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Research paper



A data-driven dynamic Bayesian network for health monitoring and maintenance decision support of marine diesel engines

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A B S T R A C T

Performance monitoring and maintenance decision-making are critical components of machinery management for ensuring the safety, reliability, and operational efficiency of maritime systems. Recent advances in sensor technologies, data transmission capabilities, machine learning, and knowledge management have accelerated the transition from traditional fixed-interval maintenance towards condition-based and predictive maintenance strategies in the maritime industry. However, the health assessment of large two-stroke marine diesel engines remains challenging due to the presence of multiple interdependent operational parameters and their temporal uncertainties under varying sea and operational conditions. To address these challenges, this paper proposes a novel data-driven Dynamic Bayesian Network (DBN) framework for the health monitoring and maintenance decision support of large two-stroke marine diesel engines. The proposed framework integrates 15 operational parameters within a unified probabilistic model to capture temporal degradation and quantify health uncertainty through dynamic probabilistic reasoning. The framework was validated using operational data from a six-cylinder MAN B&W 6S50MC-C main engine. A five-day case study showed that cylinders 4 and 6 remained in the AMBER health state, while cylinder 5 was predicted to deteriorate from GREEN to AMBER after two days of operation, demonstrating the model's capability to predict health degradation trends. Sensitivity analysis identified Total Base Number (TBN) and iron content as the most influential indicators affecting engine health. Furthermore, water mist catcher performance, fuel viscosity, and exhaust temperature deviation exhibited the largest temporal variations, with average deviations of 4.31%, 3.91%, and 3.37%, respectively. The results demonstrate that the proposed DBN framework effectively captures temporal dependencies and operational uncertainty, enabling dynamic health assessment and risk-informed maintenance decision-making. By integrating multiple interdependent degradation factors within a unified probabilistic framework, the proposed approach provides an effective tool for condition-based maintenance and establishes a practical foundation for future maritime digital twin and intelligent maintenance applications.

Nomenclature

CCAI	Calculated Carbon Aromaticity Index
CPT	Conditional Probability Table
CREAM	Cognitive Relaibility and Error Analysis Method
DAG	Direct Acyclic Graphs
DBN	Dynamic Bayesian Network
DFT	Dynamic Fault Tree
EER	Emergency Escape & Rescue

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FEAP	FOBAS Engine Assessment Programme
FOBAS	FOBAS Oil Bunker Analysis & Advisory Service
GT	Gross Tonnage
LS2S	Low-Speed Two-Stroke (Marine Diesel Engine)
MARPOL	International Convention for the Prevention of Pollution from Ships
MIC	Microbiologically Influenced Corrosion
MIP	Mean Indicated Pressure
TBN	Total Base Number
TPT	Transition Probability Table
WMC	Water Mist Catcher

1. Introduction

Reliable propulsion performance is of paramount importance for ensuring maritime safety, operational continuity, and economic efficiency in shipping operations. Large low-speed two-stroke (LS2S) marine diesel engines remain dominant in propulsion systems for ocean-going vessels, accounting for a substantial proportion of the global merchant fleet (Sea-web, 2020). Due to the critical role of propulsion systems in maritime transportation, marine propulsion failures may lead to severe operational disruptions, costly emergency repairs, environmental risks, and, in extreme cases, catastrophic maritime accidents. An analysis of marine accident investigations reveals that machinery failure accounts for around 24% of marine accidents in the UK merchant fleet for ship sizes exceeding 100 GT (Douglas, 2007). Maintaining the smooth operation of large two-stroke marine engines is crucial, as propulsion failures result in significant economic loss in the form of costly repair bills and disruptions to the vessel schedule. The Swedish Club (2018) reported that machinery-related claims make up approximately 47% of insurance underwriters' total claims. Out of these machinery claims, 28% are related to main engine damage, which incurs the highest costs, averaging around USD 650,000 per claim. These statistics highlight the critical importance of improving the reliability, health monitoring, and maintenance management of marine propulsion systems.

Despite continuous advances in engine design, control technologies, and operational management, large two-stroke marine diesel engines continue to operate under highly dynamic and uncertain maritime environments. Variations in operational conditions, fuel quality, engine loading profiles, and sea states significantly complicate machinery condition assessment and maintenance planning. Furthermore, evidence from industrial operational data indicates that marine engine failures are often caused by multiple interdependent factors rather than isolated single-component faults. For example, the Lloyd's Register (LR) fuel-testing business, Fuel Oil Bunker Analysis and Advisory Service (FOBAS), regularly deals with fuel-related operational issues reported by ships participating in their fuel-testing program. Over a six-month period from November 2019 to June 2020, FOBAS observed a twofold increase (from 15% to 31%) in the number of cases involving cylinder component damage in diesel engines. Notably, all of these cases were linked to the ships' large two-stroke main engines (FOBAS, 2020). Investigations into these incidents revealed that complex interactions among multiple operational and degradation-related factors contributed to engine failures. Such characteristics demonstrate the necessity for advanced health monitoring frameworks capable of dynamically modelling temporal dependencies, operational uncertainty, and interdependent degradation behaviours in marine propulsion systems.

Traditional maintenance strategies in the maritime industry have historically relied on fixed-interval or schedule-based maintenance practices. Although such approaches provide a basic level of operational reliability, they often fail to adequately capture the actual machinery condition and degradation behaviour under real operating conditions. As a result, conventional maintenance approaches may either lead to premature maintenance actions or increase the risk of unexpected failures and emergency repairs.

Recent developments in intelligent maritime systems, sensor technologies, and digital data acquisition have accelerated the transition from traditional maintenance strategies towards condition-based maintenance and predictive maintenance frameworks. Modern marine engines are increasingly equipped with advanced monitoring systems capable of continuously collecting large volumes of operational and performance-related data. Together with advances in machine learning, probabilistic reasoning, and knowledge management technologies, these developments provide new opportunities for intelligent health monitoring and maintenance decision support in maritime systems. In particular, emerging technologies such as digital twins, probabilistic health assessment, and intelligent maintenance frameworks have demonstrated strong potential for improving machinery condition awareness, operational reliability, and maintenance efficiency across complex engineering systems.

Among the available approaches for machinery health management, probabilistic methods have attracted growing attention due to their capability to model uncertainty and dynamically infer machinery conditions from incomplete and noisy operational data. Bayesian Networks (BN) and Dynamic Bayesian Networks (DBN), in particular, provide powerful frameworks for representing causal relationships, temporal dependencies, and uncertainty propagation within complex engineering systems. Compared with conventional deterministic or static data-driven approaches, DBN is capable of continuously updating machinery health states over time as new operational information becomes available. Such characteristics make DBN particularly suitable for maritime applications, where engine performance and degradation behaviour are strongly influenced by uncertain and time-varying operational environments.

Several studies have investigated the application of machine learning, fault diagnosis, and condition monitoring techniques for marine engine systems. Existing research has explored methods including artificial neural networks, support vector machines, fuzzy logic systems, and Bayesian inference techniques for machinery fault detection and performance monitoring. Nevertheless, the current literature still exhibits several important limitations. First, many existing studies focus on a limited number of operational parameters and fail to comprehensively represent the complex interdependencies among engine health indicators. Second, numerous existing approaches employ static modelling frameworks that inadequately capture the temporal evolution of machinery degradation and operational uncertainties. Third, many current studies primarily focus on fault detection and classification tasks while providing limited support for maintenance-oriented health assessment and intelligent maintenance decision-making. Consequently, there remains a strong need for uncertainty-aware and dynamically adaptive health monitoring frameworks capable of supporting intelligent maritime maintenance applications under realistic operational conditions.

To address these research gaps, this paper proposes a novel data-driven Dynamic Bayesian Network framework for the health monitoring and maintenance decision support of large two-stroke marine diesel engines. The proposed framework integrates multiple interdependent operational variables and temporal characteristics within a unified probabilistic modelling environment to dynamically assess engine operational health conditions. Operational data obtained from Lloyd's Register databases are analysed and incorporated into the DBN framework to enable uncertainty-aware machinery condition inference and maintenance-oriented health evaluation.

Compared with existing marine engine health monitoring approaches, the proposed framework offers several important advantages. First, the developed DBN model enables dynamic probabilistic reasoning by incorporating temporal dependencies among engine operational parameters. Second, multiple interdependent degradation-related factors are integrated into a unified health assessment framework, allowing more comprehensive machinery condition awareness. Third, the

proposed approach supports maintenance decision-making through probabilistic health evaluation and dynamic operational state inference. Furthermore, the developed framework provides practical implications for condition-based maintenance and future intelligent maritime maintenance systems, while also offering potential relevance for probabilistic digital twin applications in maritime engineering.

The main contributions of this study are summarised as follows:

(1) A novel data-driven DBN framework is developed for the health monitoring and operational condition assessment of large two-stroke marine diesel engines.
(2) Multiple interdependent operational and temporal factors are integrated into a unified probabilistic framework for uncertainty-aware machinery health assessment.
(3) The proposed framework supports maintenance decision-making through dynamic health inference and probabilistic operational state evaluation.

2. Literature review

This section reviews the existing applications of DBN in the maritime and offshore domain. It summarizes recent studies and compares their strengths and limitations. This review identifies the research gap and provides the motivation for the proposed DBN framework.

2.1. DBN applications in maritime and offshore engineering

DBN have been increasingly adopted in maritime and offshore engineering applications to model time-dependent processes such as maritime navigational safety (Çelik et al., 2026; Guo et al., 2023; Q. Liu et al., 2023), offshore oil and gas operational safety (Dong et al., 2026; Hamdan and Wang, 2024; C. Wang et al., 2021), risk management of subsea pipelines (Yazdi et al., 2023), maritime accidents (Qiu et al., 2026), oil spills (Liu et al., 2023) in particular, machine operation safety (Ahmed et al., 2023; Guo et al., 2022; Han et al., 2024), structural safety (Morato et al., 2022), and so on. DBN applications are mainly categorised by their ability to account for the dynamic structure of variables in a temporal space.

A risk evaluation analysis of ship pilotage operation in the Yangtze River estuary was conducted by using a DBN model which was integrated with the Functional Resonance Analysis Method (FRAM) (Guo et al., 2023). In the DBN model, the uncertainty methods used for the configuration of Prior Probabilities (PP), Conditional Probability Tables (CPTs), and Transition Probability Tables (TPTs) include the Dempster-Shafer (D-S) theory, a Parameter Adaptive Learning Algorithm (PALA), and a Markov chain, respectively. As a result, it is crucial to emphasise that the superposition between the wind-current factors and navigation density factors will result in a notable escalation in collision risk. Z. Li et al. (2022) developed a risk performance model based on the DBN and D-S evidence theory to increase ship navigation safety in Arctic waters. The model covers both subjective data from expert judgment and objective data from marine meteorology and shipborne sensors. The inference of collision risk performance of LNG carriers, along with the main influential factors, was observed for 24 h. The primary risk encountered in Arctic summer waters arises from challenging-to-detect obstacles, icebergs, and reefs, within the channel. In addition to the dynamic risk assessment of surface vessels, the navigational safety of underwater vehicles was assessed by the DBN method through structure learning and parametric learning based on the D-S evidence theory along the pre-defined route plan (M. Li et al., 2022). Here, DBN also demonstrated a notable capacity for integrating qualitative data and quantitative data based on underwater vehicle records for 14 days. Hu et al. (2025) proposed a hybrid HMM–DBN approach to evaluate the resilience of maritime traffic systems involving LNG-fueled vessels, highlighting the effectiveness of DBN in capturing complex temporal interactions among vessel operations, environmental conditions, and safety-related factors. Similarly, Ge et al. (2026) developed a DBN-based framework integrated with Markov chains to assess the time-varying resilience of maritime LNG transportation systems under natural, human-related, intentional, and geopolitical disruptions. By representing resilience through robustness, redundancy, rapidity, and resourcefulness, the framework enabled changes in system performance and subsequent recovery to be evaluated over time, identifying port management and operational efficiency as major contributors to overall resilience. Beyond these applications, recent studies have extended DBN-based risk modelling to different navigational environments and operational scales. Vairo et al. (2026) incorporated the temporal progression of tanker voyages into a DBN framework, allowing navigational risk to be updated across successive transit phases in constrained waterways. At a broader geographical scale, Zou et al. (2026) combined environmental observations with DBN modelling to investigate the spatiotemporal variation of coastal shipping risk, revealing marked regional differences associated with seasonal and extreme weather conditions. Similar approaches have also been applied to navigation under more complex operational and security conditions. Zhu et al. (2024) integrated STPA with DBN to evaluate convoy operations in Arctic ice-covered waters, identifying sea ice and crew-related factors as major contributors to operational risk. Meanwhile, Fan et al. (2024) examined the temporal risk profile of maritime trade routes through a DBN incorporating accident and security-related information, demonstrating how the relative influence of threats such as terrorism, piracy, and military conflict can vary over time. From a collision-avoidance perspective, Mahipala et al. (2026) employed a DBN to predict the response behaviour of manned vessels within a collaborative collision-avoidance framework for mixed manned-unmanned traffic. By accounting for the likely intentions and reactions of conventionally operated vessels, the approach supported more informed manoeuvring decisions by autonomous vessels.

The reason for the extensive implementation of DBN in the context of offshore oil and gas operational safety can be attributed to its relevance to the marine operation environment. Within the framework of DBN applications, dynamic risk assessment of offshore operation stages such as drilling (C. Wang et al., 2022), gas hydrates depressurisation (C. Wang et al., 2021), and plugging and abandonment (C. Wang et al., 2023) are thoroughly examined. For instance, Wang et al. (2022) developed an uncertain DBN through the transition probability matrix to perform dynamic risk analysis of deepwater gas hydrate drilling for 20 days of operational duration. In the methodology, the prior probability of equipment failures was quantified through the utilisation of fuzzy theory and expert judgment. The transformation from the Bow-Tie (BT) model to the Bayesian Network (BN) model was achieved by means of a mapping algorithm. Wu et al. (2022) presented a hybrid-DBN approach with the purpose of dynamically analysing the performance of safety barriers in the drilling operation stage to prevent subsea downhole leakage incidents. To account for the dynamic impact during continuous inspection phases, multi-state-based multiphase Markov models were formulated. A fault tree model was configured to facilitate the analysis of leakage causes and logical causality, and then it was translated into a BN at the beginning of the dynamic analysis. Liu et al. (2022) presented a novel approach utilising a DBN and the Kauffman NK model to quantify the level of risk coupling in subsea blowout accidents during drilling operations. This study defined the various forms of risk coupling resulting from human, electrical, hydraulic, and mechanical factors. Here, the NK model has been employed to assess the extent of correlation and risk coupling among the factors associated with unsafe events. While offshore natural gas hydrate production was in operation, C. Wang et al. (2021) developed a GO method-based model to prevent the secondary formation of natural gas hydrates and then mapped it into the DBN model. To reduce the impact of subjective factors on the Cognitive Reliability and Error Analysis Method (CREAM) calculations, G1 and entropy weight methods were combined with the weighting method, which was called the fuzzy CREAM method, as an improved

version of the traditional CREAM. After an offshore well is abandoned, it is necessary to perform the Plugging and Abandonment (P&A) operation. Wang et al. (2023) proposed an assessment approach based on the DBN to analyze the dynamic risk associated with riserless intervention systems in the P&A operation. In the methodology part, the DBN derived from a fault tree model was interconnected with the DBN derived from the GO model, resulting in the comprehensive DBN graph structure for each phase. The results indicated that the reservoir abandonment phase exhibited the most significant impact on the risk associated with the P&A operation process. The objective of the DBN application was to guide operators during 360 h for the execution of a mission, ensuring the safe and reliable achievement of mission objectives. Due to its inherent characteristics, an offshore platform is susceptible to various accidents, such as the release of hazardous chemicals, fires, and explosions. Consequently, the implementation of Emergency Escape and Rescue (EER) plans assumes a critical role as the final protective measure to safeguard personnel safety in the event of a significant accident (Callesen et al., 2021). Y. Wang et al. (2021) conducted a DBN-based quantitative analysis of the reliability of different EER strategies implemented on offshore platforms. In the DBN model, the methods for the configuration of CPTs and TPTs were based on the Bayesian estimation method with a junction tree reasoning engine and a Markov method, respectively. As a result, the reliability of the emergency evacuation was expected to exhibit a progressive increase due to human errors and organisational factors over a 10-year time slot.

