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Developing an advanced reliability analysis framework for marine systems operations and maintenance

Abdullahi Abdulkarim Daya *, Iraklis Lazakis

Department of Naval Architecture, Ocean and Marine Engineering, University of Strathclyde, United Kingdom

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ABSTRACT

Power generation system reliability is of great concern for all ship operators irrespective of sector, as it provides the highest utility and ensures collective safety of operators, passengers, equipment and cargo. A novel approach to system reliability analysis using DFTA, FMECA and BBN applied to 4 DGs has been conducted. The outcomes provide insight on faults and component criticality to vessel maintenance and availability. Building from the understanding of how multiple factors can influenced maintenance in addition to routine or age-related wear and tear of machinery. This research looked into operators' peculiar challenges regarding environment, operational demands and technology challenges that affects maintenance and system reliability. A framework based on outputs from DFTA minimal cut set, RPN from FMECA were used as inputs for BBN to analyse ship marine DG system availability. A BBN influence diagram was used to build a maintenance strategy DSS. Overall outcome for the maintenance strategy selection DSS indicates relatively high unavailability. Therefore, DGs with low availability were recommended to be on Corrective action and ConMon, while DGs with good availability were recommended to be on PMS.

1. Introduction

The foundation of system reliability rests on two primary pillars, the first of which is intrinsic to the system's architecture and the second is obtained via maintenance strategy and execution. The capacity of the operator to effectively follow the maintenance plan set by an organisation helps to reduce failure and maintain the system's excellent operating condition between maintenance intervals. In this respect, the maintenance department's objective will be to use all available strategies to guarantee that failures are not only minimised, but also handled in an efficient and timely way. This might imply efficient maintenance, such as utilising the proper lubricants, changing filters when due or depending on their condition, and ensuring that spare parts inventory reflects component failure and replacement rate. Moreover, the International Safety Management (ISM) code provides guidance to all ship operators, and the document underlined the necessity for companies and ship operators to develop additional requirements to assist effective ship system maintenance (IACS,2018). In addition, it requires ship operators to identify equipment and technical systems whose sudden failure might lead to dangerous circumstances (IMO, 2018).

The existing maintenance strategy namely Corrective, Predictive, Preventive and Condition based maintenance are often selectively combined using reliability analysis procedures to come up with other hybrid maintenance strategies(Lazakis et al., 2018). In particular, the wide application of Planned Maintenance System (PMS) and Reliability Centred Maintenance (RCM) in the industry can be attributed to adaptation of more than one maintenance approach to provide maintenance for entire systems (Karatuğ and Arslanoğlu, 2022). In general maintenance guidelines for machinery and equipment forming a system are obtained from the Original Equipment Manufacturers (OEM) Manual. Similarly, alternative elaborate maintenance procedures are equally provided by Classification societies through guidance notes which provides relevant options and information to operators who desire such services (ABS, 2016; IACS, 2021). Moreover, maintenance management systems such as Computerised Maintenance Management System (CMMS) that are stand-alone or come as a part of Enterprise Management System (EMS) are also provided by Classification Societies, Asset management companies, or the maintenance division of the organisation(Eriksen et al., 2021). For instance, American Bureau of Shipping (ABS) and DNV-GL provides leading edge maintenance management system such as NS maintenance management and ship manager software respectively(ABS, 2016).

Overall, there are multiple channels which ship operators can access

* Corresponding author.
E-mail address: abdullahi.a.daya@strath.ac.uk (A.A. Daya).

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Nomenclature

ABS(NS)	American Bureau of Shipping (Nautical System)
BBN	Bayesian Belief Network
BE	Basic Event
BSI	British Standards Institution
CBM	Condition Based Maintenance
CMMS	Computerised Maintenance Management System
CPT	Conditional Probability Table
DFTA	Dynamic Fault Tree
DG	Diesel Generator
DNV	Det Norske Veritas
DSS	Decision Support System
EMS	Enterprise Management System
ETA	Event Tree Analysis
FDEP	Functional Dependency
FMEA	Failure Mode and Effect Analysis
FMECA	Failure Mode Effect and Criticality Analysis
FTA	Fault Tree Analysis
IM	Importance Measure
IMO	International Maritime Organisation
ISM code	International Safety Management
LED	Light-emitting diode
MCS	Minimal Cut Set
MDT	Mean Down Time
MRO	Maintenance Repair and Overhaul
MTTF	Mean Time to Failure
NASA	National Aeronautics and Space Administration
NPRD	Non-Electronic Reliability Data
NSWC	Naval Surface Warfare Centre
NUREG	Nuclear Regulatory Report
OEM	Original Equipment Manufacturer
OPV	Offshore Patrol Vessel
OREDA	offshore and Onshore Reliability Data
PAND	Priority- AND
PMS	Planned Maintenance System
RCM	Reliability Centred Maintenance
SEQ	Sequence Enforcing

operation and maintenance support except that most of this support being enterprise and generic in nature may not be as dynamic and responsive as the operator would want. Hence the need for researchers to provides solutions to both regulators and operators. Maintenance as defined by (BS, 2010) is the combination of all technical, administrative and managerial actions during the life cycle of an item intended to retain it in, or restore it to, a state in which it can perform the required function. Therefore, by emphasising key phrases in the definition, "retain" and "restore"; refer to maintenance activities, while "perform" and "function" refer to the utility needed from the system or equipment. It follows that all maintenance procedures would be designed to guarantee that a system is available at all times within acceptable reliability limits. These limits are defined by factors which largely depends on the reliability inherent to the equipment and its usage. Other factors are to do with operators' environment, maintenance staff competencies, spare parts sourcing and maintenance strategy employed. In this regard the OREDA handbook provides a good reference on multiple equipment reliability analysis approach with acceptable generalisation regarding operating environment and equipment specific reliabilities (Lazakis et al., 2018; Marving Rausand and Arnljot, 2021).

In this regard this paper will present the development of an advanced reliability analysis framework for marine systems operations and maintenance through application of reliability analysis tools for identifying maintenance critical components. The methodology also provides a maintenance decision support system for maintenance critical components on board ships. Considering this, the work is organised into parts, with Section 2 providing a critical evaluation of system reliability analysis tools, Section 3 presenting the innovative approach of this research, and Section 4 discussing the case study application of the technique. Section 5 presents Results and Discussion, while Section 6 presents Conclusions and Recommendations for Future Research.

2. Critical review on system reliability analysis

System reliability analysis is central to the successful implementation of any maintenance strategy as it provides clear insight on machinery behaviour and the impacts of failure on availability of machineries up to system levels (Ahn et al., 2022; Bahoo et al., 2022a; Daya and Lazakis, 2022). Accordingly, reliability analysis tools are widely used to support maintenance strategy selection or implementation in line with organisational objectives. Therefore, various maintenance strategy such as Reliability Centred Maintenance, Risk based Maintenance, Total Productive Maintenance, Risk and Reliability Based Maintenance etc draw from existing maintenance approach using system reliability analysis to provide a tailored maintenance system(Cheliotis et al., 2020). RCM developed in the aviation industry and United States Navy in the 1970s (NAVSEA, 2007) provides clear intersection on the combination of various maintenance strategy and used of reliability tools. For instance, the guidelines for the development and implementation of RCM by the Royal Navy and United States Navy considered the role of PMS and CBM as a requirement for achieving any RCM program(MoD, 2007; NAVSEA, 2007). While the nature of PMS stipulates time-based approach, that of CBM relies on sensor deployments hence the place of system reliability analysis to harness the weakness in both(Cicek and Celik, 2013; Cipollini et al., 2018; Velasco-Gallego and Lazakis, 2022a). In general reliability analysis tools examine the effects and risk of failure by considering quantitative and qualitative aspects of machinery maintenance and operations data (Karatuğ and Arslanoğlu, 2022).

