0.128	0.00670	0.2010
11	Mechanical failure–general	MCG	0.0134	0.255	0.01340	0.4010
12	Starting unit	STU	0.0134	0.256	0.01340	0.4020
13	Out of adjustment	OOA	0.0134	0.256	0.01340	0.4020
14	Fail to start on demand	FTS	0.0524	1	0.03330	1



**Figure 21** Overheating, FTA

**Table 7** Different events related to OTH and their occurrence probabilities

Number	Component	Symbol	Probability
1	Subunit	SU	0.0067
2	Breakage	BR	OR-gate
3	Subunit	SU	0.0067
4	Loosness	LO	OR-gate
5	Pump	P	0.0067
6	Material failure–general	MFG	OR-gate
7	Heat exchanger	HE	0.0067
8	Exhaust	EH	0.0067
9	Overheating	OV	OR-gate
10	Pump	P	0.0067
11	Vibrations	VI	OR-gate

and corresponding subsystems by defining weak points from the perspective of the failure probability. Then, applying redundant system design and comparing results with and without redundancy provides essential insights regarding maintenance planning. Thanks to redundant system design, failure probability can be decreased for weak points, so ships that navigate long distances can perform more sustainable operations. Otherwise, a maintenance team should be transferred to the ship location to fix the system and sustain the ship’s navigation. In this sense, investing in the redundant system could save costs from maintenance and operational expenses. In addition, maintenance planning for the port durations of a ship with higher autonomy degree can be managed by examining failure probability with redundant system arrangement.