The utilisation of DBN applications for managing the integrity risks associated with Microbiologically Influenced Corrosion (MIC) in subsea pipelines is quite widespread. Solutions enable decision-makers to select the most optimal combination of integrity management actions, considering the trade-off between reliability and cost. For example, Yazdi et al. (2023) presented a multi-objective functional approach that incorporated Dynamic Continuous Bayesian Network modelling, aimed at minimising the operational risk associated with MIC over a 40-year period. In addition to the DBN phase, during the optimisation phase, the Genetic Algorithm (GA) was employed as a stochastic approach to attain optimal solutions, primarily due to its extensive effectiveness and efficient ability to conduct global searches. One further resilience assessment of a subsea pipeline employing DBN was introduced by Yazdi et al. (2022) in order to maintain the performance under the time-varying interdependent stochastic conditions in a period of 0-70 months. Prior probabilities in the DBN model were obtained by the Best Worst Method (BWM). In addition, Adumene et al. (2021) conducted a dynamic risk analysis of marine and offshore systems subjected to stochastic degradation caused by microbial influence in order to capture the key factors. As an advantage of the DBN, the model effectively captured the dynamic non-linear interactions from corrosion influencing factors, enabling accurate predictions of the degradation rate of offshore systems during operation. More recently, Yakubu et al. (2026) developed a DBN-based framework to represent the progressive risk associated with corrosion under insulation in offshore pipelines, linking susceptibility and degradation states with time-dependent failure consequences. The framework also accommodates newly available inspection or operational information, supporting the evaluation of alternative inspection and mitigation strategies as pipeline conditions evolve.

Maritime emergencies and accidents can evolve dynamically under changing operational and environmental conditions, making the assessment of their progression and potential consequences an important area for DBN applications. Among these applications, oil spills pose significant risks to the marine ecosystem, particularly under extreme weather conditions. Z. Liu et al. (2023) introduced an innovative DBN-based approach for dynamically assessing and quantifying the risk of oil spills under extreme wind conditions. The proposed approach was implemented on the Laizhou Bay. The primary dynamic variable in this study was the wind speed, which was continuously monitored and recorded over a period of 24 h. The dispersion relation of oil in water was also represented in the DBN model. The model has the capability to effectively handle uncertainty. Furthermore, this method exhibits a universal nature and can be applied to different fields. Zhang et al. (2026) proposed a scenario-driven DBN framework to support emergency decision-making in ship oil spill accidents. By combining scenario prediction with probabilistic inference, the study enabled the assessment of accident evolution pathways under alternative response measures, demonstrating the capability of DBN to support adaptive and proactive emergency management in complex maritime incidents. Beyond oil-spill response, DBN has increasingly been employed to represent the temporal development of maritime accident and emergency scenarios. Qiu et al. (2026) combined information extracted from accident reports using a large language model with a two-slice DBN to examine transitions from primary to secondary accidents and identify the factors governing their subsequent consequences. Focusing specifically on ship fires and explosions, S. Wang et al. (2026) integrated ontology-assisted text mining with a multi-slice DBN to reconstruct causal dependencies and model the progression from precursors to fire initiation and subsequent escalation. DBN-based emergency evolution has also received particular attention in Arctic shipping. T. Wang et al. (2025) modelled grounding emergency scenarios by jointly considering changing environmental conditions, available response resources, and emergency actions across different Arctic seas. In a related data-driven study, T. Wang et al. (2025) investigated multiple types of Arctic maritime accidents and showed that both environmental conditions and the effectiveness of response measures can substantially alter the subsequent evolution of an emergency scenario.

From the view of machine operation safety, an investigation into the operational reliability of a marine electrical propulsion system was conducted using a DBN method as a case study (Guo et al., 2022). In the methodology, multidimensional monitoring data from sensors were mapped into component states by applying an XGBoost technique. The CPTs were quantified through the utilisation of the confusion matrix. The system's operational reliability was subject to monitoring over 360 h, divided into four phases. Based on temporal observations, the decision was made to intervene in the system during the phase characterised by low reliability. Building on this direction, Meng et al. (2026) combined real-time fault diagnosis with DBN inference to continuously update the reliability of a diesel-electric hybrid propulsion system for MASS, connecting component-level condition information with system-level reliability assessment. Similarly, Luo et al. (2026) addressed the coupled behaviour of software and hardware in intelligent ship systems by integrating Petri nets with DBN, enabling fault propagation paths and their effects on autonomous navigation system reliability to be represented dynamically.

Additionally, researchers also conducted research based on DBN in maritime-related applications. For example, Cao et al. (2025) developed a DBN-based reliability framework for ship standby systems, demonstrating the capability of DBN to represent the dynamic effects of redundancy and maintenance actions over extended operational periods. Similarly, L. Wang et al. (2025) coupled DBN with particle filtering for online fatigue assessment of floating offshore wind turbine mooring lines, enabling cumulative fatigue damage to be updated sequentially from monitoring information and providing a basis for condition-informed maintenance decisions. Tobon-Mejia et al. (2012) used DBN to diagnose and predict the wear in a machining tool. P. P. Y. Wu et al. (2018) used DBN inference to evaluate the environmental impact of dredging on seagrass. Nie et al. (2019) applied a DBN method to estimate the effects of rainfall intensity on slope failure (sliding) and make a comparison with the results based on the logistic regression and a deterministic method. Qian et al. (2020) employed a DBN for risk assessment and comparison of five key areas of Northwest Arctic navigational safety at different times over the past 10+ years. Tran et al. (2020) modelled the degradation patterns of timber structures to determine the reliability aspects using a DBN. When analysing the variances in application methods employed by well-established studies in

this particular field, Ramírez and Utne (2015) used parametric models, simulating the changing conditions of the system over time, complemented with Monte-Carlo simulation. Similarly, Jiang and Lu (2020) utilised a Poisson distribution equation to determine the probabilities at multiple discrete time slices. Moreover, Murphy (2002) provided a detailed overview of DBN learning, inference and a combination of algorithms which can be applied based on the context and problem statement. Weber and Simon (2016) explored various modelling options, such as the use of Dynamic Fault Trees (DFTs), which also employ a graphical representation. However, DFTs show limitations in terms of representing a binary state, making them less suitable for modelling a multi-state system. The study identifies DBNs as particularly useful in this regard, as they enable the assessment of machinery degradation while taking into account operational factors with multiple states.

The results of the above-mentioned literature analysis stimulate the new exploration of using the DBN in the health assessment of two-stroke marine engine modelling because of its revealed advantages, including:

(1) Temporal modelling: unlike the conventional BN, DBN incorporates a temporal dimension, enabling the representation of changes over time. This is particularly beneficial for understanding and modelling the probability of engine health satisfaction as influenced by the daily-based schedule in this work.
(2) Improved understanding: DBN offers a deeper insight into how systems evolve over discrete time intervals, making them invaluable for understanding complex relationships between the nodes in the model.
(3) Enhanced decision-making: The graphical nature of DBN simplifies the representation of intricate systems, facilitating more effective decision-making in diverse and uncertain conditions. A deep analysis of DBN applications is carried out in the subsequent part to compare the details and the research content.

2.2. Comparative analysis of DBN applications

As listed in Table 1, the comparison of DBN applications reveals how integrating the time dimension improves the effectiveness of conventional BN models. There does not seem to be a standardised DBN model development process, and these studies have followed a few unique pathways tailored to specific applications. According to Table 1, some important findings from the above studies are summarised as follows:

(1) Parameter learning and assigning a suitable temporal dimension largely depend on the chosen time slices, whether they are hours, days, months, or years, for granularity.
(2) The critical aspect is to devise an appropriate method for establishing TPTs. A common approach involves using statistical modelling techniques (e.g., Gaussian, Poisson, or Monte-Carlo distributions) in combination with expert judgments and real data. However, the choice of method should align with the system boundaries, DBN structure, and availability of data.
(3) Software selection offers two options, with both providing adequate DBN functionality. However, the results may depend on data-handling capacity and functionality, as DBN (relying on time slices) can become computationally intractable.
(4) DBN sensitivity analysis can be employed to gauge the proportional impact of specific parameters on the output and vice versa.
(5) For further development of DBN capabilities as a diagnostic and prognostic tool in certain applications, it is essential to define key failure modes and operational limits for comparison.

Table 1 provides a comparative overview of DBN applications across maritime, offshore, and other relevant engineering domains, covering studies published between 2013 and 2026. The literature was identified through searches of major academic databases using combinations of keywords such as “dynamic Bayesian network”, “maritime safety”, “offshore safety”, “navigation risk”, “reliability”, and “risk assessment”, complemented by relevant studies identified through reference screening. Studies were selected based on their relevance to the application of DBN for dynamic risk, safety, reliability, degradation, resilience, and emergency assessment, and were compared in terms of research area, methodology, software, dataset, temporal structure, and research focus. While the comparison was intended to capture representative developments rather than constitute a systematic review, potential selection bias may remain due to the chosen databases, search terms, and relevance-based screening.

Although previous studies have demonstrated the effectiveness of DBN in dynamic risk assessment, reliability analysis, and prognostic applications, several important limitations remain. First, existing studies are typically developed for specific applications, such as navigational safety, offshore operations, or machinery reliability, and rarely provide a unified framework capable of jointly modelling multiple interdependent operational parameters for marine diesel engine health assessment. Second, transition probability specification and parameter learning often rely on expert knowledge or application-specific assumptions, limiting model generalisability and practical adaptability. Third, dynamic health assessment is seldom integrated with maintenance decision support, particularly for large two-stroke marine diesel engines operating under uncertain and time-varying conditions. These limitations highlight the need for a unified probabilistic framework that captures temporal dependencies, quantifies operational uncertainty, and supports condition-based maintenance decision-making. This need motivates the DBN framework proposed in this study.

3. Methodology

The BN models are based on Directed Acyclic Graphs (DAGs) to facilitate reasoning under uncertain conditions (Ramírez and Utne, 2015). However, one of the drawbacks of the conventional BN model is that it represents a static condition and would only reflect the output for a particular time slice (P. P. Y. Wu et al., 2018). The DBN addresses this issue by bringing in the temporal dimension in the BN, which can be extremely useful to understand and model component/machinery degradation as a function of time, maintenance actions and operational factors (Weber and Simon, 2016). Moreover, the graphical nature of DBN makes them valuable tools for simplifying complex, interconnected systems, allowing decision-makers to handle diverse and uncertain conditions more effectively (Khan et al., 2020).

In essence, a DBN is an extension of a regular BN designed to capture changes that unfold over discrete time intervals (Cai et al., 2013). A DBN model typically includes at least two time slices, representing the temporal progression, as illustrated in Fig. 1, encompassing the current time, t, and a subsequent time slice, $t+1$.

The variables Z (leaf/target node) are linked to X, Y and N (parent nodes) within each time slice (t & $t+1$) through intra-slice connections, while inter-slice (temporal) arcs connect the nodes X_t, Y_t and N_t with X_{t+1}, Y_{t+1} and N_{t+1}. The provided example illustrates a form of dynamic BN inference known as *prediction*, where analysis moves forward from the current time step, t, to a future time step, $t+1$ (Ramírez and Utne, 2015). The other two types of DBN inference are *filtering* and *smoothing*. *Filtering* is used to compute the system state at the current time step, denoted as t, whereas smoothing is employed to determine the state at previous time steps, typically denoted as t-1. In simple terms, smoothing at t-n can be applied for system diagnostics, while prediction at $t+n$ can be utilised for prognostics. The value of n depends on the specific applications. The DBN is capable of supporting both the temporal and non-temporal nodes within the same model. For instance, in the scenario described earlier, X, Y, and N are temporal nodes, whereas node Z is not. However, the posterior probability of node Z could automatically change from Z_t to Z_{t+1} due to the shifting probability of its parent temporal nodes.

For a BN model, a CPT is essential to illustrate the conditional

Table 1
The retrieved DBN studies in the field of marine and offshore operations.