To this end, various researchers have implemented the use of tools such as FTA, ETA and RBD mostly combined to provide maintenance analysis approach in order to overcome issues such as discretisation, linguistic restriction, and expert judgment (Duan and Zhou, 2012; Jun and Kim, 2017; Kampitsis and Panagiotidou, 2022; Khakzad et al., 2011). Research efforts by (Konstantinos Dikis et al., 2010; Lazakis and Ölçer, 2015; Lazakis et al., 2010; Velasco-Gallego and Lazakis, 2022a) implemented a risk and reliability assessment methods of FMECA and FTA as well as using Fuzzy Multi Criteria Decision Making Approach (FCDMA) in order to identify critical components and provide maintenance decision support for ships with focus on equipment risk and criticality to maintenance. Other tools such as Bayesian belief networks, Monte Carlo simulation, Markov chains, Petri Nets and Weibull analysis among others have been applied to model maintenance planning (Kabir and Papadopoulos, 2019; Leimeister and Kolios, 2018; Melani et al., 2018). On the other hand, complex system reliability analysis requiring inputs that are largely non-binary and continuous with stochastic failure behaviour would require different approach to address temporal system state or a repairable mechanical system that can operate satisfactorily at degraded condition. Recent research efforts have also focused on ship machinery real-time anomaly detection for fault diagnosis (Velasco-Gallego and Lazakis, 2022a); application of Bayesian and machine learning-based fault detection and diagnostics (Cheliotis et all, 2022); real-time data-driven missing data imputation evaluation for short-term sensor data of marine systems (Velasco-Gallego and Lazakis, 2022a); and the development of a time series imaging approach for fault classification (Velasco-Gallego and Lazakis, 2022b). Therefore, additional flexibility to produce a representative model taking all possible consideration will be required. Consequently, researchers have resorted to the use of multiple tools to accommodate system dependences and complexities of multi system (Marving Rausand and Arnljot, 2021; Piadeh et al., 2018; Velasco-Gallego and Lazakis, 2022a, 2022b). This strategy enables the use of multiple data types for reliability analysis and the use of tools in a more flexible manner(Leimeister and Kolios, 2018). Accordingly, a critical review highlighting the strengths and weaknesses of the reliability tools used for this research will discussed.

2.1. Fault tree analysis

Fault tree analysis (FTA) is a static method for analysing component faults in systems or equipment by identifying all possible causes of likely failures and impacts on the system through the logical analysis of dependencies in the basic events that lead to the undesired event, the top event of the fault tree(Lazakis et al., 2018{NASA, 2002 #136)}. FTA is an important tool for reliability and risk analysis as it provides critical information used to prioritise the importance of the contributors to the undesired events(Relex et al., 2003). It utilises Boolean law by applying gates and events to describe faulty components and possible event(s) that could develop a fault. Therefore, FTA is an important tool for reliability and risk analysis as it provides critical information used to prioritise the importance of the contributors to the undesired event i.e fault or failure. However, it has some shortcomings to do with sequence dependencies, temporal order of occurrence and redundancies due to standby systems, consequently DFTA was developed to overcome these constraints in the static FT.

The dynamic gates which include Priority and gate (PAND), Sequence Enforcing gate (SEQ), Functional Dependency gate (FDEP), Spare gate (SPARE) and the spare event when added to the FTA structure becomes Dynamic FTA (NASA, 2002). In the PAND gate events are prioritised from left to right such that the left most event (fault) is considered first before the next; similarly, SEQ considers events in left to right fashion however rather than prioritising it enforces hence ensuring that events follow the expected failure mechanism(Kabir, 2017). On the other hand, the FDEP though evaluate events from left to right it does that considering the occurrence of primary, or causal event which is independent of other faults to the right(Kabir, 2017). The SPARE gate and event have unique attributes and functions; though events are evaluated from left to right as obtained in other gates, the dormancy factor feature of the spare event makes lot of difference. The dormancy factor is a measure of the ratio between failure and operational rate of the spare event in the standby mode (NASA, 2002). A cold spare has dormancy factor 0, a hot spare has dormancy factor 1 and a warm spare has a dormancy factor between 0 and 1(Relex et al., 2003). The application of dynamic gates and use of spare gates to analysis improvements in maintenance approach was presented in (Lazakis et al., 2010; Kabir, 2017 #437) both authors demonstrated how these dynamic gates can be applied to model time and sequence dependent failures.

In this regard, the dynamic gates in combination with other static gates provide a much robust yet simple structure compared to tools like Markov Chains and RBD. Therefore, DFTA is suitable for modelling complex systems failure behaviour with respect to sequence and dependencies, particularly where the temporal order of the occurrence of events is important to analysis(Chiacchio et al., 2016; Jakkula et al., 2020; NASA, 2002). This is particularly important in order to account for the failure dynamics of static and dynamic system, while not disregarding the impact of environmental elements, temperature and other factors. The reliability of mechanical systems does not follow constant failure rate as obtained in electrical systems such as semiconductor, LED and software(Relex et al., 2003). Reliability data bases for mechanical components such as OREDA, NUREG, NSWC, NPRD provide high quality failure rate information on various components and procedures for conducting reliability predictions (Marving Rausand and Arnljot, 2021). However, component failure rates for repairable mechanical systems are influenced by multiple factors and may not follow constant failure rates of generic distribution such as Weibull, Normal, Lognormal the likes (Anantharaman et al., 2018; Scheu et al., 2017). Hence, DFTA provides a platform that is capable for analysing reparable system while considering other factors such as dependencies and temporal behaviour or partially operating state analysis(Marko Cerpin, 2002; Zhou et al., 2022). Therefore, this makes it very relevant in analysing system improvements as presented in (Daya A.A 2021; Turan et al., 2012). Overall, these additional gates provided more scope in DFT analysis (Kabir, 2017; Ruijters and Stoelinga, 2015) which can be used to factor repair or improvements due to routine maintenance. Moreover, additional outputs such as reliability importance measures and minimal cuts sets in the DFTA are equally influenced by the logic structure of the model, meaning that the output of static FT and a dynamic FT analysis will be significantly different and reflective of the whatever dependencies exist in the model.

The DFTA provides additional outputs which are the reliability importance measures (IM) and minimal cut set. The IM provide a means to identify the most critical component/situation that contributes to the occurrence of the low/basic event leading up to equipment failure or top event occurrence (Chen et al., 2021; Kuzu and Senol, 2021 #768)}. Therefore assisting in identifying the event that, if improved, is most likely to produce significant improvement in equipment or system performance (Relex et al., 2003). In retrospect the MCS provide insights on failure or fault development, in that MCS are the smallest set of basic events, which if they all occur will result in the top event occurring (NASA, 2002). Therefore, improving the MCS can greatly improve overall system reliability.

Similarly, the IM could provide vital information on components to the maintenance crew and ship owners prioritization of actions that could ensure equipment/system reliability through holding of right spares onboard or additional maintenance options. The main IM approaches are Birnbaum (Bir), Fussell-Vesely(F-V) and Criticality (Cri) (Lazakis et al., 2018). The Bir IM evaluates the occurrence of the top events based on the probability of its occurring or not occurring, hence the higher the probability the higher the chances of top event occurring (Relex et al., 2003). Criticality (Cri) IM is calculated in a similar way to Bir IM except that it considers the probability in the occurrence of the basic event to the occurrences of the top event. The F-V calculation adopts an entirely different approach in that; it uses the minimal cut set summation i.e., the minimum number of basic events that contribute to the top event. Therefore, the F-V consider the contribution of the basic event to occurrence of the top event irrespective of how it contributes to the failure.