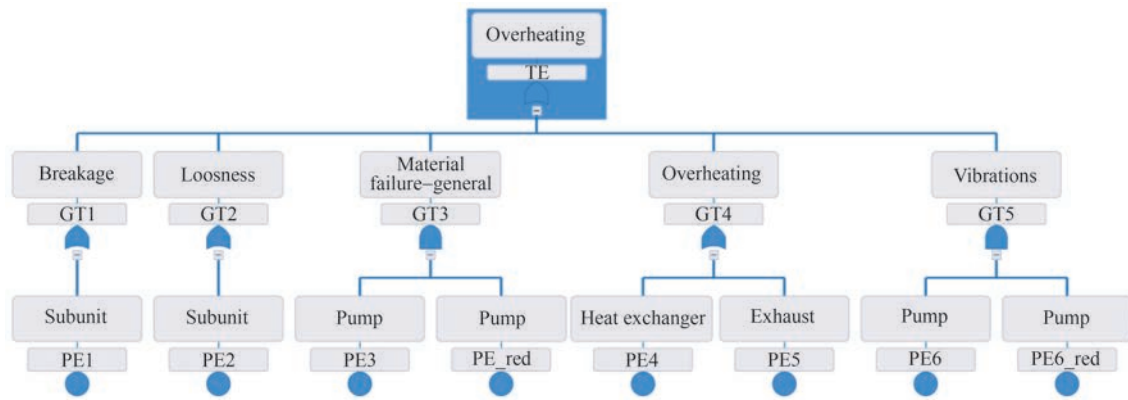


Figure 22 Overheating, FTA, redundancy

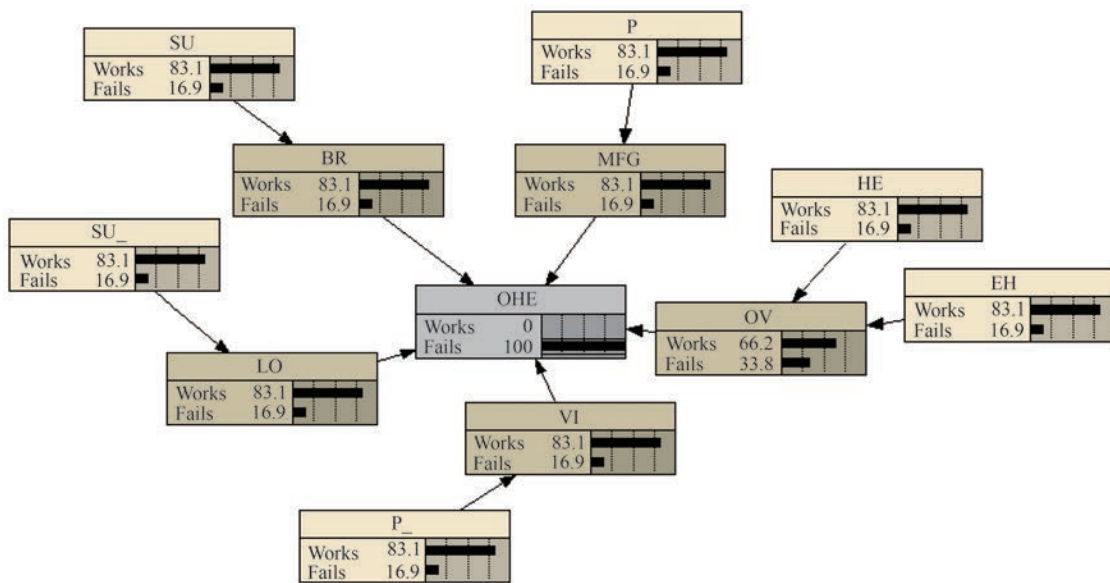


Figure 23 BN representing OHE

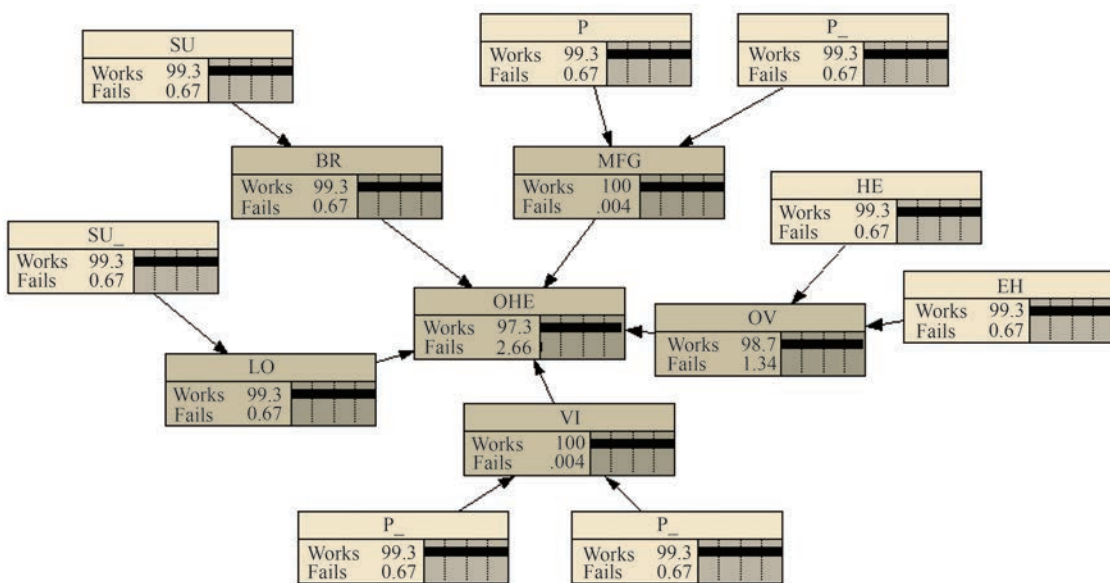


Figure 24 BN representing OHE redundancy

**Table 8** Prior and posterior probabilities of different events related to OTH

Number	Component	Symbol	First modelling		Redundancy	
			Prior	Posterior	Prior	Posterior
1	Subunit	SU	0.0067	0.169	0.00670	0.2520
2	Breakage	BR	0.0067	0.169	0.00670	0.2520
3	Subunit	SU	0.0067	0.169	0.00670	0.2520
4	Loosness	LO	0.0067	0.169	0.00670	0.2520
5	Pump	P	0.0067	0.169	0.00670	0.0083
6	Pump	P	–	–	0.00670	0.0083
7	Material failure–general	MFG	0.0067	0.169	0.00004	0.0017
8	Heat exchanger	HE	0.0067	0.169	0.00670	0.2520
9	Exhaust	EH	0.0067	0.169	0.00670	0.2520
10	Overheating	OV	0.0134	0.338	0.01340	0.5020
11	Pump	P	0.0067	0.169	0.00670	0.0083
12	Pump	P	–	–	0.00670	0.0083
13	Vibrations	VI	0.0067	0.169	0.00004	0.0017
14	Overheating	OHE	0.0395	1	0.02660	1

## 5 Conclusions

This paper investigates reliability of combustion engine by means of FTA and BN. Bayesian Networks offer a robust framework for analysing the reliability of complex systems, demonstrating greater adaptability and flexibility compared to FTA. A detailed examination of the combustion engine reveals several key factors essential to system reliability and safety. Critical failures such as: ELU, FTS, STP, HIO, OHE, and NOI have been identified as significant risks to the operational efficiency of the combustion engine, necessitating careful management and risk mitigation strategies. To enhance system safety, the paper proposes the implementation of redundancy of the parts that have the greatest failure rate to reduce the likelihood of accidents of overall system.

The main conclusions of this study can be summarized as follows:

1) Fault trees rely on strict Boolean logic with only AND and OR combinations, while BNs provide greater flexibility by allowing multiple states per node and more general ways to combine influences, making them an extension of fault trees for reliability analysis. BNs update prior probabilities to more specific posterior probabilities by incorporating new observations, offering insights that better reflect the characteristics of the specific accident studied.

Six failure events—ELU, FTS, STP, HIO, OHE, and NOI—can lead to critical failure, with ELU and FTS having the greatest impact, largely driven by leakage and gen-

eral mechanical failure.

2) Probability of ELU occurrence is decreased by 31.88% by adding redundant pump and piping.

3) Probability of FTS occurrence is decreased by 36.45% by adding redundant battery.

4) Probability of OHE occurrence is decreased by 42.78% by adding redundant pump.

5) Adding redundancy decreases the probability of failure occurrence but at the same time increases the cost and makes the system more complicated. But if the cost of failure is high, as in case of autonomous shipping, redundancy is often an attractive option.

Future research needs to be focused on redundancy of ship machinery with respect to higher autonomy degree. With the increasing adoption of autonomous systems in marine installations, reliability and safety are highlighted as essential prerequisites for their successful deployment. In this sense it is desirable to establish relation between costs and redundancy in order to prove that the autonomous vessels are as safe as their conventional equivalents. Autonomous systems must maintain a high level of reliability to ensure stable and safe operation under varying conditions. Additionally, it is crucial to guarantee that these systems can effectively detect and respond to critical situations, such as ELU, FTS and OHE faults, in order to reduce the risks of significant malfunctions or operational disruptions. Ultimately, the advancement of autonomous systems in marine installations marks a pivotal step toward a more efficient, safer, and competitive maritime industry.

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**Competing interest** The authors have no competing interests to declare that are relevant to the content of this article.

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