Refs	Research areas	Methods	Software	Datasets	Time slice (Δt)	Research content
Cai et al. (2013)	Offshore (Human factors)	DBN; FT	NETICA	Expert judgements	Weeks; (0:52); $\Delta t = 1$	Discusses how the DBN model is applied to analyze and model human factors' contribution to offshore blowouts. This analysis might involve identifying critical actions, decision points, and the effect of training and procedures.
Ramírez and Utne (2015)	Oil & gas upstream (Machinery degradation model)	DBN	-	Empirical data	Years; (30:50); $\Delta t = 1$	Proposes a methodology for evaluating the remaining useful life of systems that are approaching the end of their expected operational lifespan.
Chang et al. (2019)	Oil & gas upstream (Subsea safety)	DBN	GeNIe	Expert judgements; Fuzzy theory	Months; (0:36); $\Delta t = 1$	Discusses how the DBN model is applied to analyze the risk of wellhead fatigue failure during its service life, considering factors like load cycles, corrosion, and other stressors.
Jiang and Lu (2020)	Maritime (Navigational safety)	DBN	NETICA	Historical accident data	Years; (0:9); $\Delta t = 1$	Explores the use of DBNs to model and predict the factors that contribute to maritime accidents, such as weather conditions, vessel traffic, and other relevant variables.
Khan et al. (2020)	Maritime (Navigational safety)	DBN	GeNIe	Hypothetical data	Hours; (0:7); $\Delta t = 1$	Provides a structured and dynamic approach to understand and mitigate the risks associated with navigation in icy and challenging environments.
Kammouh et al. (2020)	Resilience (Transportation systems)	DBN	GeNIe	Literature research	Sequential; ($t = 0, 1, 2, \ldots$)	Identifies how the framework is applied to evaluate the resilience of engineering systems. This could involve assessing the system's response to various disruptions, identifying critical components, and making recommendations for improving resilience.
Liu et al. (2020)	Oil & gas upstream (Subsea safety and degradation)	DBN	NETICA	OREDA database	Hours; (1:10000); $\Delta t = 1000$	Focuses on the development and application of a DBN methodology for diagnosing faults in subsea Christmas trees. Subsea Christmas trees are complex and critical components of underwater oil and gas production systems.
Qian et al. (2020)	Maritime (Navigational safety)	DBN	-	Historical data; Real-time data	Monthly; (0:6); $\Delta t = 1$	Explains how the DBN model is applied to assess and predict dynamic environmental risks in the Arctic Northwest Passage, considering factors such as ice melt, navigation hazards, and potential environmental impacts.
Tran et al. (2020)	Civil (Reliability and inspection)	DBN	-	Inspection data	Years; (0:40); $\Delta t = 1$	Model the spatial deterioration of timber structures subjected to decay, considering factors such as moisture content, fungal growth, and structural degradation.
C. Wang et al. (2020)	Oil & gas upstream (Subsea maintenance methods)	DBN	NETICA	OREDA database	Monthly; (0:300)	Analyzes how these maintenance methods (like regular check-ups, fixing issues when they arise, or maintenance based on condition monitoring) impact the system's reliability (how well it works) and availability (how often it's operational).
Y. Wang et al. (2021)	Oil & gas upstream (Operational safety)	DBN	NETICA	Historical accident data	Years; (0:10); $\Delta t = 1$	Discusses how the DBN model is applied to analyze the reliability of evacuation procedures on offshore platforms during various emergency scenarios, including factors such as response time, available resources, and personnel behavior.
Guo et al. (2022)	Maritime (Machine operation safety)	DBN; XGBoost	GeNIe	Monitoring data	Hours; (1:1000); $\Delta t = 1$	Focuses on the application of a combined methodology using DBN and XGBoost for the operational reliability evaluation of complex systems, electric motor in particular.
Morato et al. (2022)	Civil and Maritime (Structural safety)	DBN; MDP	-	Experimental data; Simulated data	Years; (0:30); $\Delta t = 1$	Plans optimal inspection and maintenance strategies for deteriorating structural components, taking factors such as component condition, inspection schedules, and maintenance interventions into account.
Guo et al. (2023)	Maritime (Navigational safety)	DBN; FRAM	GeNIe	Expert judgements; Literature	Minutes; (0:270); $\Delta t = 6$	Analyzes the evolution of risk in ship pilotage operations over time. This could include examining how various elements and events contribute to risk dynamics.
Z. Liu et al. (2023)	Oil & gas upstream (Oil spill)	DBN	-	Historical environmental data;	Hours; (0:24); $\Delta t = 3$	Discusses how the DBN model is applied to assess the risk of marine oil spills, considering various scenarios and factors that contribute to spill incidents and their impacts.
Yazdi et al. (2023)	Oil & gas upstream (Subsea pipeline safety)	DBN	GeNIe	Inspection data	Years; (0:40); $\Delta t = 1$	Focuses on the development of a dynamic model for managing the integrity and assessing the risk of microbiologically influenced corrosion (MIC) in subsea pipelines, including predicting the potential for corrosion and the implications for pipeline integrity.
L. Fan et al. (2025)	Maritime (Port State Control and ship safety)	DBN; ML	–	Inspection data	Inspections; (1:10); $\Delta t = 1$	Investigates the dynamic effects of ship deficiencies and detention outcomes across consecutive PSC inspections and compares the inspection mechanisms of the Tokyo and Indian Ocean MoUs. The model also evaluates cross-MoU effects to examine how inspection outcomes in one regime influence subsequent ship safety outcomes in another.

(*continued on next page*)

Table 1 (*continued*)

Refs	Research areas	Methods	Software	Datasets	Time slice (Δt)	Research content
L. Wang et al. (2025)	Offshore renewable energy (Structural reliability and fatigue)	DBN; Particle Filter (PF)	OpenFAST MoorDyn TurbSim	Experimental data; Simulated data	Sequential; (t = 0, 1, 2, …)	Develops an online fatigue assessment framework for floating offshore wind turbine mooring lines by combining DBN with particle filtering. The framework continuously updates fatigue damage and crack-growth estimates using sequential loading and environmental information.
T. Wang et al. (2025)	Maritime (Arctic emergency management)	DBN; Markov chain Evidential Reasoning (ER)	–	Historical accident data; Historical environmental data; Emergency-resource information	Days; (0:4); Δt = 1	Models the dynamic evolution of ship-grounding emergency scenarios in Arctic waters by considering changing environmental conditions, emergency measures and the availability of response resources. The model evaluates how these factors influence expected and unexpected accident-evolution pathways across different Arctic seas.
Qiu et al. (2026)	Maritime (Accident evolution and secondary accidents)	DBN; LLM; EM	GeNIe DeepSeek	Historical accident data	Two stages; (t_0: t_1); Δt = 1	Integrates an LLM-based semantic extraction approach with a two-slice DBN to model the progression of maritime accidents from primary to secondary events and their final consequences. The framework extracts structured accident chains from investigation reports and identifies the factors influencing accident escalation.
Meng et al. (2026)	Maritime (MASS propulsion system reliability)	DBN; VMD; Fault diagnosis	–	Component failure-rate data; Operational data	Days; (0:30); Δt = 1	Develops a diagnosis-informed DBN framework for real-time reliability assessment of a diesel-electric hybrid propulsion system for MASS. Component-level fault information obtained through machine-learning-based diagnosis is introduced as dynamic evidence to update system-level reliability and support proactive maintenance decisions.

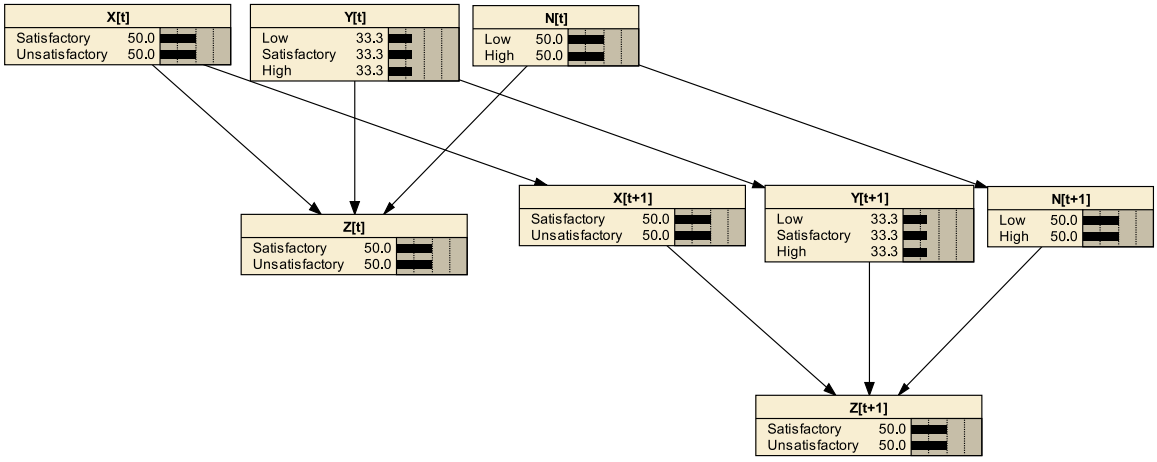


Fig. 1. DBN with two-time slices.

dependence between variables. In contrast, the DBN requires TPTs for nodes connected by temporal arcs to represent probabilistic temporal dependence across different time slices. To construct TPTs, the literature review highlighted several distinct and hybrid statistical approaches, which can broadly be divided into four categories: (1) Expert elicitation, (2) Empirical (operational) data, (3) Statistical and mathematical model simulations, and (4) Combination of any of the above.

3.1. Construct the DBN model

A BN model for engine health assessment has been developed by Usman et al. (2017). It however fails to take into account operational factors and temporal dimensions for Low Speed 2-Stroke (LS2S) engine performance assessment. To improve the BN model and extend it into a new DBN model, the input operational factors influencing the parent nodes in the BN have been reviewed and summarised in Table 2, while the rationale for the selection criteria of these parameters has been documented in Usman et al. (2017) and Usman (2021).

As an example, three conditionally independent factors, namely scavenge air temperature, pressure, and performance of water mist catcher, influence the quality of scavenge air supplied to the LS2S engine. Due to their interrelated nature, the existing BN model is extended to establish these factors as parent nodes affecting scavenge air quality. The other four key parameters are handled in a similar manner, as illustrated in Fig. 2. This model was constructed using Netica.

In Fig. 2, the content of the diagram above the 'green' line contains the nodes that have been incorporated into the DAG developed by Usman et al. (2017) and Usman (2021). For the development of the DBN model, it is crucial to select an appropriate time granularity to demonstrate the model's effectiveness. In the case of LS2S engine operational modelling, it is essential to ensure that the elapsed time between two consecutive data points is not too large, as this could result in the loss of

Table 2
Input operational factors of the BN model.

Operational parameters (influenced factors)	States of influenced factors (children nodes)	Influencing factors (parent nodes)	States of influencing nodes (parent nodes)
Scavenge air quality	1) Satisfactory & 2) Unsatisfactory	Air pressure	1) Low & 2) Satisfactory
		Air temperature	1) Low, 2) Satisfactory & 3) High
		Performance of Water Mist Catcher (WMC)	1) Satisfactory & 2) Unsatisfactory
Fuel quality (at engine inlet)	1) Satisfactory & 2) Unsatisfactory	Catalyst fines level	1) Satisfactory & 2) High
		Viscosity	1) Low, 2) Satisfactory & 3) High
		Water	1) Satisfactory & 2) High
		Ash content	1) Satisfactory & 2) High
		Combustion performance (Calculated Carbon Aromaticity Index (CCAI))	1) Satisfactory & 2) High
Engine maintenance	1) Satisfactory & 2) Unsatisfactory	Work orders completion	1) Satisfactory & 2) Unsatisfactory
		Availability of the asset	1) Satisfactory & 2) Unsatisfactory
Cylinder Lube Oil (CLO) feed settings	1) Satisfactory & 2) Unsatisfactory	Iron content	1) Satisfactory & 2) High
		Total Base Number (TBN)	1) Low, 2) Satisfactory & 3) High
Engine settings	1) Satisfactory & 2) Unsatisfactory	Pmax – Pcomp	1) Low, 2) Satisfactory & 3) High
		Mean Indicative Pressure (MIP) deviation	1) Unsatisfactory & 2) Satisfactory
		Exhaust (temp) Deviation	1) Unsatisfactory & 2) Satisfactory

important information. While some systems can collect data every minute or hour through sensors or onboard monitoring devices, access to such data is often restricted due to non-disclosure agreements between the technology suppliers and the operators.

FOBAS receives regular LS2S engine operations data from ships, which can be utilised for modelling. However, the data collection and sampling intervals are typically months apart, making it challenging to fully represent the dynamic conditions of two-stroke engine operations. Therefore, a 24-h time interval has been considered appropriate for modelling the engine operations through a DBN. This interval aligns with the onboard *noon-figures* routine for detailed entry into the engine-room logbook. Consequently, the data has been collected from the corresponding logbook.

It is important to note that each engine may exhibit variations, especially under changing operational conditions. In this study, an average rate of change is to be considered over 24 h. However, operators who use this assessment model in the future could adjust the rate of change but only when real-time data that supports to fine-tune the time granularity to suit prevailing operational conditions becomes available. Fig. 3 illustrates the flowchart adopted for developing the DBN model for LS2S engine assessment.

There are four key steps, namely: i) generating a DBN from the expanded BN, ii) establishing the transition probability tables, iii) sensitivity analysis and, finally, iv) demonstrating DBN functionality through a case study. In the development of these four steps, the rate of changes of the fifteen parent nodes is subject to a temporal pattern, and TPTs need to be incorporated into the newly developed DBN (Step 1).

3.2. Establish transition probability tables

In this study, a 24-h time interval, aligning with the *noon-figures* routine, has been selected to develop the TPTs. To maintain the model's generality, a panel of experts has been consulted to provide their professional judgements on the average deviations of various engine parameters during the prescribed period.

The adopted approach combines an algorithm with expert judgement to account for the potentially random nature of deviation in two-stroke engine parameters over the defined time period. Given the probabilistic nature of the TPTs development, a suitable probability distribution must be chosen and integrated with the expert opinions.

The Poisson distribution is a discrete probability distribution commonly used to describe the number of random events occurring within a unit of time. In this context, the approach employed by (Jiang and Lu, 2020) has been considered a suitable candidate. This approach assumes the influencing parameters (i.e., occurrences) can be treated as random events following a Poisson distribution. Specifically, the study assumes that the average deviation of a parameter per unit of time is denoted by λ, and the probability of a particular influential factor occurring n times can be calculated as follows:

$$P\{N(t+\Delta t)-N(t)=n\}=\frac{e^{-\lambda\Delta t}(\lambda\Delta t)^n}{n!} \tag{1}$$

If a parameter's output condition changes to fully satisfactory (S) at time t with the quantitative representation of 1, then the probability that the parameter remains unsatisfactory (U) from time t to $t+\Delta t$ (i.e., no change, 0) can be calculated as:

$$\begin{aligned} &P\{N(t,t+\Delta t)=U\,|N(t)=S\}\\ &=\frac{P\{N(t)=U,N(t,t+\Delta t)-N(t)=0\}}{P\{N(t)=U\}}\\ &=\frac{P\{N(t)=U\}\times P\{N(t,t+\Delta t)-N(t)=0\}}{P\{N(t)=U\}}\\ &=P\{N(t,t+\Delta t)-N(t)=0\} \end{aligned} \tag{2}$$

Using Eq. (2) to calculate the values from Eq. (1):

$$P\{N(t,t+\Delta t)-N(t)=0\}=\frac{e^{-\lambda\Delta t}(\lambda\Delta t)^0}{0!}=e^{-\lambda\Delta t} \tag{3}$$

If a parameter condition is satisfactory (S) at time t, the probability that the parameter condition remains satisfactory (S) from time t to $t+\Delta t$ (i.e., 1) can be calculated as:

$$\begin{aligned} &P\{N(t,t+\Delta t)=S|N(t)=S\}\\ &=\frac{P\{N(t)=1,N(t,t+\Delta t)-N(t)=1\}}{P\{N(t)=1\}}\\ &=\frac{P\{N(t)=1\}\times P\{N(t,t+\Delta t)-N(t)=1\}}{P\{N(t)=1\}}\\ &=P\{N(t,t+\Delta t)-N(t)=1\} \end{aligned} \tag{4}$$

Using Eq. (4) to calculate the values from Eq. (1):

$$P\{N(t,t+\Delta t)-N(t)=1\}=\frac{e^{-\lambda\Delta t}(\lambda\Delta t)^1}{1!}=\lambda\Delta t e^{-\lambda\Delta t} \tag{5}$$

For any influential factor, the probability distribution of the next state depends only on the current state and not the sequence of preceding events. Assuming that a parameter's present state is unsatisfactory ($X_t=U$), then the probability of the parameter being satisfactory at