Maintenance planning for complex system is dynamic and therefore constantly changing, the more reason why organisation adopts different maintenance strategy that could fit the operational requirement or machinery condition (Soliman, 2020{Heinz P. Bloch, 2006 #9)}. In this regard DFTA though a robust tool is not able to adequately address issues such as CCF, human error, natural events including subjective factors such as maintenance delays, spare part quality and skills shortages. Accordingly, to overcome some of these factors, DFTA has equally been combined with other tools to achieve additional research goals such as decision support or analysis requiring some level of subjective inputs (Codetta-Raiteri and Portinale, 2017; Zhou et al., 2022). Accordingly, DFTA is combine with other tools to improve quality and coverage of analysis such as machine learning based tools for diagnostics and prognosis analysis(Cheliotis et al., 2020; Eriksen et al., 2021) DFTA, FMECA and other tools(Daya A.A 2021; Karatuğ and Arslanoğlu, 2022). On the other hand, the constraints imposed by the DFTA structure and the deterministic nature of the input as well as the output makes it restrictive to model certain machinery failures. Overcoming this challenge in this research was done through the use of FMECA, as it provides the required robust framework to holistically analyse failures with all the dynamics involved.

2.2. Failure mode effect and criticality analysis

Failure Mode Effect and Criticality Analysis is an evaluation technique to determine the impact of failure or malfunction of system, equipment or components failures by evaluating and prioritising the effect of individual failures (Daya and Lazakis, 2022; NASA, 2008). FMECA is composed of 2 analyses, FMEA and Criticality Analysis (CA) (Fu et al., 2022). The FMEA is focused on how equipment and system have failed or may fail to perform their function and the effects of these failures, to identify any required corrective actions for implementation to eliminate or minimize the likelihood of severity of failure. While criticality analysis is done to enable prioritization of the failure modes for potential corrective action(Astrom, 2002; Ceylan et al., 2022). FMECA is a widely used tool for reliability, criticality and risk analysis across industry and academia, as it does not require much technical knowledge but provides good insight into system failures or malfunction (DoD, 1989; Marving Rausand and Arnljot, 2021). Cicek and Celik (2013) presented an approach for identifying and controlling potential failure or operational errors that trigger crankcase explosion using FMECA. In (Lazakis et al., 2018) FMEA was used for defect analysis on ship main propulsion engine by identifying critical engine failures for maintenance decision making. FMEA can equally be modified for specific application as presented in (Niculita et al., 2017; Shafiee et al., 2016) where a modified Ageing Failure Mode and Effects Analysis (AFMEA) and Functional Failure Mode Effects and Criticality Analysis (FFMECA) was done for the techno-economic life extension analysis of offshore structure and ship systems respectively.

FMECA is a major component used for system analysis of important maintenance concepts such as RCM and PMS as it presents a clear view of equipment, component and personnel interaction and how risk and reliability issues can be mitigated. Mechanical system component failure analysis with FMECA is generally robust particularly in establishing modes of failure and efforts to mitigate or prevent them, however is not practically possible to determine the probability of occurrence for each identified failure rate (NSWC, 2011). In this regard, is common to see FMECA being used alongside other tools for system reliability study (DoD, 2005; Melani et al., 2018). This is more so, as the analysis depends on qualitative inputs that can be influenced by the experience or sentiments of respondents, hence subjective(Lazakis and Ölçer, 2015). Overall, the limitation due to the subjectivity and interpretation of results can be addressed by ranking; using weights, fuzzy methods or hierarchical approach such AHP (Lazakis and Ölçer, 2015; Saaty, 2016). Accordingly, this paper has adopted the use of FMECA for system reliability analysis in order to account for expert knowledge in failure and mission critical component analysis. FMECA also help capture some subjective operator sentiments which could agree or disagree with reliability results obtained from objective methodologies such as FTA (Marving Rausand and Arnljot, 2021; NASA, 2002). Accordingly, to address the challenge of interpretation and subjectivity in FMECA analysis a weighting method was introduced to account for experience and years in service of all respondents(Ceylan et al., 2022). In doing these, issues of under scoring or over scoring certain failures due to inexperience or narrow judgement can be addressed, hence providing a balanced failure analysis.

2.3. Bayesian belief networks

Bayesian Belief Networks (BBN) provides a good platform for dependability analysis, cause, effect and inferential analysis in a wide range of sectors covering health care, human reliability, machinery system reliability and decision support system (Ahn et al., 2022; BayesFusion, 2020; P. Weber et al., 2012). BBN are represented as direct acyclic graph (DAG) which consist of chance nodes (variables) representing possible outcomes of system states and a given set of arrows (connections) indicating dependability/relationships(Bahoo et al., 2022b; BayesFusion, 2020; Canbulat et al., 2019). The nodes takes variable inputs in BBN analysis which can be continues or discreet and are not restricted to single top event, hence providing great flexibility unlike fault tress or RBD(Kabir and Papadopoulos, 2019). BBN can be used to represent cause and effect between parts of system or equipment by identifying potential causes of failure. Authors have used BBN for fault and diagnostic analysis as well decision support system (DSS), for instance Jun and Kim (2017) presented a Bayesian based fault identification system for CBM by discretising continues parameters based on maximum likelihood estimation (MLE) to identify failure conditions; the research used the discretised feature as binary inputs for the BBN conditional probability table (CPT). Similarly to address port energy efficiency towards the reduction ships emission during port calls a strategy using BBNs was presented in (Canbulat et al., 2019). This research also provides how BBN conditional probability can efficiently in-cooperate expert knowledge to provide vital inputs in decision making variables in areas where there is in adequate data or literature.

Bayesian updating or inference provides bases for the use of influence diagrams in decisions analysis by computing the impact of new evidence to the probability of events and the influence on all related nodes(BayesFusion, 2020). As such BN provide a good platform for DSS especially in maintenance strategy selection when considering several dependent and independent factors. Conducting system reliability and maintenance analysis demands in puts from multiple sources which the BN platform can accommodate as compared to other tools. Papers by Jun and Kim (2017) and Li et al. (2020) provide methodologies for the use of BBN in reliability analysis, however, while (Jun and Kim, 2017) focused on fault diagnose (Li et al., 2020) emphases on component reliability with limited analysis on factors affecting the reliability. Furthermore, BBN have been used to provide inferential analysis in conjunction with other tools such as Markov chain and Petri-nets especially in risk and reliability analysis (Galagedarage Don and Khan, 2019; Kabir and Papadopoulos, 2019; Kampitsis and Panagiotidou, 2022; Khakzad et al., 2011). BBN based DSS are widely applied in maritime industry to handle operational issues such as human factors and procedural issues such as maintenance (Ahn and Kurt, 2020; Kampitsis and Panagiotidou, 2022). Similarly in the field of ship system reliability analysis (Velasco-Gallego and Lazakis, 2022b)has presented on the use of BBN and FTA for ship machinery cooling system reliability analysis and DSS. Likewise, Bahoo et al. (Bahoo et al., 2022) applied a combination BBN and Markov chain Monte Carlo simulation to analyses machinery reliability estimation onboard autonomous ships to help maintenance planning and decision.

Maintenance planning and decision marking for ship systems can be complex due to the operational nature, space constraint and onboard environment. Hence maintenance as well as spare parts holding must be carefully considered so that failures and repairs are adequately prioritised to avoid problems with onboard spare parts holding and technical skills mix. Therefore, notwithstanding the rigorous efforts by authors in the field of ship system reliability there exist some important gaps in the literature. Some of this includes, not clearly identifying component criticality to system availability, maintenance action prioritization to reflect failure severity as regard vessel operational demands and selecting maintenance decision to reflect operator's sentiment. Providing solution to these problems require a systematic approach to system reliability analysis. Accordingly, this paper presents a novel methodology, which involves the combination DFTA, FMECA and BBN reliability analysis tools to conduct component criticality analysis, system failure dependency and influence as well as decision support system.