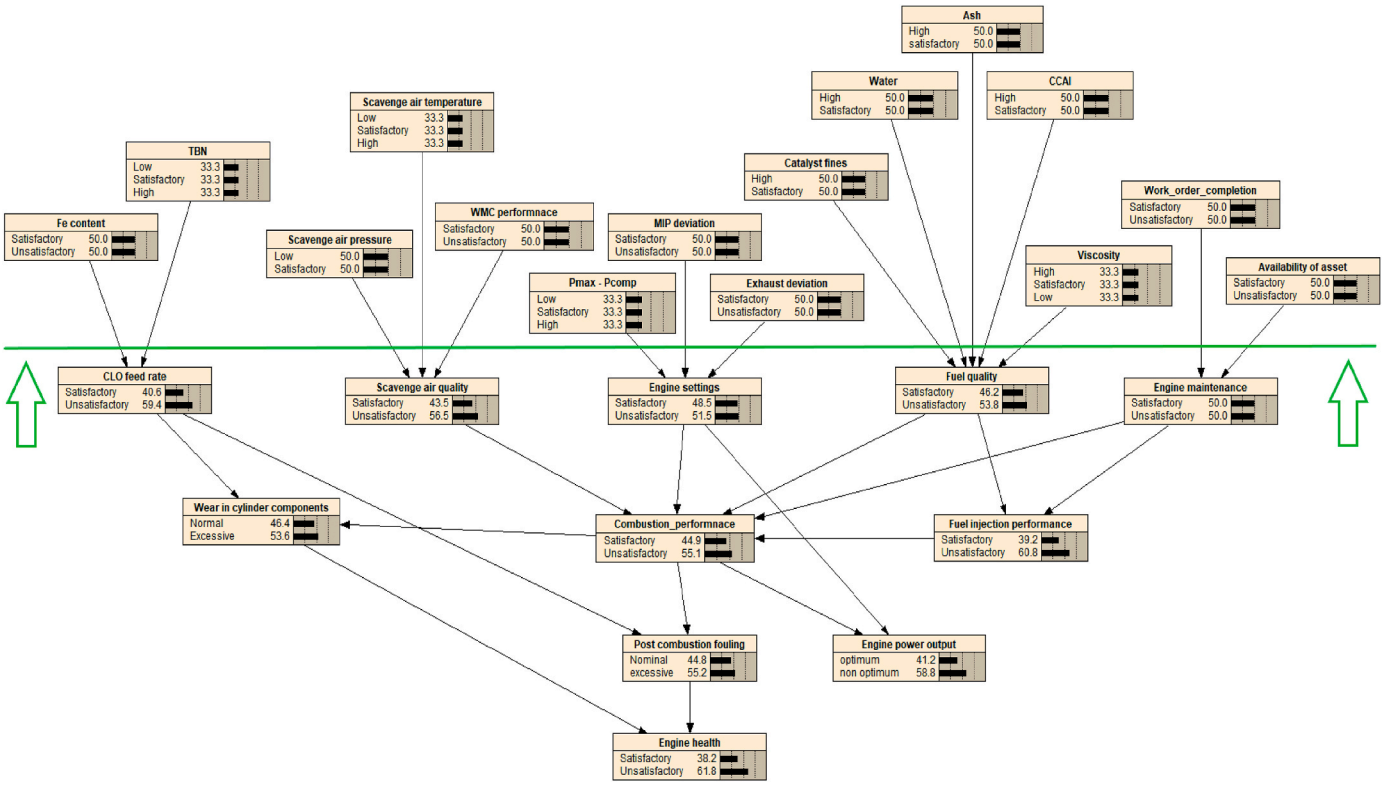


Fig. 2. Expanded BN model for two-stroke engine health assessment.

$t+1$ ($P(X_{t+1} = S \mid X_t = U)$) can be calculated using a Bayesian algorithm equation:

$$P(X_{t+1}=S|X_t=U)=\frac{P(X_{t+1}=S,X_t=U)}{P(X_t=U|X_{t+1}=S)\times P(X_{t+1}=S)+P(X_t=U|X_{t+1}=U)\times P(X_{t+1}=U)}$$

Here, the value of the denominator is equal to 1, hence:

$$P(X_{t+1}=S|X_t=U)=P(X_{t+1}=S,X_t=U)$$

Inserting this into Eq. (5):

$$=P(X_{t+1}=S,X_t=U)=\lambda\times(1)e^{-\lambda\times(1)}=\lambda e^{-\lambda} \quad (6)$$

With

$$P(X_{t+1}=S|X_t=U)+P(X_{t+1}=U|X_t=U)=1$$

Then

$$P(X_{t+1}=U|X_t=U)=1-\lambda e^{-\lambda} \quad (7)$$

Conversely,

$$P(X_{t+1}=S|X_t=S)=\frac{P(X_{t+1}=S,X_t=S)}{P(X_t=S|X_{t+1}=S)\times P(X_{t+1}=S)+P(X_t=S|X_{t+1}=S)\times P(X_{t+1}=S)} \quad (8)$$

Here, the value of the denominator is equal to 1, hence:

$$P(X_{t+1}=S|X_t=S)=P(X_{t+1}=S,X_t=S)$$

Similarly, using Eq. (3):

$$P(X_{t+1}=S|X_t=S)=P(X_{t+1}=S,X_t=S)=e^{-\lambda\times(1)}=e^{-\lambda} \quad (9)$$

$$P(X_{t+1}=U|X_t=S)+P(X_{t+1}=S|X_t=S)=1$$

Then

$$P(X_{t+1}=U|X_t=S)=1-e^{-\lambda} \quad (10)$$

Hence, four probabilistic conditions (Eqs. (6)–(10)) have been derived and listed as follows:

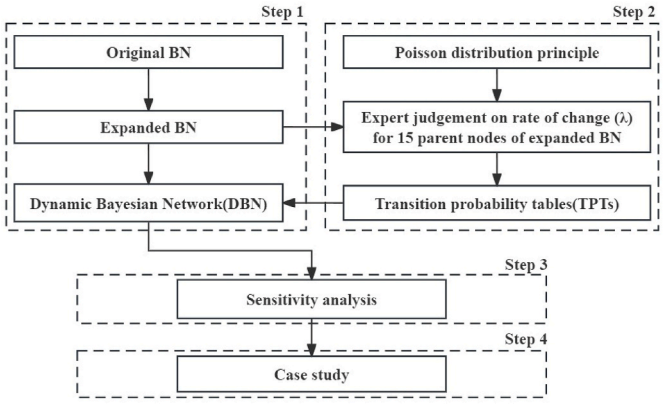


Fig. 3. DBN for two-stroke engine health assessment.

$$\begin{aligned} P(X_{t+1} = S, X_t = U) &= \lambda e^{-\lambda} \\ P(X_{t+1} = U | X_t = U) &= 1 - \lambda e^{-\lambda} \\ P(X_{t+1} = S, X_t = S) &= e^{-\lambda} \\ P(X_{t+1} = U | X_t = S) &= 1 - e^{-\lambda} \end{aligned} \tag{11}$$

In the expanded BN shown in Figs. 2 and 15 parent nodes are identified, and their values may change between time slices, necessitating the development of TPTs for each of them.

These parent nodes exhibit varying 'rates of change' denoted as λ, with some remaining constant throughout a given time frame. For instance, the CCAI value remains unchanged, while others, like MIP deviation, may frequently change depending on operational conditions. Moreover, a few of these changes might be positive (i.e., improvements), whilst others are negative (i.e., degrading performance). Table 3 provides a comprehensive list of the parameters within the DBN, including their temporal dimension and associated descriptions.

In Table 3, the parameters have been divided into three categories:

- Orange shaded (Nos. 1- 4): These are the parameters whose values are likely to deviate in a 24-h period depending on the operational conditions, and corresponding measurements are part of the regular noon-figures.
- Blue shaded (Nos. 5- 11): These are the parameters whose values are likely to deviate in a 24-h period depending on the operational conditions; however, corresponding measurements are not part of the regular noon-figures.

Table 3
List of parent nodes of the DBN with the temporal dimension.

No.	Parameter	Measurement over a time slice
1	Scavenge air pressure	Quantifiable (part of the noon figures). This would vary based on operating conditions such as engine load, T/C performance, and airflow resistance in the scavenge system.
2	Scavenge air temperature	Quantifiable (part of the noon-figures). This would vary based on ambient conditions and the efficiency of the scavenge cooler.
3	Exhaust temp deviation	Quantifiable. It is an integral part of regular record keeping (measurement can be either through local thermometers or remote sensors connected to the engine control system).
4	Viscosity of fuel	Quantifiable: readings are taken through the viscosity controller and gauges at the fuel inlet.
5	Iron content	This is not a regular 24-hour reading unless the ship is fitted with an online condition monitoring device (e.g., liner scan) or carries an onboard testing device. However, there can be a trajectory of increasing iron content to indicate failure propagation (distinguishing between magnetic iron and total iron through onboard testing can be tricky).
6	TBN	Similar to the iron content. It could be determined through onboard testing of drain oil samples; however, it is not a regularly tested parameter.
7	Water mist catcher performance	Water mist catcher performance can be determined by measuring the amount of water collected and comparing this with the expected water collection as described in the engine's operations manual.
8	$P_{max} - P_{comp}$	These pressure measurements are not continuously measured on older engines; however, on newer designs, cylinder pressures are continuously monitored through sensor technology.
9	MIP deviation	Same as item 8 (above).
10	Catalyst fines in fuel	It is usually measured in the bunker drip sample, with ships sometimes taking system samples and sending them to labs for analysis. However, these are not regular 24-hour measurement parameters.
11	Water in fuel	The same comments were made as item 10 regarding catalyst fines.
12	Ash content of the fuel	It should remain constant; however, there may be a rare possibility of minor deviation. This can occur if a small amount of inorganic sediment, settled at the tank bottoms, makes its way to the engine inlet in poor weather conditions. For simplicity, the ash content in fuel has been considered unchanged for the same fuel in use over a 24-hour period.
13	CCAI of fuel	It should remain constant over a 24-hour period, assuming a homogenous blend of fuel is in use.
14	Work order completion	There is no expected deviation in a normal 24-hour period of operation.
15	Asset availability	There is no expected deviation in a normal 24-hour period of operation.

Table 4
The details of the domain experts consulted for the study.

Expert	Experience (Years)	Education (Level)	Expertise
1	25	Bachelor's	Expert 1 currently works for an engine manufacturer and designer. As a marine engineer, the expert has extensive engine operations and maintenance, and troubleshooting experience.
2	30+	Master's	Expert 2 is an ex-chief engineer currently working in a classification society as a senior specialist in piping and machinery and is an authority on plan approval. His operational, maintenance and troubleshooting experience with LS2S engines is extensive.
3	28	PhD	Expert 3 is currently working for a large ship operator as a fleet energy efficiency manager. He was an ex-seagoing engineer with experience as a senior researcher in a classification society, before joining an LS2S engine design company as chief engineer on a large engines project.
4	30+	Master's	Expert 4 is a veteran marine engineer with extensive onboard experience. For the last 15 years, he has worked in a classification society, leading a team of experts on the MARPOL regulatory regime, and is also an expert in the field of innovative exhaust gas scrubber technology with a strong connection to the LS2S engine technology.
5	25	Master's	Expert 5 has extensive industry experience gained whilst serving on oil tankers and bulk carriers as a marine engineer. For the last 12 years, he has been working in a classification society in the marine consultancy department as a lead specialist, helping ship operators with asset management and supporting their operations through fuel and lube testing.
6	30+	HND	With 43 years of industry experience, expert 6 is currently working for a European shipping operator in a leading position. He spent 30 years as an onboard chief engineer, mainly as chief engineer, and is now serving as technical superintendent responsible for a number of onboard change management programmes, such as the 1st January 2020 implementation of low sulphur fuels.

- Green shaded (Nos. 12 -15): These are the parameters whose values are unlikely to deviate in 24-h engine operations; hence, they are considered constant.

In view of the above details, all parameters outlined under orange and blue shades require to be assigned a rate of change λ. A group of subject matter experts has been consulted to provide their expertise on the parameters shaded in orange and blue. It is important to note that the blue-shaded parameters are considerably more complex, as their measurements are not included in the regular onboard daily data collection.

To assess the variability of operational parameters (parent nodes) over a specific time framework, it is understood that these will vary based on current operating conditions. For this study, a panel of experts with experience in the operation, design and maintenance of LS2S engines has been consulted to estimate the percentage deviation, denoted as 'λ', from satisfactory/ideal operation over a 24-h period under relatively stable conditions. The rationale for using percentage deviation instead of direct parameter measurement is to ensure consistency in the model output. Nevertheless, it is recognised that the criteria of the deviations need to be fine-tuned by developing certain operational scenarios, which could be specific to particular engines or ships. This study adopts an overall performance assessment approach, applying a generic condition to test the model. Six experts have been selected for their qualifications and backgrounds, which are outlined in Table 4.

Table 5
Classification scheme to assign weights to experts.

Criteria	Classification	Score
Education Level (EL)	PhD	5
	Master	4
	Bachelor	3
	HND	2
	School-level	1
Professional Experience (PE)	$\geq$ 30 Years	10
	20 - 29	8
	10 - 19	6
	6 - 9	4
	$\leq$ 5	2
Organisational Responsibility (OR)	Executive	5
	Lead	4
	Senior	3
	Engineer	2
	Technician/Worker	1

Table 6
Weight estimation of each expert.

Expert number	Education	Experience (years)	Responsibility	Score (S)	Normalised weightage (w_i)
1	Bachelor	22 (20-29)	Senior	3 + 8+3 = 14	0.143
2	Masters	32 (≥30)	Senior	4 + 10+3 = 17	0.173
3	PhD	26 (20-29)	Executive	5 + 8+5 = 18	0.184
4	Master	31 (≥30)	Senior	4 + 10+3 = 17	0.173
5	Master	22 (20-29)	Lead	4 + 8+4 = 16	0.163
6	HND	43 (≥30)	Lead	2 + 10+4 = 16	0.163

Given differences in professional roles, years of experience, educational backgrounds, and subject-matter expertise, the experts were expected to exhibit different levels of judgment reliability. To account for these differences, expert judgments were weighted using the systematic classification scheme proposed by Lavasani et al. (2012), whereby greater weight was assigned to experts with higher levels of relevant expertise. This structured weighting approach enhances the reliability and credibility of the evaluation by ensuring that the results are primarily informed by the most qualified experts. Table 5 provides the content of the classification scheme.

The weight (w_i) of individual expert i is obtained by first estimating individual scores (S_i) using the following equations:

$$S_i = \text{EL of expert}_i + \text{PE of expert}_i + \text{OR of expert}_i$$

$$w_i = \frac{S_i}{\sum_{i=1}^{n} S_i} \tag{12}$$

where $\sum_{i=1}^{n} w_i = 1$ ($n = 1, 2 \ldots, 6$).

Table 7
Expert judgements for selected parameter deviation (in percentage) over 24-h two-stroke engine operations.

	Parameter	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6
1	Scavenge air pressure	2	3	1	2	6	2
2	Scavenge air temp.	3	3	1	4	4	3
3	Exhaust temp deviation	2	7	3	1	5	2
4	Viscosity of fuel	6	4	3	1	8	2
5	Iron content	1	-	1	-	0.5	-
6	TBN	1	-	4	-	1	-
7	WMC performance	3	1	4	3	10	5
8	$P_{max} - P_{comp}$	2	5	2.5	2	3	-
9	MIP deviation	4	2	1	2	6	1
10	Catalyst fines in fuel	4	-	0.5	-	10	-
11	Water in fuel	1	1	1.5	-	1	-

Based on the classification results listed in Table 5, each expert's score and subsequent weight have been estimated and are shown in Table 6.

The results of Table 6 imply an insignificant difference in the overall weighting of the six experts providing the expert judgements. Table 7 summarizes the input received from each individual expert.

Table 7 indicates that experts 2, 4 and 6 chose not to provide judgements on certain parameters due to the high level of associated uncertainty. They questioned whether there was sufficient evidence to suggest significant changes in the parameter over a short period. Moreover, expert 4 commented in his response that ranges might better depict the operating envelopes, as fixed values can be subject to interpretation. Expert 6 also emphasised an important assumption that the same fuel is being used, highlighting that a switch from high sulphur to low sulphur fuel could significantly alter operating conditions.

To integrate these judgements, a simple aggregation approach proposed by Pristrom et al. (2016) is employed. This approach calculates

Table 9
TPT for the scavenge air pressure.

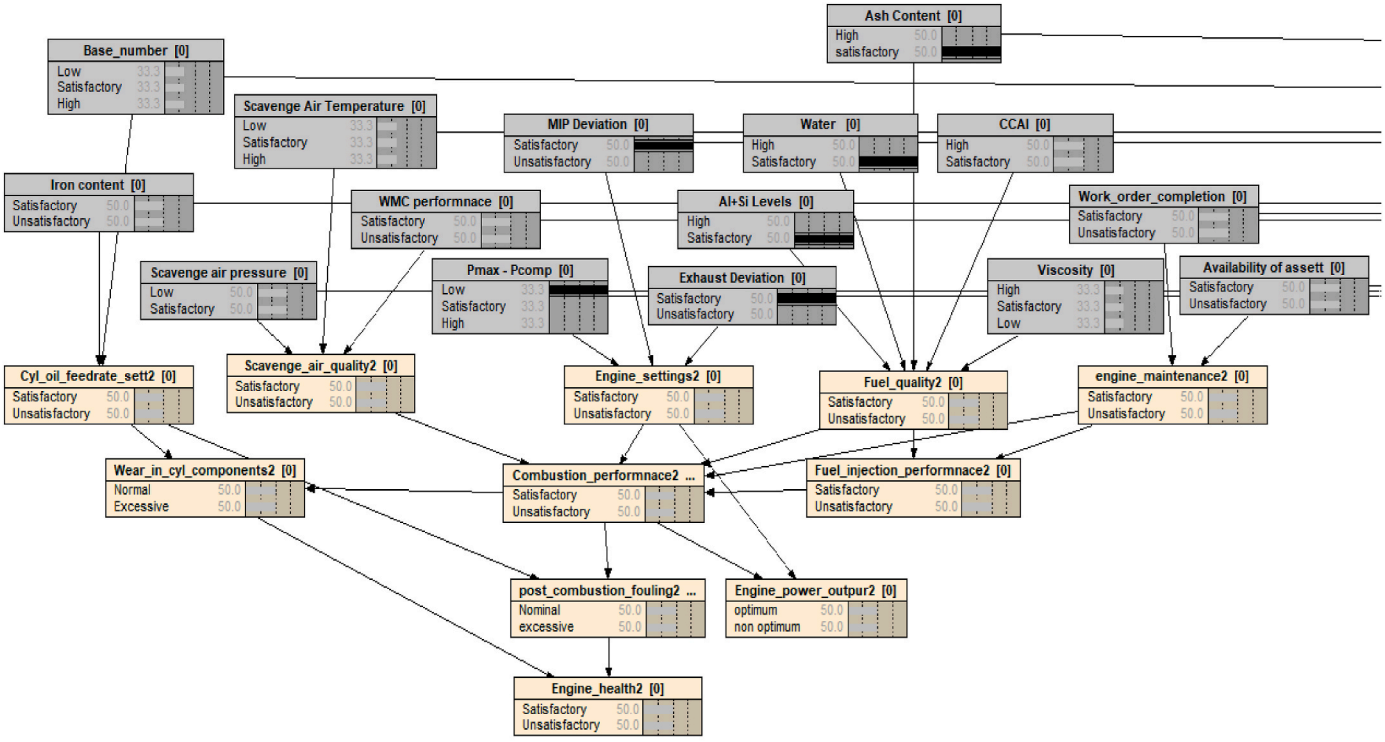
t	t+1	
	Low	Satisfactory
Low	$1-\lambda e^{-\lambda} = 0.974$	$\lambda e^{-\lambda} = 0.026$
Satisfactory	$1-e^{-\lambda} = 0.026$	$e^{-\lambda} = 0.974$

Table 10
TPT for the scavenge air temperature.

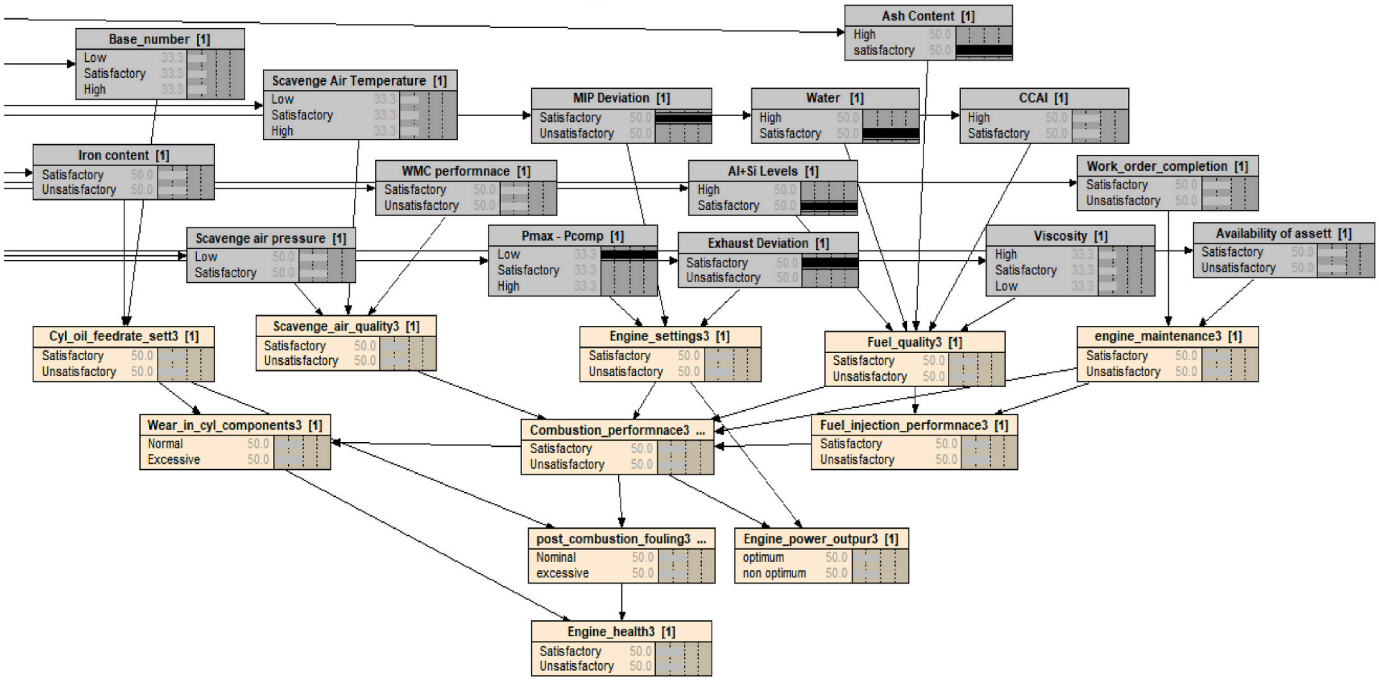
t	t+1		
	Low	Satisfactory	high
Low	$1-\lambda e^{-\lambda} = 0.971$	$\lambda e^{-\lambda} = 0.029$	0
Satisfactory	$0.50(1-e^{-\lambda}) = 0.014$	$e^{-\lambda} = 0.971$	$0.50(1-e^{-\lambda}) = 0.014$
High	0	$\lambda e^{-\lambda} = 0.029$	$1-\lambda e^{-\lambda} = 0.971$

Table 8
Aggregated percentage deviation from expert elicitation.

	Parameter	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6	Aggregate (percentage)	Aggregate (λ) (Decimal)
1	Scavenge air pressure	0.29	0.52	0.18	0.35	0.98	0.33	2.64	0.0264
2	Scavenge air temperature	0.43	0.52	0.18	0.69	0.65	0.49	2.97	0.0297
3	Exhaust temp deviation	0.29	1.21	0.55	0.17	0.82	0.33	3.37	0.0337
4	Viscosity of fuel	0.86	0.69	0.55	0.17	1.31	0.33	3.91	0.0391
5	Iron content	0.14	-	0.18	-	0.08	-	0.41	0.0041
6	TBN	0.14	-	0.73	-	0.16	-	1.04	0.0104
7	Water mist catcher performance	0.43	0.17	0.73	0.52	1.63	0.82	4.31	0.0431
8	$P_{max} - P_{comp}$	0.29	0.87	0.46	0.35	0.49	-	2.45	0.0245
9	MIP deviation	0.57	0.35	0.18	0.35	0.98	0.16	2.59	0.0259
10	Catalyst fines in fuel	0.57	-	0.09	-	1.63	-	2.30	0.023
11	Water in fuel	0.14	0.17	0.28	-	0.16	-	0.76	0.0076



(a) time slice $t = 0$



(b) time slice $t = 1$

Fig. 4. DBN for LS2S engine health assessment (at two-time slices, '0' and '1').

the combined judgement, denoted as x, from each expert's judgement, represented by x_i, and the collective weight of all six experts.

$$x = w_1 \times x_1 + w_2 \times x_2 + w_3 \times x_3 + w_4 \times x_4 + w_5 \times x_5 + w_6 \times x_6$$

where w_i is the weight of each expert derived as per Table 6. For example, scavenge air temperature deviation has been assigned by six experts as 3%, 3%, 1%, 4%, 4%, and 3%, respectively. Thus, the aggregate final percentage deviation for scavenge air temperature will

be as follows:

$$x_{scave\ temp} = w_1 \times x_1 + w_2 \times x_2 + w_3 \times x_3 + w_4 \times x_4 + w_5 \times x_5 + w_6 \times x_6 = 0.163 \times 4 + 0.173 \times 3 + 0.173 \times 4 + 0.143 \times 3 + 0.163 \times 3 + 0.184 \times 1 = 2.97 \quad (13)$$

Similarly, the final values of the other parameters have been defined as detailed in Table 8.

The remaining four parameters, highlighted in green within Table 3, have been considered constant with zero deviation over a 24-h period. The subsequent step involves establishing the TPTs for each of these parameters, which will be used to construct the DBN using Eqs. (6)–(10).

Scavenge air pressure: The aggregate deviation, as per Tables 8, is 0.0264. The transition probabilities are computed by employing these equations, which are presented in Table 9.

For a parameter with three states, such as scavenge air temperature, and exhibiting a deviation of 2.97%, the TPT can be found in Table 10.

Here, it has been assumed that there is an equal probability of transitioning from a 'satisfactory' state to either of two undesirable states, i.e., 'low' or 'high', from 't' to 't+1'. This transition is determined by the prevailing operational circumstances. Moreover, the likelihood of a parameter state, such as 'low' scavenge air temperature at 't', shifting to the opposite extreme, 'high', at 't+1' is extremely low, and vice versa. Therefore, a value of '0' has been assigned to represent this minimal probability. This consideration is particularly valid given the relatively short time period being analysed. TPT for the other 13 operational parameters have been derived and are provided in Appendix A.

The expanded BN structure (Fig. 2), with its existing connections and CPTs for a single time slice, is used to integrate the TPT and extend the model over multiple time slices. The parent nodes (depicted as grey boxes) in the BN model account for the temporal dimension, while the probabilities of child and leaf nodes (illustrated as yellow boxes) in different time slices change as normal posterior probabilities, as demonstrated in Fig. 4.

4. Case study

4.1. Case description

In order to demonstrate the model's functionality, a case study is briefly introduced here while the full details are documented in Usman

Table 11
Prior probabilities from a case study are used as input to the DBN at $t(0)$.

	Parameter	State	Probability in percentage for six cylinders					
			1	2	3	4	5	6
1	Scavenge air pressure	Low	51	51	51	51	51	51
		Satisfactory	49	49	49	49	49	49
2	Scavenge air temperature	Low	0	0	0	0	0	0
		Satisfactory	63	63	63	63	63	63
		High	37	37	37	37	37	37
3	Exhaust temp dev.	Satisfactory	100	90	50	40	100	30
		Unsatisfactory	0	10	50	60	0	70
4	Fuel inlet Viscosity	Low	0	0	0	0	0	0
		Satisfactory	87.5	87.5	87.5	87.5	87.5	87.5
		High	12.5	12.5	12.5	12.5	12.5	12.5
5	Iron content	Satisfactory	66	57.5	71.2	0	38.8	41.3
		Unsatisfactory	34	42.5	28.8	100	61.2	58.7
6	TBN	Low	0	9	0	0	1	6
		Satisfactory	100	91	100	100	99	94
		High	0	0	0	0	0	0
7	WMC performance	Satisfactory	90	90	90	90	90	90
		Unsatisfactory	10	10	10	10	10	10
8	$P_{max} - P_{comp}$	Low	100	100	100	100	100	100
		Satisfactory	0	0	0	0	0	0
		High	0	0	0	0	0	0
9	MIP deviation	Satisfactory	100	100	100	100	100	100
		Unsatisfactory	0	0	0	0	0	0
10	Catalyst fines	Satisfactory	100	100	100	100	100	100
		High	0	0	0	0	0	0
11	Water	Satisfactory	100	100	100	100	100	100
		High	0	0	0	0	0	0
12	Ash	Satisfactory	100	100	100	100	100	100
		High	0	0	0	0	0	0
13	CCAI	Satisfactory	47.5	47.5	47.5	47.5	47.5	47.5
		High	52.5	52.5	52.5	52.5	52.5	52.5
14	Work order completion	Satisfactory	71	85	71	86	100	71
		Unsatisfactory	29	14	29	14	0	29
15	Asset availability	Satisfactory	70	70	70	70	70	70
		Unsatisfactory	30	30	30	30	30	30

(2021).