The presented methodology provides a detailed and comprehensive analysis that identifies critical components in relation to ship availability and maintenance effort in an inclusive manner that can account for operator concerns, OEMs' recommendations, and environmental influence. Unlike data driven approaches which rely on machinery health parameters or statistical methods such as distribution, residual life estimation through Mean Time To Failure (MTTF) which depend on failure rates, hence are unable to provide detailed information on failure and their causes. Other graphical approaches such as the bathtub curve also relies on failure rate data, which is insufficient to identify issues such as single point failure, common cause failures or critical components within a system and its components. Moreover, machinery failures can occur due to material or design defects, age/wear out and poor maintenance or intrusively actual maintenance action. Therefore, a hybrid approach taking into account the multiple dynamics in system reliability and failure mechanics needs to be developed. Accordingly, to develop a ship reliability analysis alongside a maintenance decision support system these selected tools provide a good match and can accommodate all the relevant variables as compared to using one or a couple of these tools. Consequently, FMECA provides outputs for mission critical components based on operator perspective, MCS provides an objective output to reflect MRO data both of which were used to build DSS using BBN. Furthermore, a case study was conducted to demonstrate the suggested novel methodology.

3. Methodology

The novel methodology presents a systematic combination of quantitative and qualitative reliability analysis approaches to ship system reliability by combining DFTA, FMECA, and BBN to address some observed gaps in the literature. This includes, for example, not explicitly defining component criticality to system availability or prioritising maintenance actions based on the severity of failures in relation to vessel operating needs and operator-led maintenance planning. A methodical approach to system dependability analysis is necessary to provide solutions for these issues. Therefore, this research presents a unique technique for conducting component criticality analysis by utilising the particular strengths of combined reliability tools as presented in Fig. 1.

3.1. Subjective inputs

A key difficulty in maintenance planning is handling equipment defects that are not fully addressed in OEM maintenance and troubleshooting manuals, such as environment-related faults, design restrictions, incorrect application, or unsuitable operation. These sorts of defects typically result in frequent equipment failures and performance deterioration, reducing system reliability and overall platform availability. However, because these defects are not well documented by the OEM and may not have been routinely experienced by operators on that or similar equipment. It is thus difficult to capture for reliability and maintenance analysis. In this context, information from operators on problems and maintenance issues would be required, thus the use of FMECA in this research.

3.1.1. FMECA

FMECA is widely applied in maintenance and risk analysis to provide clear understanding and procedure on what could go wrong, how it could go wrong, why it goes wrong, and how it can be corrected or addressed (Marving Rausand and Arnljot, 2021). The Criticality Analysis (CA) provides a means of identifying the events, occurrence or components that need more attention to avoid more serious or catastrophic situations(Melani et al., 2018). FMECA is a bottom-up approach which provides a systematic methodology to gain deep insight on failures and their course on an equipment or system. Therefore, measuring criticality in FMECA helps to explicitly bring out the most critical component failure which can assist in maintenance actions and planning. In this regard subjective operator inputs were obtained using FMECA, the relevance of which can be described in 2 folds. The first is to evaluate operator sentiments and priorities specially to do with failures and maintenance challenges such as expertise and causes of extended down times. This was also used to establish maintenance critical failures and machinery parts. The second aspect was to validate critical components obtained using DFTA qualitative analysis. Therefore, to establish these 2 goals using FMECA analysis a questionnaire was produced and distributed using the Qualtrics survey software; Table 1 is a template of the FMECA table used.

The survey questions were aimed at identifying components that presents the greatest challenge to the conduct of maintenance onboard using risk priority number. The RPN use 3 categorical variables namely identification, severity and likelihood usually measured in a linear scale based on increasing importance i.e 1 – 10. The scale used for the analysis is presented in Table 2, which shows the linear and Likert scale including colour codes representing respective scale values (Jeong et al., 2018; Tan et al., 2011).

Furthermore, in this study, criticality was employed instead of detectability since enhanced sensor and monitoring have substantially increased the level at which problems are identified, either through set alarm levels or an emergency shutdown system. For the sake of clarity, criticality, determines the immediate impact of failure event to the

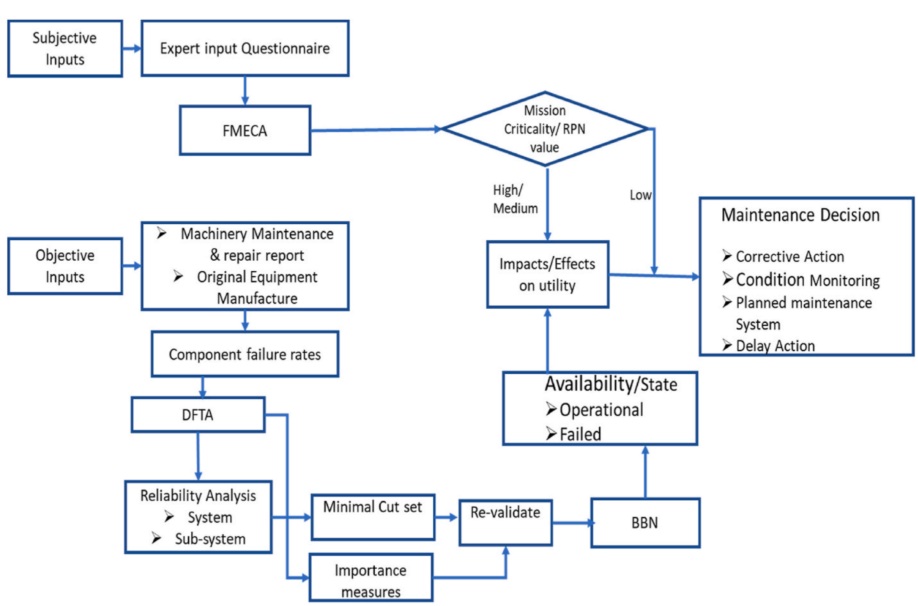

Fig. 1. Flowchart of novel methodology.

Table 1
Sample FMECA table.

Subsystem	Component	Function	Description of Failure			Effects of Failure				Safeguards		Criticality	Severity	Likelihood	RPN
			Mode	**Causes**	**Detection**	**Local**	**Global**	**Influence**	**TTR**	**Prevention**	**Mitigation**	**1–10**	**1–10**	**1–10**	**CxSxL**

equipment availability and functions. Therefore, a failure mode due to which the ship will not achieve one or more of the mission's targets and/or the safety of whole vessel is at risk until the failure is rectified(NASA, 2008). The next is Severity, severity assesses how the failure impacts on the operational availability of the equipment or system regarding normal operation and the duration it takes to be repaired or restored to normal operational levels. Severity is described as the worst potential consequence of the failure determined by the degree of injury, property damage or system damage that could occur. Lastly, likelihood and refers to the failure rate of the component including possibility and frequency of the fault occurring over a certain time frame (DoD, 1980).

The above explanation provides a guide to help respondents assess all the criteria against the candidate failures and components. Thereafter the responses were aggregated through a weight system to obtain single outcome to quantify the 3 criteria needed for calculating the RPN which are Criticality (C), Severity (S) and Likelihood (L). The RPN was used to get the mission criticality of the components or faults which is given by RPN = CxSxL scored on a scale 1–100; 1 being minor or low and 100 being very high score as regards impact. The FMECA was conducted through a survey completed by the engineering personnel of the organisation most of whom are either electrical or marine engineers with varied level of technical knowledge and experience. In this regard, a 2-weight system was introduced to account for experience and expertise, as presented in Table 3. Accordingly, all individual inputs were evaluated to reflect years of experience and specialisation of the respondents. For instance, response on piston failure by a marine engineer with 12 years' experience will have more weight compared to that of electrical engineer with same experience and verse vasa if the response were to be on alternator parts.

Adopting the above weights, individual responses were evaluated according to experience and specialisation to obtain the population mean, equation (1). Thereafter a weighted average is taken for each grouped experience, equation (2), which provides single category for criticality analysis to obtain the RPN using equation (3). However, the linear values used for the criteria were between |1–10| while the FMAEC RPN was 0 ≤RPN ≥300. In this regard equation (4) was used to obtain normalised RPN within the range of |1–100|

$$population\ mean\ \mu = \frac{\sum x}{N} \qquad \text{equation 1}$$

$$Weighted\ average\ w = \frac{\sum_{i=1}^{n} w_i X_i}{\sum_{i=1}^{n} w_i} \qquad \text{equation 2}$$

$$RPN = \sum_{i=\leq 1} Cw_i \times Sw_i \times Lw_i \qquad \text{equation 3}$$

$$RPN_{norm} = \frac{X - min(X)}{max(X) - min(X)} = \qquad \text{equation 4}$$

3.2. Objective inputs

The methodology adopted in this research draws from multiple data sources some of which are raw machinery log data, maintenance and repair data including technical reports, others are output from tools used in the research. This process enables a more robust analysis especially considering that the duration of the research will not allow verification or implementation of the methodology onboard. Accordingly, the objective inputs are independent numerical variables and not controlled by the modeler. These includes failure rates obtained from machinery failure data used as inputs for the DFTA, RPN values from FMECA, and MCS probabilities from the DFTA results used as inputs in the BBN. Furthermore, availability percentages from the BBN were used to build the DSS model which was complemented by MCS from the DFTA.

Table 2
Definition of Criteria.

Linear scale (1-10)	Severity Level	Criticality Level	Likelihood Level	Failure Rate
1	**Minor**: Failure or event that has little or no significant impact to system capability and availability	**Minor:** A component failure or event that has no immediate impact on platform or personnel safety.	**Remote:** Failure is unlikely.	10^{-5} - 10^{-6}
2-3	**Low**: Failure or event that could cause slight deterioration of system capability but will not affect it availability. System may require minor repair action.	**Low:** Failure or event that could cause slight delay/deterioration system capability but will not affect its availability.	**Low:** Isolated failure associated with component or equipment	10^{-4} - 10^{-5}
4-6	**Marginal (Moderate):** Failure could result to deterioration in system capability which may require unscheduled repair or may cause minor health hazard or injury to the user.	**Marginal (Moderate):** A Failure that could result to deterioration in system capability and availability which may require unscheduled repair that can be conducted by ship staff	**Moderate:** Occasional failure but not in major proportions.	10^{-3}-10^{-4}
7-8	**Critical (High):** Failure causes loss of system capability and availability or may cause a serious health hazard or serious injury to the user.	**Critical (High):** Failure that results to loss of system capability and can influence the efficient operation of other systems.	**High:** Generally associated with components or system which often fail	10^{-2}-10^{-3}
9-10	**Major (Very High):** A potential failure could cause complete system loss and /or death of user(s). A failure event which may lead to extended downtime due to spare parts or OEM assistance.	**Major (Very High):** A potential failure could cause complete system loss that will require FSG or OEM assistance	**Very High:** A component or equipment with very high failure rate	10^{-1} - 10^{-2}

Table 3
FMECA Respondents and weights.

Experience	Weights	S	Weights	Ag Weight	Applied weight (%)
0–5years	50	WKO/WKD	0	50 + 0	0.5
5–11 years	60	WKDWEO/ MEO	0	60 + 0	0.6
11–15 years	65	WEO/MEO	5	65 + 5	0.7
15–20 years	70	FSWEO/ FSMEO	10	70 + 10	0.8
20–24 years	75	FSMO/FSG CMDR	15	75 + 15	0.9
24–28 years	80	FSMO/FSG CMDR	20	80 + 20	1
28–35 years	100	FSG CMDR	0	100 + 0	1

3.2.1. DFTA

The dynamic fault tree analysis is an extension of standard fault tree analysis that provides for time or sequence dependent analysis and can also prioritise events for analysis. DFTA is selected for this study in order to utilise its system dependent relationship on the effect of component failures. The DFTA tool used for machinery/system reliability and availability analysis used input data generated from the operational records of 4 diesel generators for a ship power generation system. Therefore, a DFTA structure representing the functional ship power generation system as well as the individual diesel generators was built. System reliability in DFTA involves generating a qualitative model of the fault tree usually from the minimal cut sets on the logic gate of the fault tree. Thereafter, quantitative analysis using reliability and maintainability data such as failure rates/frequency, failure probability, mean time to failure or repair rate can be used (Relex et al., 2003), by calculating the unavailability and the unreliability of the system to be done.

Accordingly, failure and maintenance data over a period of 6 calendar years obtained from the maintenance records was processed to generate components failure rates ($\curlywedge$) based on equation (5). The model structure was built using both static and dynamic FT gates and events to reflect the mode of failures and in other cases dependency and sequence. Therefore, top events and sub-events were modelled using dynamic gates while gates connecting to the main system were modelled using static FTs this procedure is necessary to reduce memory usage and improve calculation time. The probabilities for the static gates used were generally AND gate equation (6), OR gate equation (7) and Voting gate . Voting gate (equation (8)) account for multiple connected components (*k out of n*) such as injection nozzles, cylinder blocks, fuel day tanks or supply line, this is because correct functioning of system requires all component but is not necessarily impaired due to a few faulty ones.

$$\curlywedge = \frac{n}{\tau} \qquad \text{equation 5}$$

Where n is number of failures (10^6) and τ is aggregated time in service of individual DG. The inputs for the gates are obtained with the below equations.

Probability of occurrence of an AND gate =

$$\Pr\{A\} = Pr\{A_1\} \bullet Pr\{A_2|A_1\} \bullet \ldots \bullet Pr\{A_n|A_{1,}A_{2,}\ldots,A_{n-1}\} \qquad \text{equation 6}$$

If all events are independent, then

$$\Pr\{A\} = Pr\{A_1\} \bullet Pr\{A_2\} \bullet \ldots \bullet Pr\{A_n\}$$

For an OR gate given A_1,A_2….., A_n as inputs and A is the output of the OR gate, the probability of its occurrence (top event) =

$$Pr\{A\} = Pr\{A_1\} + Pr\{A_2|\sim A_1\} + \ldots + Pr\{A_n|\sim A_1, \sim A_2, \ldots \sim A_{n-1}\} \qquad \text{equation 7}$$

If all events are independent

$$Pr\{A\} = Pr\{A_1\} + Pr\{A_2\} \bullet Pr\{\sim A_1\} + \ldots + Pr\{A_n\} \bullet Pr\{\sim A_1\} \bullet Pr\{\sim A_2\} \bullet \ldots \bullet Pr\{\sim A_{n-1}\}$$

$$= PrP\{A_1\} + Pr\{A_2\} \bullet (1 - Pr\{A_1\}) + \ldots + Pr\{A_n\} \bullet (1 - Pr\{A_1\}) \bullet (1 - Pr\{A_2\}) \bullet \ldots \bullet (1 - Pr\{A_{n-1}\})$$

$$= 1 - (1 - Pr\{A_1\}) \bullet (1 - Pr\{A_2\}) \bullet \ldots \bullet (1 - Pr\{A_{n-1}\})$$

In the above formular A is the top event, A_1, A_2 …., A_n are lower events.