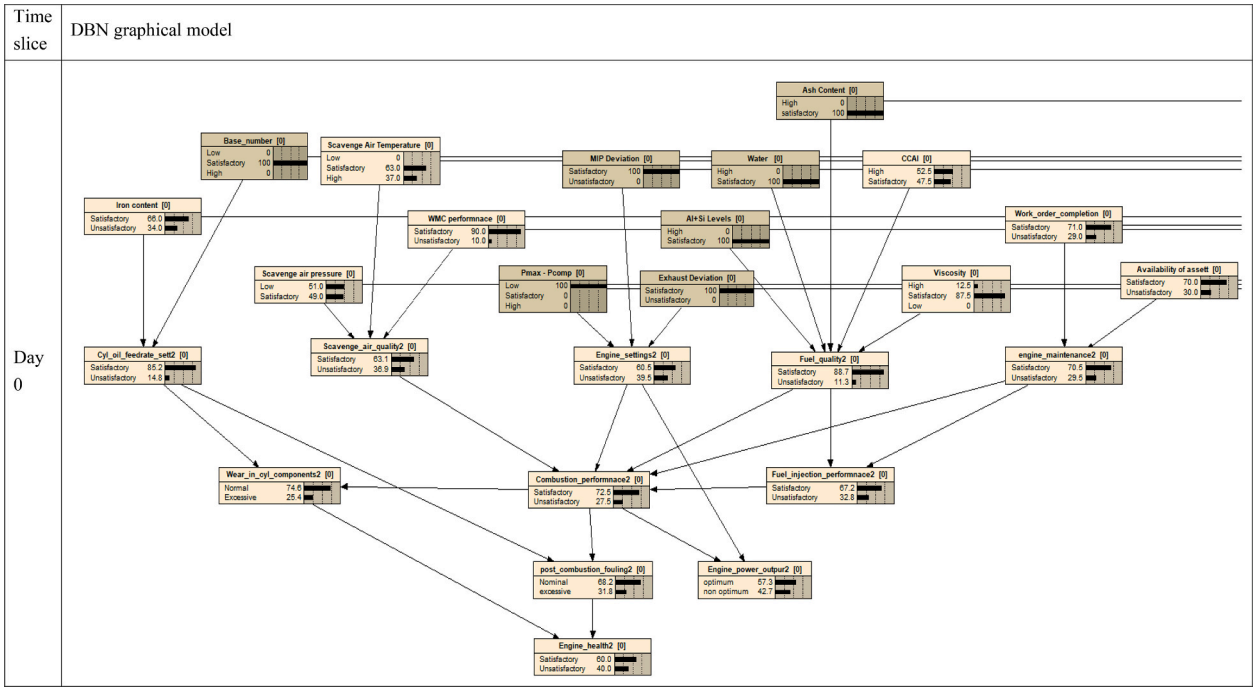
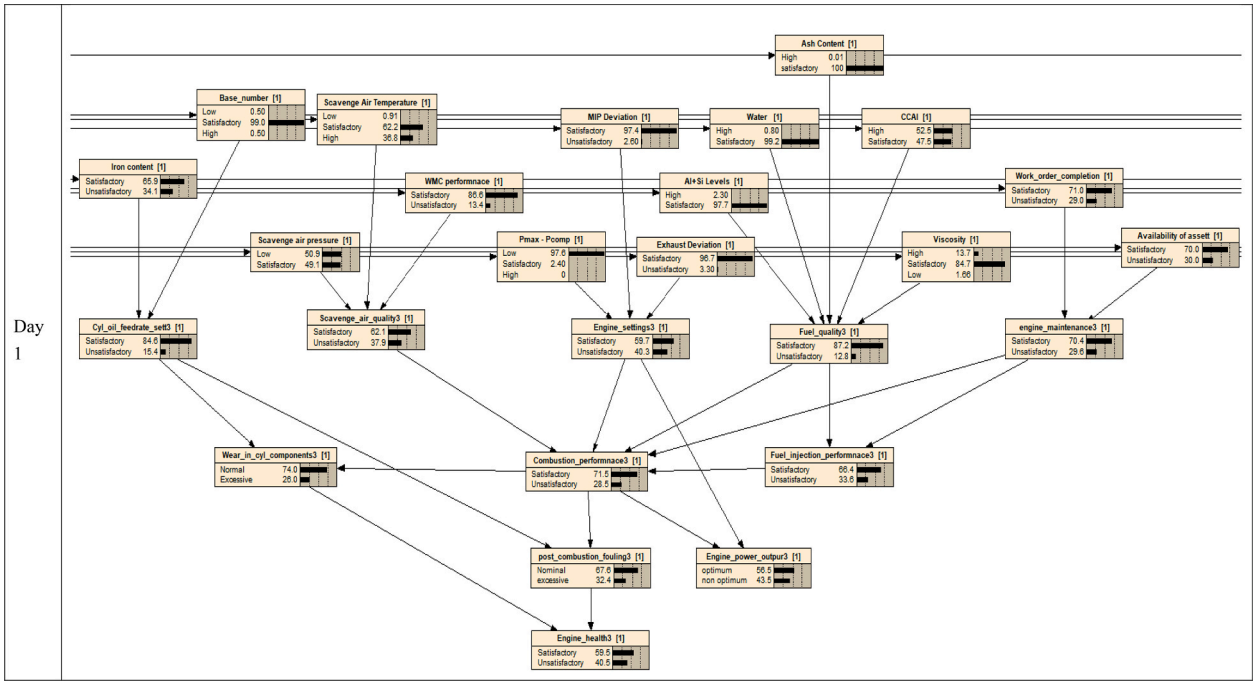
A Handymax bulk carrier registered on the FEAP, 2017 programme sent main engine data and samples for analysis. The ship has a six-cylinder MAN B&W 6S50MC-C engine installed, driving a fixed-pitch propeller. Based on the case description and the associated previous studies (Usman, 2021; Usman et al., 2017). The prior probabilities for the BN model for a six-cylinder engine were derived and shown in Table 11. These probabilities have been incorporated into the DBN as input for time slice $t(0)$ to calculate the probability of 'satisfactory' engine health in subsequent time slices. To conduct the case study, a simulation of engine operation spanning five days has been implemented to evaluate the engine performance.

The unconditional probabilities for cylinder 1 serve as input for the DBN built-in NETICA, which involves six-time slices representing a five-day simulation of engine operation (see Table 12).

Similarly, the other five cylinders are also modelled, and a final value for 'satisfactory' engine health was computed, as summarised in Fig. 5.

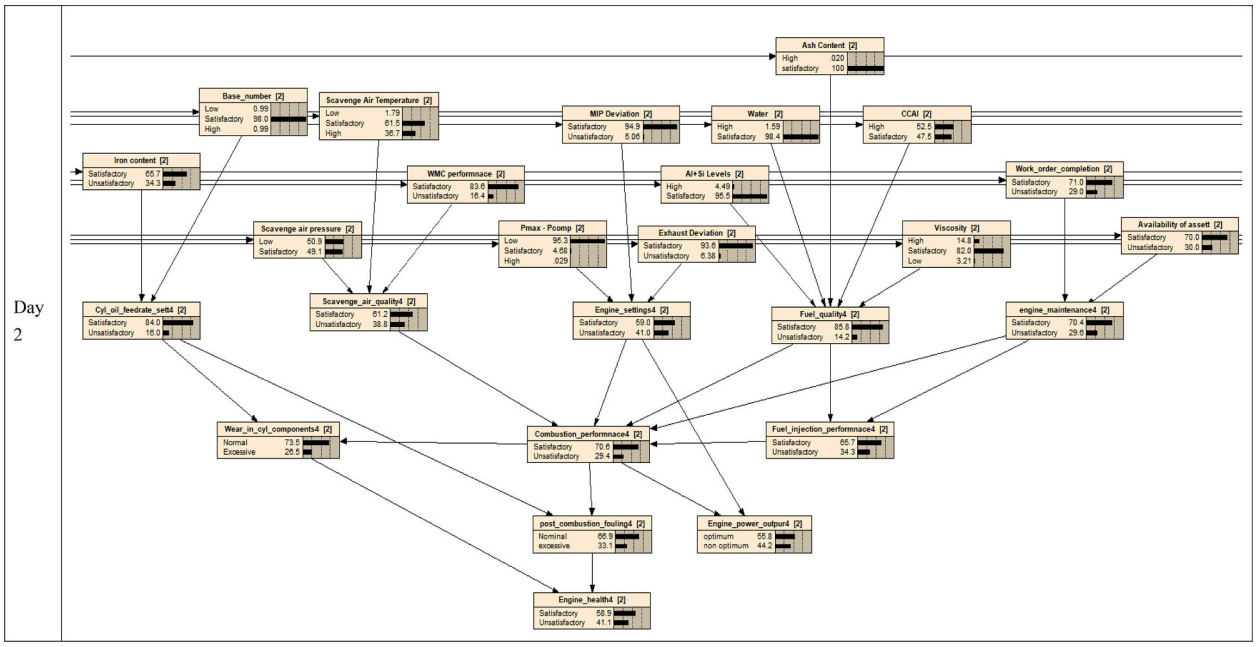
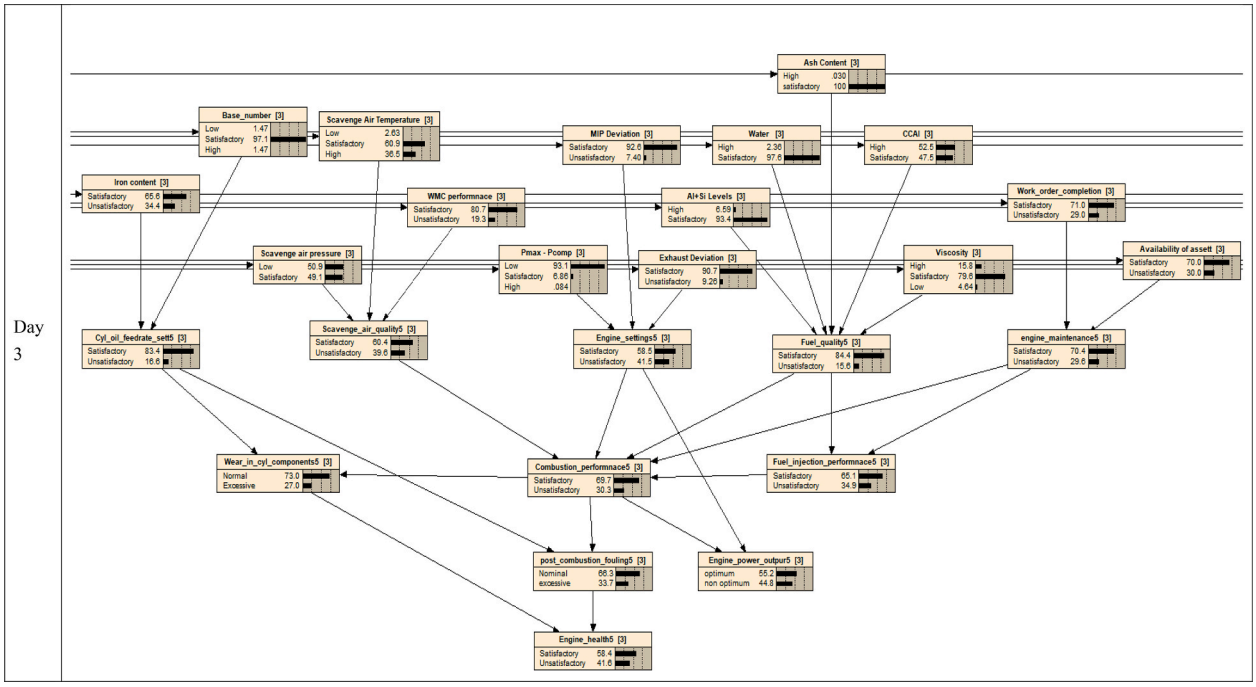
The results from all cylinders have been categorised using the criteria

Table 12
DBN time slices for cylinder 1.

Time slice	DBN graphical model
Day 0	
Day 1	

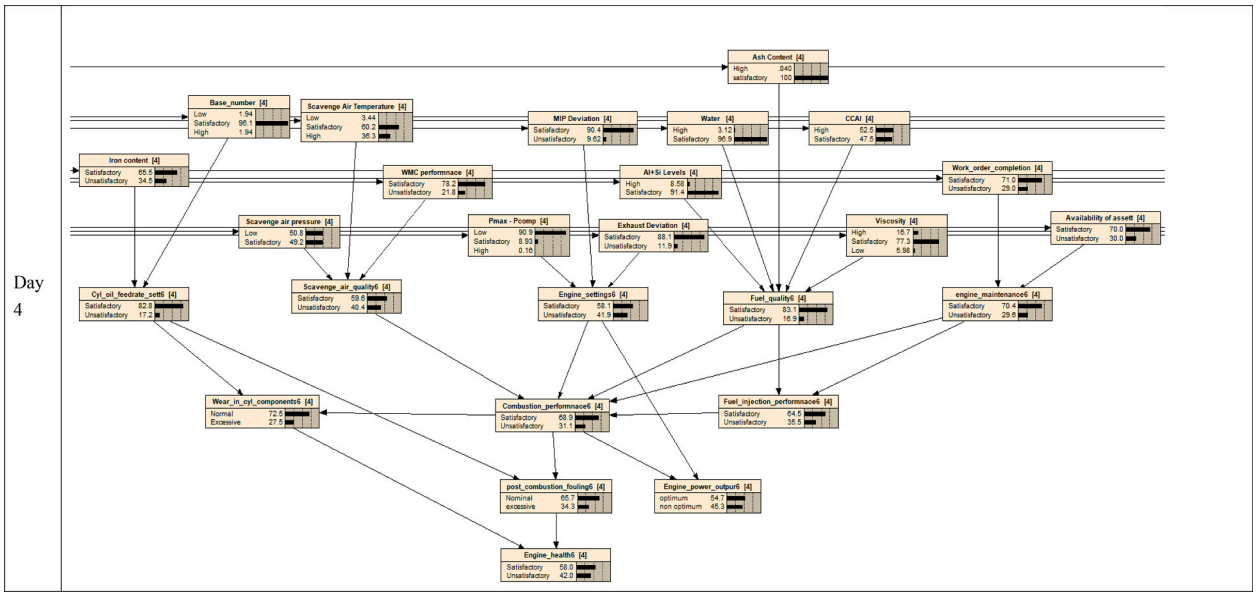
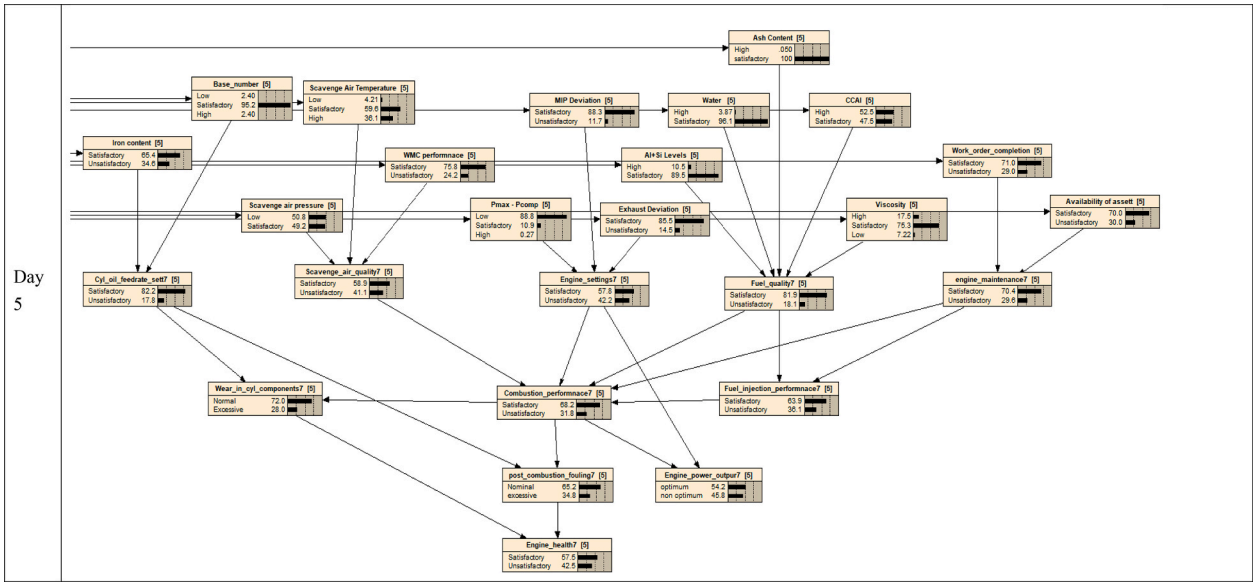
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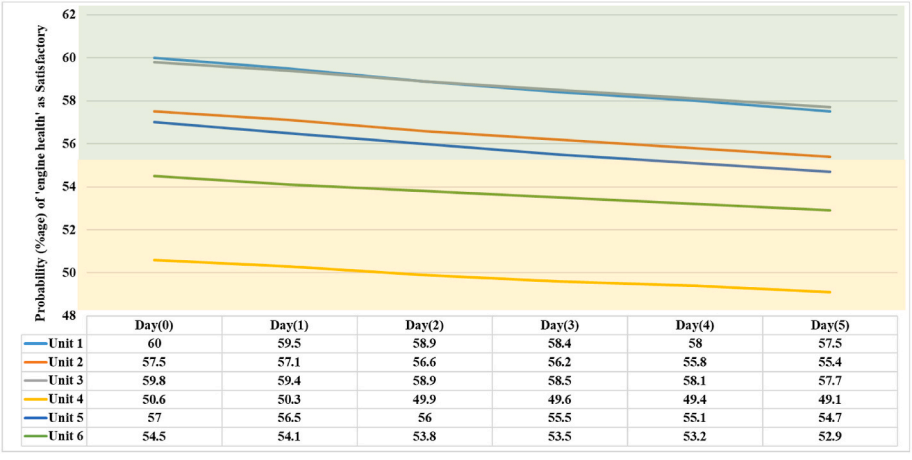
Table 12 (*continued*)