Voting gate:

$$PrA = C_k^n(r)^k(1-r)^{n-k} + \ldots + C_n^n\,(r)^n(1-r)^{n-n} \qquad \text{equation 8}$$

The MCS for top event is obtain via equation (9).

$$T = M_1 + M_2 + \ldots + M_K \qquad \text{equation 9}$$

Where T is the top event and M_i are the MSC. On the other hand, the MCS for a specific component can be given by $M_i = X_1 \bullet X_2 \bullet \ldots \bullet X_n$ equation 10

The MCS from the DFTA was used as input for the BBN condition probability analysis.

3.3. BBN

Bayesian belief networks provide efficient and flexible platform for the conduct of numerical analysis to aid decision making impacted by conflicting priorities. BBNs can be up dated with new data at any point during the analysis thereby providing a very efficient tool for decision support system especially for complex system maintenance analysis (Sakar et al., 2021). BBN analysis is conducted based on DAG structure consisting of nodes of various shapes representing events and their probabilities, connected to arrows indicating dependencies or influence. Conditional probability tables (CPT) of discrete or continues variables provide inputs for the nodes in the influence diagrams. The CPT can be updated according to data availability which provide the evidence (E) and event occurring. The evidence is used by the BN's inference engine to update the prior occurrence of event, equation (13) (F.V. Jensen, 2007).

$$P(U|E) = \frac{P(U,E)}{P(E)} = \frac{P(U,E)}{\sum_U P(U,E)} \qquad \text{equation 13}$$

The above equation represents the overall structure of the influence diagram for a BN structure analysis. In this case the conditional probabilities of failure are presented as parent event and faults are presented as children P (Failure|Fault event). In this regard the influence diagrams for the building the maintenance DSS was generated using the CPT output of BBN which provides the availability of the DGs. Overall, the parent/child relationship of the BN structure is derived from the Bayesian theorem and chain rule that enables the quantification of relationships among the variables. Hence the joint probability distribution *of P(U)* represented by child(ren) A_i for each node on the network can be evaluated based on equation (14).

$$P(U) = \prod_{i=1}^{n} P(A_i|Pa(A_i)) \qquad \text{equation 14}$$

Where $Pa(A_i)$ are the parents of *Ai in P(U)* reflects the overall relation of the nodes in the network.

Accordingly, the Bayesian network and influence diagram for the DSS were build using the Genie software (BayesFusion, 2020). Building the DSS require different approach as it requires utility inputs as value for decision choices. Therefore, first step in BBN analysis was to get sub-system availability using the MCS probability of occurrence obtained from the DFT analysis used as probabilities for the CPT of all the chance nodes. The BN chance nodes have 3 levels, first level identifies the probability of occurrence of the fault as a child of a component failure indicating either failed or not failed. The failure node represent components that are linked as child nodes to subsystem node which provides the output as either available or not available depending on probability of occurrence of MCS in CPT; Fig. 2 presents a simple sketch of the BBN structure node relationships and options.

The BN availability output together with the FMECA RPN provides vital inputs for the DSS in addition to maintenance strategy choices. The influence diagram for the maintenance decision support use additional nodes namely, decision and utility (value) nodes, each of which provides a complementary evaluation of the input variables. The decision nodes take in variable assigned by the decision maker in order to model available decision variables (BayesFusion, 2020). In this case the decision variables are the maintenance strategy options in Table 4.The second node is the value node also called utility, this node provides a measure of the desirability of the output of the decision process and quantified by the utility of each possible outcome of the parent node (BayesFusion, 2020). The last node is the chance nodes which contain

Table 4
Maintenance strategy options.

Maintenance Strategy	Definition	RPN Range
Corrective Action	This is recommended for very high to high mission critical component or faults for example sea water supply pump impeller, fuel supply pump, automatic voltage regulator faults etc.	75–100
Condition Monitoring	This strategy serves as intervention to ensure system availability targeted at component or failures whose early identification could avert major operational delays.	55–75
Planned Maintenance System	The PMS maintenance choices prioritise time dependent component failures with no immediate impacts to availability repair requirements.	35–55
Delay Action	Delay action maintenance choice is directed at those components with good resilience or sufficient redundancy such that there is little or no danger to personnel and system safety.	0–35

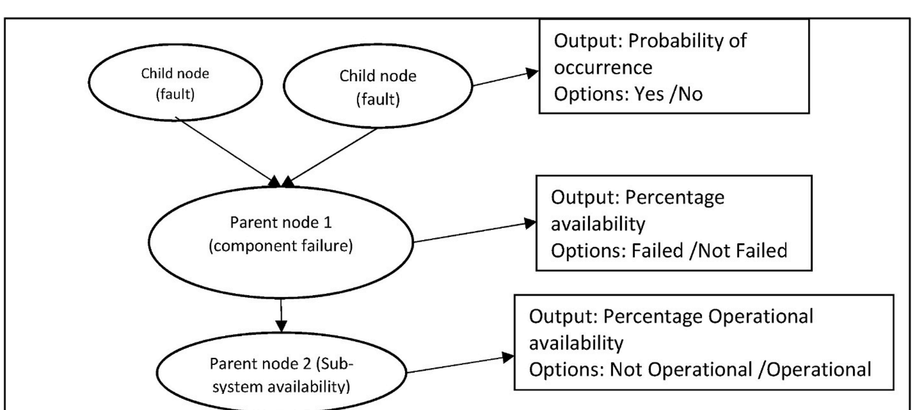

Fig. 2. BBN structure node relationships and options.

Table 5
DSS ranking scale.

Linear Scale (1-10)	Severity Level	Criticality Level	Likelihood Level	Maintenance Decision	Normalised RPN (Utility Value)
0	Minor	Minor	Remote	Delay Action	0-35
1-4	Low	Low	Low	Delay Action/PMS	
4-6	Moderate	Moderate	Moderate	PMS	35-55
6-8	High	High	High	ConMon/Corrective Action	55-75
8-10	Very High	Very High	Very High	Corrective Action	75-100

random variables representing uncertainties or probabilities that are relevant to the occurrence of the events(BayesFusion, 2020). As explained earlier, they represent probabilities of MCS of the components of each sub-system as inputs in CPT. Therefore, these 3 nodes formed the methodology of the DSS which interpret the desired outcomes based on the available choices while; the value node takes in continues variables as a measure of the parent nodes (subcomponent) criticality. In this way the utility value nodes provide the expected utility of a parent node or top event feeding it to decision node to get its availability percentage; while the decision node in the influence diagram contains maintenance decision choices which are dependent on the RPN variables inputs in value nodes as shown Table 5.

The definition in Table 4 provide a general guidance in the maintenance selection process in the DSS and used in the decision nodes. Making the selection depend on 2 variables which include the RPN and availability. In this regard the normalised RPN factors down time, maintenance cost and lost utility due to failure have been accounted for; while the availability factors in component availability within operational period were equally addressed. Hence all the DGs are evaluated based on 2 main factors which are availability and system criticality based on RPN values as presented in Table 5.

4. Case study

The power generation system provides the most vital utility on board ships which suggests the level of redundancy and design resilience usually provided by ship builders. These features are common for both merchant and naval ships though with significant high operational demand for the naval platforms. Failure of the power generation system for naval platforms has several implications especially considering the number of personnel onboard, and vulnerability due to loss of weapons, surveillance and habitation platforms usage. The location and type of failure are important factors to be considered in maintenance planning due to logistics and OEM related concerns. In this regard the suggested case study implements a novel methodology through the combination of reliability analysis tools to address maintenance challnegs on the power generation plant onboard and offshore patrol vessel (OPV).