Time slice	DBN graphical model
Day 2	
Day 3	

(*continued on next page*)

Table 12 (*continued*)

Time slice	DBN graphical model
Day 4	
Day 5	



	Day(0)	Day(1)	Day(2)	Day(3)	Day(4)	Day(5)
Unit 1	60	59.5	58.9	58.4	58	57.5
Unit 2	57.5	57.1	56.6	56.2	55.8	55.4
Unit 3	59.8	59.4	58.9	58.5	58.1	57.7
Unit 4	50.6	50.3	49.9	49.6	49.4	49.1
Unit 5	57	56.5	56	55.5	55.1	54.7
Unit 6	54.5	54.1	53.8	53.5	53.2	52.9

Fig. 5. Engine operation over a five-day period (unit means cylinder unit).

of GREEN, AMBER and RED, as established in the previous section. There are a few new findings of high-valued practical implications, as follows:

- While most cylinders are currently operating within the satisfactory GREEN zone, cylinders 4 and 6 fell into the AMBER zone, indicating the need for attention.
- Cylinder 5 is projected to enter the AMBER zone after two days of operation, whilst cylinder 2 remains in the GREEN zone. However, the trend suggests that if the engine continues to operate for an extended period, cylinder 2 may also transition into the AMBER zone.
- The model's output reveals that cylinders 1 and 3 are the most satisfactory in terms of operation. Cylinder 1 starts at the highest level of satisfactory condition at day (0); however, it has a steeper slope compared to cylinder 3, implying that operating conditions are likely to deteriorate more rapidly for cylinder 1 than for cylinder 3.

These results underscore the utility of the DBN as a valuable and quick diagnostic tool for engine operators. It allows them to assess and potentially predict the performance of the engine, providing ample time to maintain operations within the GREEN zone for all cylinders on the upcoming voyage.

4.2. Validation and sensitivity analysis

Sensitivity analysis has been performed for the BN developed, following the criteria defined by Pristrom et al. (2016). When it comes to the DBN, similar principles can be applied to observe the impact of minor adjustments to the input parameters to output (Kammouh et al., 2020). Two primary axioms can guide this analysis:

1) As the DBN is expanded over time, the sensitivity of the parent node (s) (those with a temporal dimension) should be directly proportional to changes made to the initial temporal clone at t_0.
2) Evaluate changes in target/leaf nodes across different time slices to identify which parent node exerts a stronger influence.

In essence, any positive or negative alteration in the subjective probability of the parent node should have a consistent and proportional effect on the posterior probabilities of the child nodes.

Axiom 1 involves evaluating the performance of each parameter (parent node) as the DBN is time-expanded using the NETICA software. Throughout this section, the DBN is expanded, with each time slice representing a 24-h period. Hence, six-time slices have been employed in this section to model five days of engine operations, which is a typical voyage duration when travelling at a nominal speed of 15 knots between two of the world's busiest ports, from Singapore to Hong Kong.[2] The results for t_0 to t_5 are presented in Fig. 6 to illustrate Axiom 1.

These results reflect the fluctuations in various parameters, aligning with the deviations previously derived through expert judgements, as outlined in Table 8. For example, parameters like WMC performance, viscosity, and exhaust temperature exhibit the highest variability, with average deviations of 3.6%, 3.2% and 2.9%, respectively, during each time slice. On the other hand, parameters like ash content, CCAI, work order completion, and asset availability remain constant throughout the study period.

Axiom 2 pertains to the assessment of the influence of different parent nodes on the target node across various time slices. To achieve this, all 15 parent nodes are individually tested by assigning a maximum 'satisfactory' score to each parameter while maintaining a fixed (balanced) prior probability for all other nodes. The target node selected to evaluate the influence of parent nodes is the 'engine health' in the *satisfactory* state. This exercise not only identifies the parent nodes with the most substantial impact on the target node but also elucidates how the posterior probability of the target node evolves with time. Fig. 7 displays the results of the DBN model simulation run using Netica.

These findings highlight that the parameter TBN holds the highest degree of influence on the target node, i.e., engine health. Even minor alterations to TBN within the DBN would have a more significant influence on engine health compared to any other parameter. Following closely as the second most influential parameter is the iron content. This suggests that 'CLO feed rate', as a child node of 'TBN' and 'iron content', could potentially be the most pivotal intermediate node within the DBN. Furthermore, the graph indicates that less influential parameters, such as 'MIP deviation' and 'exhaust temperature deviations', tend to improve over time. In contrast, the most influential parameter, 'TBN', exhibits a slight degradation over time. The observed skewness of these results is primarily attributed to the TPTs of the parent nodes.

As demonstrated in Fig. 8, when all the parameter states are assigned an equal prior probability distribution, the probability of engine health seems to show a slight improvement in subsequent time slices, as depicted by the blue line in Fig. 9. Similarly, the model undergoes testing with the parent nodes set to either 100% 'satisfactory' (indicated by the orange line) or 100% 'unsatisfactory' (represented by the grey line), as illustrated in Fig. 9.

These results offer valuable insights into how the model reacts to various extreme inputs and its corresponding output trends throughout the specified time period. They also reveal nearly linear trends across all three input scenarios. Notably, the slope of the orange line (representing all the parent nodes as 'satisfactory') is steeper at 0.9 compared to the grey line (indicating all the parent nodes as unsatisfactory) at 0.5 and the blue line (with equal prior probabilities for parent nodes) at 0.125. These initial observations align with the anticipated behaviour of a machinery system in practical application. The model indicates a degradation from a highly desirable state unless corrective actions are taken to maintain high performance, which would entail incorporating fresh model inputs based on new information. Similarly, there is a gradual recovery from extremely poor operational conditions, which is not unexpected, either due to incremental adjustments made by crews or organic improvements in the operational conditions leading to a positive impact on engine health.

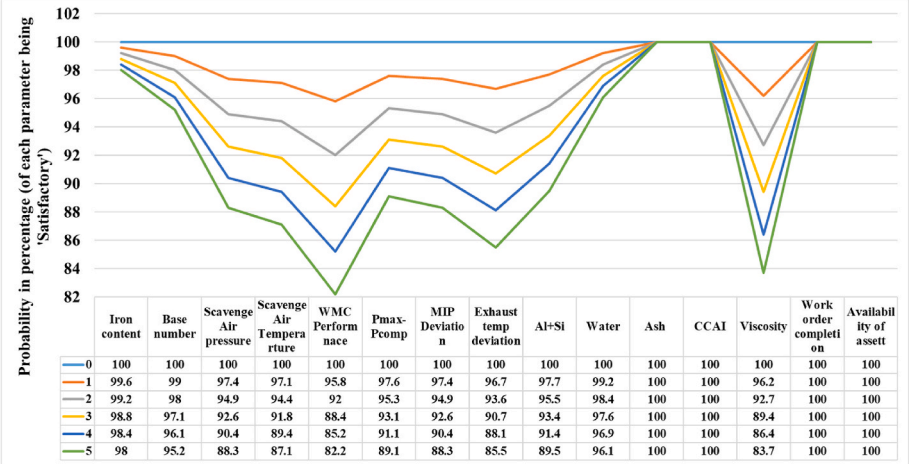
The model can be expanded to encompass as many time slices (days) as needed or reduced to a minimum of one-day operation, creating a two time slice model. As a predictive tool, the DBN can be further expanded to determine a probable time frame within which performance degradation is likely to reach a critical level, necessitating intervention. However, this requires the definition of zones/limits, as described in Fig. 10.

As can be seen from Fig. 10, the engine is operating between two extreme probability values for 'satisfactory' engine health of 18.1% to 74.4%. Consequently, the graph has been divided into three colour-coded zones as follows:

1) GREEN: The engine operates within 'satisfactory' levels, and the recommended course of action is to continue with standard best practices.
2) AMBER: The engine operates at somewhat reduced 'satisfactory' levels, requiring caution and necessitating further investigation to identify the parameter in need of improvement to restore the rating to the GREEN zone.
3) RED: The engine is operating at 'unsatisfactory' levels, demanding immediate action to investigate and improve the situation, as continuous operation in the RED zone could result in a machinery breakdown.

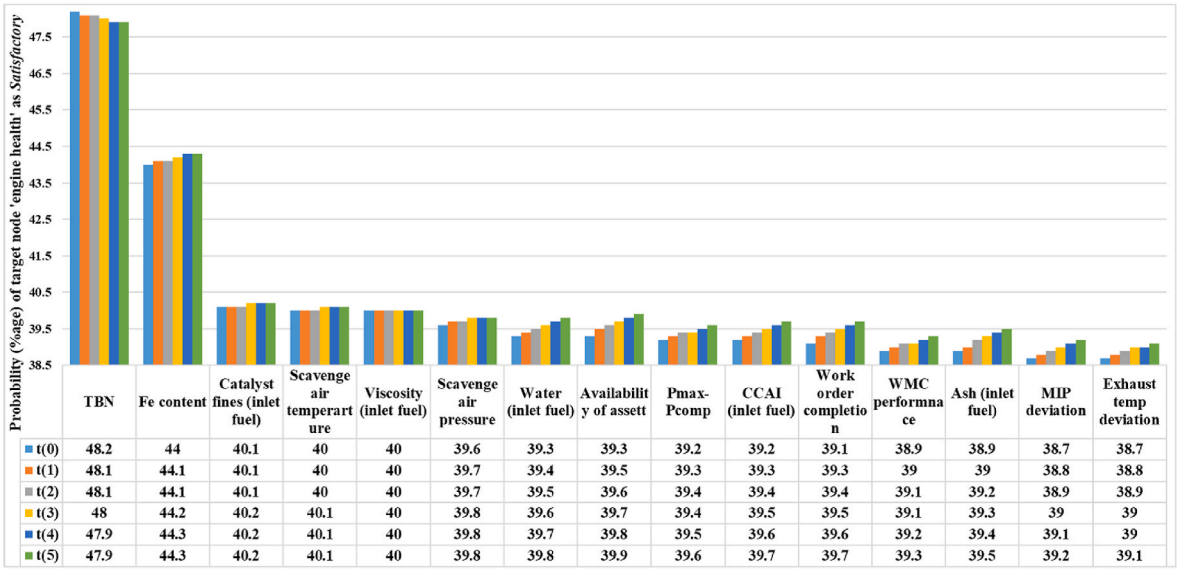
The three colour-coded operating zones are evenly distributed on the graph, outlined as follows:

[2] http://ports.com/sea-route/port-of-singapore,singapore/port-of-humen,hong-kong/.



	Iron content	Base number	Scavenge Air pressure	Scavenge Air Temperature	WMC Performance	Pmax-Pcomp	MIP Deviation	Exhaust temp deviation	Al+Si	Water	Ash	CCAI	Viscosity	Work order completion	Availability of assett
0	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100
1	99.6	99	97.4	97.1	95.8	97.6	97.4	96.7	97.7	99.2	100	100	96.2	100	100
2	99.2	98	94.9	94.4	92	95.3	94.9	93.6	95.5	98.4	100	100	92.7	100	100
3	98.8	97.1	92.6	91.8	88.4	93.1	92.6	90.7	93.4	97.6	100	100	89.4	100	100
4	98.4	96.1	90.4	89.4	85.2	91.1	90.4	88.1	91.4	96.9	100	100	86.4	100	100
5	98	95.2	88.3	87.1	82.2	89.1	88.3	85.5	89.5	96.1	100	100	83.7	100	100

Fig. 6. Change in probability of each parent node state 'Satisfactory' over six-time slices.



	TBN	Fe content	Catalyst fines (inlet fuel)	Scavenge air temperature	Viscosity (inlet fuel)	Scavenge air pressure	Water (inlet fuel)	Availability of assett	Pmax-Pcomp	CCAI (inlet fuel)	Work order completion	WMC performance	Ash (inlet fuel)	MIP deviation	Exhaust temp deviation
t(0)	48.2	44	40.1	40	40	39.6	39.3	39.3	39.2	39.2	39.1	38.9	38.9	38.7	38.7
t(1)	48.1	44.1	40.1	40	40	39.7	39.4	39.5	39.3	39.3	39.3	39	39	38.8	38.8
t(2)	48.1	44.1	40.1	40	40	39.7	39.5	39.6	39.4	39.4	39.4	39.1	39.2	38.9	38.9
t(3)	48	44.2	40.2	40.1	40	39.8	39.6	39.7	39.4	39.5	39.5	39.1	39.3	39	39
t(4)	47.9	44.3	40.2	40.1	40	39.8	39.7	39.8	39.5	39.6	39.6	39.2	39.4	39.1	39
t(5)	47.9	44.3	40.2	40.1	40	39.8	39.8	39.9	39.6	39.7	39.7	39.3	39.5	39.2	39.1

Fig. 7. Degree of influence on target node over five time slices of parent nodes.

P {max(satisfactory)} = 74.4%
P {min(satisfactory)} = 18.1%
P {max(satisfactory)}- P {min(satisfactory)} = 56.3%

Each zone is allocated an equal share, which equates to (56.3/3)% = 18.7% assigned to each zone. This means that the GREEN operating zone covers probabilities above 55.6%, the AMBER zone is between 37% and 55.6%, and the RED zone is below 37%.

It is worth noting that these quantitative thresholds for the three engine operational ranges can be further fine-tuned through onboard engine data analytics, as they can vary, mainly depending on factors like engine type/design, running hours, operating conditions, and other variables.