Accordingly, data analysis for this research was designed to cover subjective and objective analysis. The subjective aspect of the case study provides intuitive guidance on model quality, while the objective part of the methodology provides numerical analysis using failure rates as inputs. The FMECA analysis presents experts judgement about failure and critical system component while the DFTA is a quantitative analysis on system component reliability. The inputs for the BN analysis were obtained from both failure rates and MCS output of the DFT analysis, while RPN numbers from FMECA analysis were used as bases for maintenance strategy selection of individual generators. Therefore, data used for the analysis includes FMECA conducted via online survey, failure rates using maintenance and repair data collected from 4 marine diesel generator plants, each rated at 400 kW and can be operated parallel or individual. This was followed by discussion about operation and maintenance process onboard including wider discussion to gain expert perception on maintenance process in the fleet.

Table 6
FMECA Respondents and weights.

Positions	Respondents	Experience	Ag Weight	Applied weight (%)
WKO/WKD	2	0–5years	50 + 0	0.5
WKDWEO/MEO	2	5–11 years	60 + 0	0.6
WEO/MEO	4	11–15 years	65 + 5	0.7
FSWEO/FSMEO	5	15–20 years	70 + 10	0.8
FSMO/FSG CMDR	3	20–24 years	75 + 15	0.9
FSMO/FSG CMDR	2	24–28 years	80 + 20	1
FSG CMDR	2	28–35 years	100 + 0	1

4.1. Subjective analysis

FMECA analysis were conducted, for the marine DGs targeted at getting expert opinion on failures mechanism and how the DGs are impact by these failures. It also provides experts judgement on how this failure affect platform availability due to issues such as, spare parts availability, technical expertise, delays due to OEM and impact of the operational environment including practices. These outcomes from the FMECA were used to generate RPN number and normalised to obtain the mission critical component, Table 6 shows respondents experience and assigned weights. The assign weights are product of experience in years and positions held.

The FMECA survey consisted of about 20 questions on various types of faults and failure conditions covering DG system including the alternator. All respondents are engineers with varying experience and specialisation. The 2 specializations are Marine and Weapon Electrical Engineers with experience levels between 5 and 35 years of service considering position occupied. The 2 variables, namely experience and specialisation were used as weights in percentages and applied to individual inputs of the respondents. Accordingly, all individual inputs were evaluated to reflect years of experience and specialisation of the respondents based on equation (14). Adopting the above weights, individual responses were evaluated according to experience and specialisation to obtain the population mean equation (15).

$$W_1 = \sum_{i>0}^{n} C_1\left(\frac{e+s}{100}\right) + C_2\left(\frac{e+s}{100}\right).....C_i\left(\frac{e+s}{100}\right) \qquad \text{equation 14}$$

Where W_1 is the weighted component score for rank 1, n is the number of respondents in that rank, C is evaluated criterion.

$$\mu = \frac{\sum x}{N} \qquad \text{equation 15}$$

Where μ is the population mean, x = data values, N = number of samples.

Using the population mean for each group the weighted RPN for each subsystem and component was evaluated and normalised to ≤100 as

Table 7
FMECA RPN values of Most critical failures.

	Component	Failure Mode	Time to repair	RPN
Cylinder Block	Crankcase	1.Cracking	1-3months	65
	Cylinder liner failure	2. Cracks 3. Scuffing 4. Seizure	1wk-3months (depending spare parts availability)	56
	Cylinder head bolts	5. Loose 6. Not tight	1-3hrs	100
	Top Cylinder gasket	7. Burnt 8. Material Failure	10-24hrs	60
	Cylinder head O-ring	9.Deformation	2 wk-2 months	60
Power Take Off	Crank Shaft	10. Surface roughness 11. Misalignment	1 month	58
	Journal Bearing	12.Friction and seizure	6hrs-2 days (with spare availability) 1-2 months (OEM to supply spares)	64
Cooling System	Heat Exchanger Tubes	13. Scale build-up 14. Leakages	30min-6hrs	64
	FW circulation pump	16. No water supply 30. Drop in pressure	2hrs-4weeks	51
	SW pump assembly	32. No SW supply 33 Drop in pressure	2-4hrs	51
	Fuel Quality	46. Loss of power 47. Erratic operation 48.Filter blockage 49. Sludge accumulation in tanks	1-2weeks	56

presented in Table 7.

4.2. Objective analysis

The objective phase of the case study provides a system reliability analysis using quantitative failure rates values of the 4 marine DGs, therefore providing a numerically objective output. The DFTA results includes component reliability, importance measures (criticality) and cut sets, which provide a significant understanding on the DGs reliability. However, it was difficult to identify specific repair, maintenance or component failure that present the highest challenge to the operators. Therefore, considering that the MCS is a combination of minimum number of events which must occur for the top event to occur (component failure); it therefor provides a good source of variables for building the BBN while taking additional inputs from the FMECA as RPN. Accordingly, this study is utilising the MCS of the DFTA to build the BN analysis by identifying top 10 most critical components as presented in Table 7 above.

The DFTA analysis provides both qualitative and quantitative calculations. The qualitative analysis is performed using the structure of the DFTA dependent on logic properties of the gates, while the quantitative analysis uses MRO data such as failure rate, MTBF, and frequency. The quantitative analysis outputs are objective results that includes system unreliability, unavailability and reliability importance measures which provide critical components failures. However, the MCS evaluation is based on the output evaluated using the logic combination of the top event occurrence usually from left to right. Therefore, to obtain the MCS the DFTA structure representing each DG was built based on the functional relationship and system boundary of the sub-systems of the respective marine DGs. MCS are product of the fault tree which forms the failure path of an evaluated fault tree, i.e the smallest set of basic events, which if they all occur will result in the top event occurring (NASA, 2002). However, it is important to note that a single basic event can equally form a cut set depending on the arrangement of the fault tree, Fig. 3 provides some instance of MCS. Sub-system 1 having an AND gate fails only when all the events have occurred however the intermediate OR gate fail when any of its BEs occur, while in the case of sub-system 2, the occurrence of BE7 or BE8 is an MCS. Similarly, occurrence of any of the BEs in sub-system 3 forms a cut set for the sub-system. This highlights potential area where improvements can be achieved through alternative maintenance approach, redesign or simply altering the system to improve its reliability.

The next step after the MCSs were obtained was to build the BBN structure using the MCS probability of occurrence as inputs to the CPT. Therefore, using a bottom-up approach, discrete chance nodes were used to model faults which are then connected to parent chance nodes representing component having probability values as inputs to the CPT, the top 10 MCS used for building the BBN are contained in Table 8. Overall, 8 subsystems and dependent components were modelled and analysed in the BN structure. The component chance nodes are linked to all possible faults including faults in other subsystems that could elicit multiple component failures that could result to greater maintenance or availability problems. The flexibility in BN which allows modelling CCF is very helpful in presenting complex failure interactions between

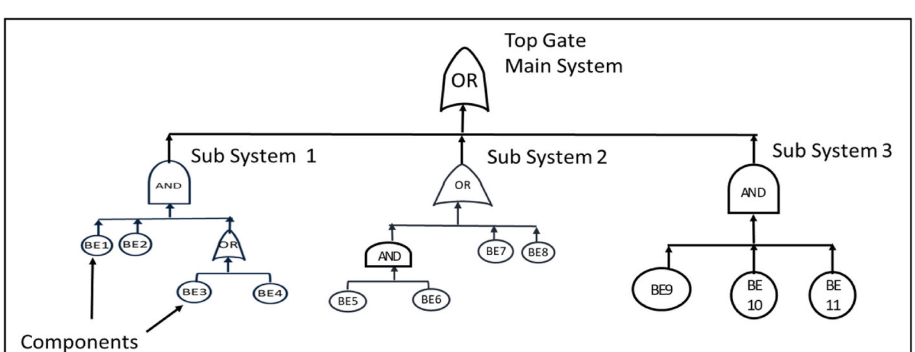

Fig. 3. Instances of MCS formation.

Table 8
Top 10 cut sets for DG1-4.