4.3. Onboard application and implications

To attain a comprehensive model validation, it is essential to apply the model onboard to assess the LS2S engine's operational performance. Below are a few key practical steps to achieve this objective:

1) The first step involves integrating the various models into a unified software package capable of receiving input from the onboard engine data management system, as well as manual input from the operator.
2) The developed software needs to be installed on the Personal Computer (PC) in the engine room.
3) The model needs to be suitably trained through actual data generated from the asset to establish benchmarks for what constitutes 'acceptable' and 'unacceptable' performance.
4) If the DBN developed is used, the operator should select an appropriate time granularity to perform either retrospective or prospective LS2S engine assessment. One of the validation pathways is to train the model with historical data and then project it forward to a point where potential failures or incidents may have occurred. Alternatively, the model can flag issues with specific cylinders, prompting further inspection to verify the model's output.

For the model's practical application onboard a ship, different design configurations may be considered based on individual system merits. As described by Griffiths (2006), a typical LS2S engine control system includes two operational panels in the engine control room: a main operational panel and a backup, which is usually a PC.

In the context of the practical application, it has been envisaged that

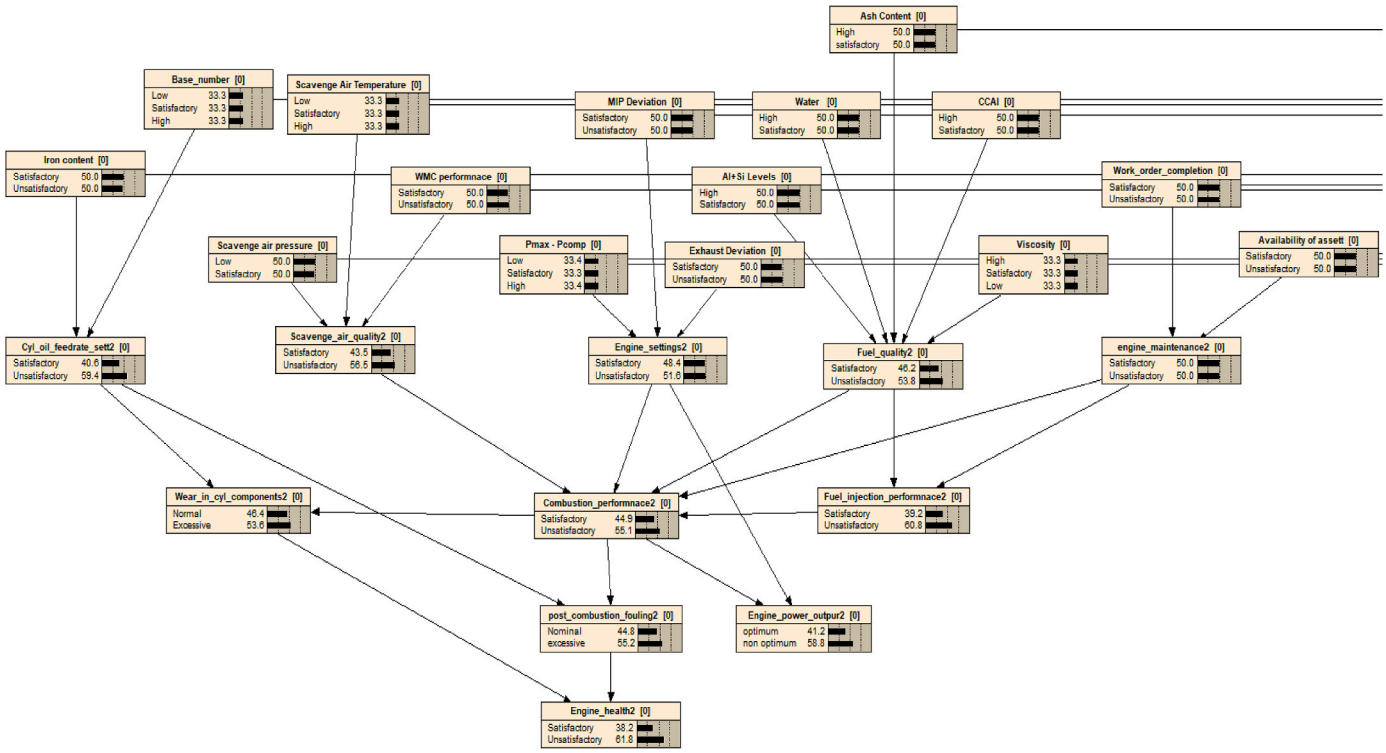


Fig. 8. DBN model at time slice t_0 and all parent nodes assigned a balanced prior probability distribution.

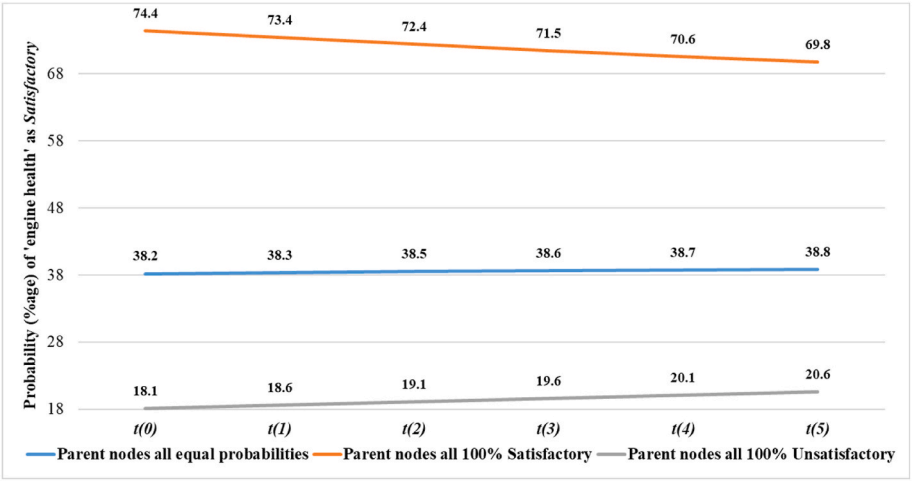


Fig. 9. 'Satisfactory' engine health under various input scenarios.

the backup operational panel (e.g., PC) receiving a direct feed of engine data will be equipped with the software constituting the BN model, as shown in Fig. 11. The direct feed, coupled with the data from parameters requiring manual input, can be input into the computer by the staff. This process will yield an engine health assessment, along with a set of practical actions to improve the LS2S operational score and performance.

The model does not intend to replace or contradict any integrated engine control system. Instead, it aims to provide additional complementary information and support for the onboard engineers to maintain the optimum operational health of the LS2S engine. If the model's outputs do not align with the prevailing operational conditions of the engine, it is advisable to conduct additional investigation to uncover the underlying reason for the apparent inconsistency.

5. Conclusions

This paper presented a DBN-based approach for the health assessment of large LS2S marine diesel engines. The proposed model extends the capability of conventional BN approaches by incorporating temporal relationships between engine operational parameters. A DBN model was developed using operational data together with expert judgement to represent the dynamic behaviour of engine conditions over time.

A major challenge in the development of the model was the construction of the TPTs. The analysis indicated that variations in several operational parameters exhibit stochastic characteristics, while direct estimation of transition probabilities from the available data was not always feasible. Therefore, expert knowledge was incorporated in the development of the TPTs for the parent nodes. Sensitivity analysis and a case study were carried out to evaluate the functionality and

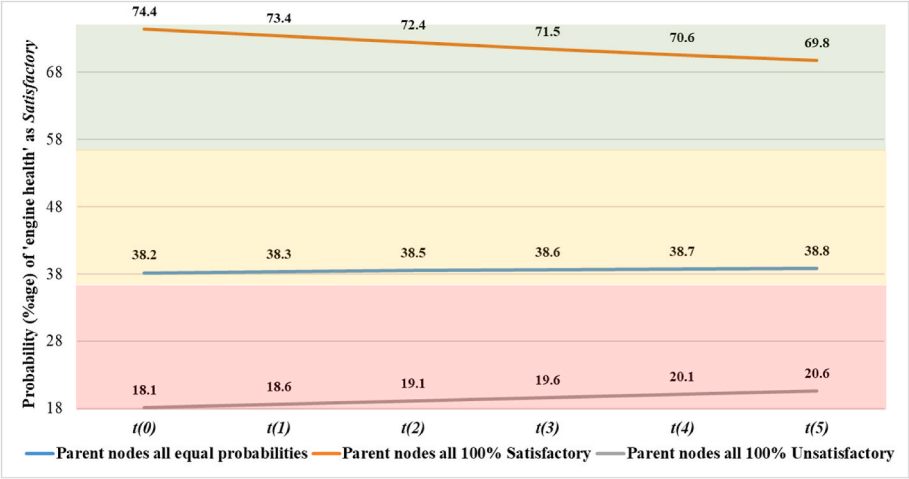


Fig. 10. Traffic light system for engine health assessment.

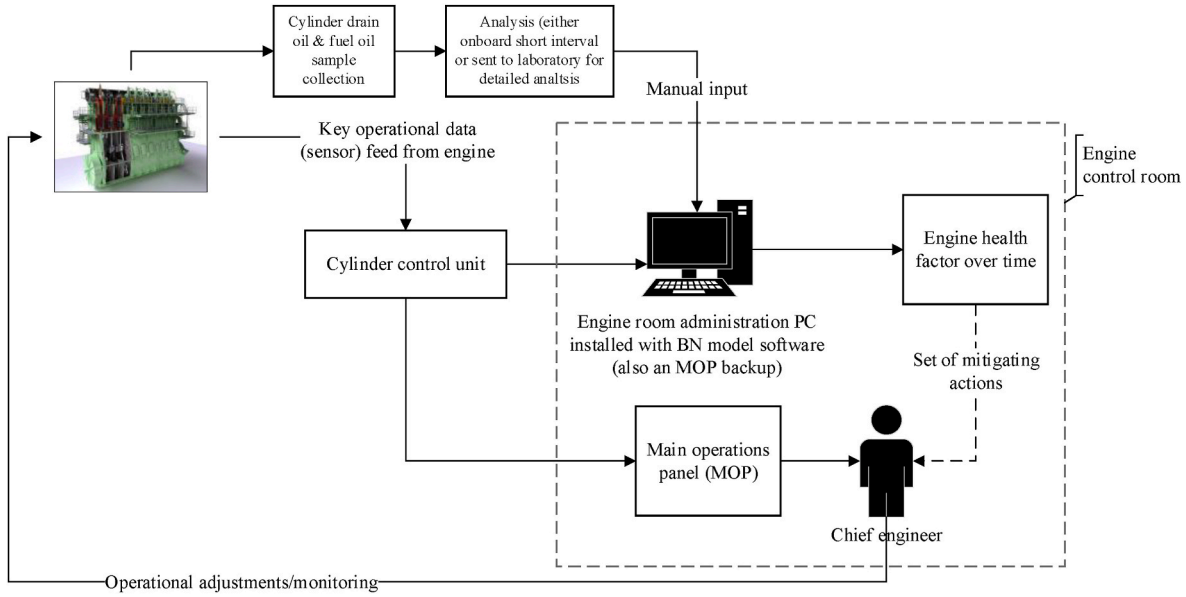


Fig. 11. Proposed model integration with the onboard engine control systems.

applicability of the proposed model.

The results demonstrate that the DBN model can support the operational health assessment of marine diesel engines by considering multiple interdependent parameters and their temporal characteristics. Compared with static assessment approaches, the proposed model provides an improved representation of changing engine conditions over time. The model also supports maintenance-related decision-making by identifying cylinders associated with relatively higher operational risk during future operations.

Several limitations of the present study should be acknowledged. The reliability of the model is dependent on the quality and completeness of the input data. Incorrect or inconsistent operational data may affect the assessment results. In addition, the current model may become less reliable under highly transient operating conditions, such as severe weather or emergency operating scenarios. Integration with onboard monitoring and control systems may improve the robustness and practical implementation of the framework.

Although a range of operational indicators were incorporated into the model, several additional parameters were excluded to avoid excessive model complexity. These include machinery running hours since overhaul, turbocharger performance, lubrication oil condition, vibration measurements, sea-state information, and torque measurements. Future work should consider incorporating these factors into the DBN framework to improve the comprehensiveness of the health assessment.

Finally, the present model was developed for LS2S engines operating on residual marine fuels. Future studies may investigate the applicability of the proposed framework to engines operating with alternative fuels, such as biofuels, methanol, and ammonia.

CRediT authorship contribution statement

Muhammad Usman: Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Data curation, Conceptualization. **Cihad Celik:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Huanhuan Li:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Zhuohua Qu:** Writing – review & editing, Writing – original

draft, Visualization, Supervision. **Chia-Hsun Chang:** Writing – review & editing, Visualization, Validation, Supervision. **Jin Wang:** Writing – review & editing, Writing – original draft, Validation, Supervision, Methodology. **Zaili Yang:** Writing – review & editing, Writing – original draft, Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

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

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Appendix A. TPTs for parent nodes

Exhaust temperature deviation ($\lambda = 3.37\%$)

t	$t+1$	
	Unsatisfactory	Satisfactory
Unsatisfactory	0.967	0.033
Satisfactory	0.033	0.967

Viscosity at engine inlet ($\lambda = 3.91\%$)

t	$t+1$		
	Low	Satisfactory	high
Low	0.962	0.038	0
Satisfactory	0.019	0.962	0.019
High	0	0.038	0.962

Iron content of cylinder drain ($\lambda = 0.41\%$)

t	$t+1$	
	Unsatisfactory	Satisfactory
Unsatisfactory	0.996	0.004
Satisfactory	0.004	0.996

TBN of cylinder drain oil ($\lambda = 1.04\%$)

t	$t+1$		
	Low	Satisfactory	high
Low	0.99	0.01	0
Satisfactory	0.005	0.99	0.005
High	0	0.01	0.99

WMC performance ($\lambda = 4.31\%$)

t	$t+1$	
	Unsatisfactory	Satisfactory
Unsatisfactory	0.958	0.041
Satisfactory	0.041	0.958

$P_{max} - P_{comp}$ ($\lambda = 2.45\%$)

t	$t+1$		
	Low	Satisfactory	high
Low	0.976	0.024	0
Satisfactory	0.012	0.976	0.012
High	0	0.024	0.976

MIP deviation ($\lambda = 2.59\%$)

t	$t+1$	
	Unsatisfactory	Satisfactory
Unsatisfactory	0.974	0.025
Satisfactory	0.025	0.974

Catalyst fines levels in fuel ($\lambda = 2.30\%$)

t	$t+1$	
	High	Satisfactory
High	0.977	0.022
Satisfactory	0.022	0.977

Water in fuel ($\lambda = 0.76\%$)

t	$t+1$	
	High	Satisfactory
High	0.992	0.008
Satisfactory	0.008	0.992

Ash content ($\lambda = 0\%$)

t	$t+1$	
	High	Satisfactory
High	1	0
Satisfactory	0	1

CCAI ($\lambda = 0\%$)

t	$t+1$	
	High	Satisfactory
High	1	0
Satisfactory	0	1

Work order completion ($\lambda = 0\%$)

t	$t+1$	
	Unsatisfactory	Satisfactory
Unsatisfactory	1	0
Satisfactory	0	1

Availability of asset ($\lambda = 0\%$)

t	t+1	
	Unsatisfactory	Satisfactory
Unsatisfactory	1	0
Satisfactory	0	1

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