DG1	DG 2	DG3	DG4
Crankshaft journal failure	Fuel Injection pump Mechanical failure	Crankshaft journal failure	HP fuel pipe leakages
Fuel Filter (1&2)	FW Heat Exchanger Fouling	FW Heat Exchanger Fouling	FW Heat exchanger tube fouling
Sea Chest blockage	Tappet clearance (In&Ex)	RW impeller Damage	Rocker arm and Tappets clearance
Tappet clearance (In&Ex)	Burnt top cylinder gasket	Turbo charger lub failure	Governor drive
Cylinder Head sealing	Clogged Air filter	Cylinder head gasket damage	Intercooler fins fouling
Fuel Lift pump defects	Injector Nozzle faults	Injector nozzles faults	Turbo charger
Turbo Charger leakages	Clogged Air filter	blocked fuel filter	Cylinder Head gasket damage
Cylinder jacket cracks	Oil filter	Piston crown damage	Loose cylinder head bolts
Low fuel pressure	No Fuel Supply	Tappet clearance	Clogged air filter
RW water impeller	Defective fuel pump	Loose cylinder head bolts	Injector camshaft failure

components that serve many systems or subsystems.

The process also enables more efficiently evaluation of the MCS and there impacts were more highlighted using BN analysis, hence one of the many reasons of using BN for this analysis. Moreover, the cumulative probability of the child nodes occurrence determines the operational health condition of the parent component node at the sub-system level; Fig. 4 is a sample of the BBN structure for DG2, showing 3 out of the 8 subsystem and an abridge part of the CPT.

A complete model for DG 3 containing all 8 sub-systems and their nodes is shown in Fig. 5. As can be seen in the structure the yellow nodes represent the failure cause, the light green nodes represent component failure while the sub-system are rectangle grey nodes with bar chart and the topmost blue node represents the DG. The arrows from the nodes are linked across sub-system to model common cause faults (CCF), which is typical of many mechanical systems especially due to temperature and load related failures. The BBN model clearly present those CCFs that can impact multiple subsystems hence provides a good reference point for the DSS.

The DSS was built on the existing BN structure and takes inputs from all the 8 subsystems and RPN values. Therefore, within the DSS process the non-availability of subsystem obtained in the BN is translated to reflect the ranking table in line with RPN structure as earlier presented in Table 5. Additional nodes namely decision and value nodes were used in conjunction with the chance nodes. The decision nodes are used to represent variables controlled by the decision maker while the value nodes provide a measure of the desirability of the decision outcomes based on DSS process as shown in Fig. 6.

Following the above process, the DSS had 2 decision nodes with maintenance strategy and criticality level options as input. Accordingly, the value nodes had RPN values that serve as measurement of how the operators perceive the impact of failure on the DGs while ship operational availability has RPN as its inputs. In this regard the 8 chance nodes connect to value node provides the DG availability inputs in percentages while the 2 decision nodes feed in decision choices as regards the DGs availability and sub-system criticality as shown in Fig. 7.

5. Results and discussion

This section presents the results of the analysis based on the implementation of the presented methodology and DGs in the case study. This section will start with the subjective analysis result on the FMECA output, thereafter the objective aspect will be presented to cover DFTA MCS use for BBN as well as the BN and DSS results.

5.1. FMECA RPN

The FMECA survey outputs provides a very important input to the overall analysis as regards what may have not been carefully accounted for in the maintenance and repair data collected from the DGs. Moreover, the MRO used was for and individual ship while the FMECA data was the response from over 20 experts with varying professional experience. Though the FMECA has in no way influenced the DFTA results it was mainly used to complement it for the second aspect of the BBN analysis which is the maintenance DSS. The fact that DFTA cannot account for issues to do with unplanned downtime, quality of replacement parts, design related unreliability and generic human factor concern. The FMECA helps in addressing these issues as well as other environmentally induced failures which were not factored during installation but were not necessarily design related. Therefore, the FMECA survey was designed to capture some of these problems, to also highlight how the operators evaluated the most critical failures to ship availability and repairs.

It is important to understand the peculiarities and the condition of Naval ship operations, as regard operational requirements and system demand onboard. A standard operating procedure for naval ships is parallel operation of DGs during certain exercises, navigational circumstances and load demands. In this regard, despite the redundancy in

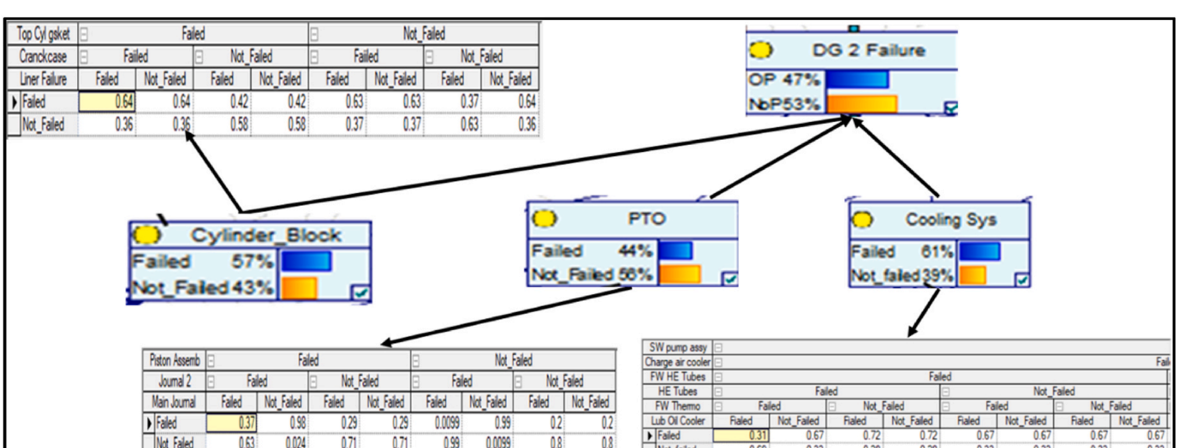

Fig. 4. Sample BBN for DG2 showing 3 subsystems and CPT tables.

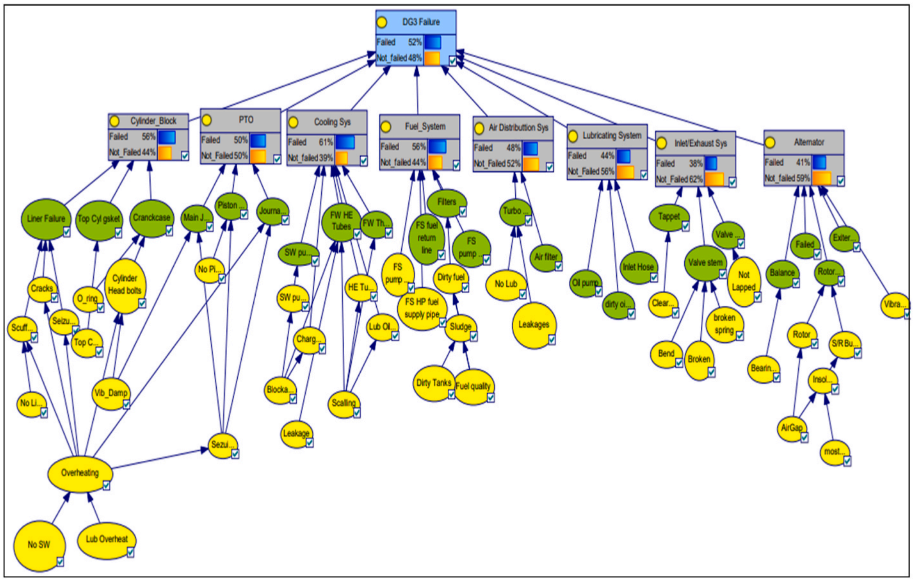

Fig. 5. BBN structure for DG 3.

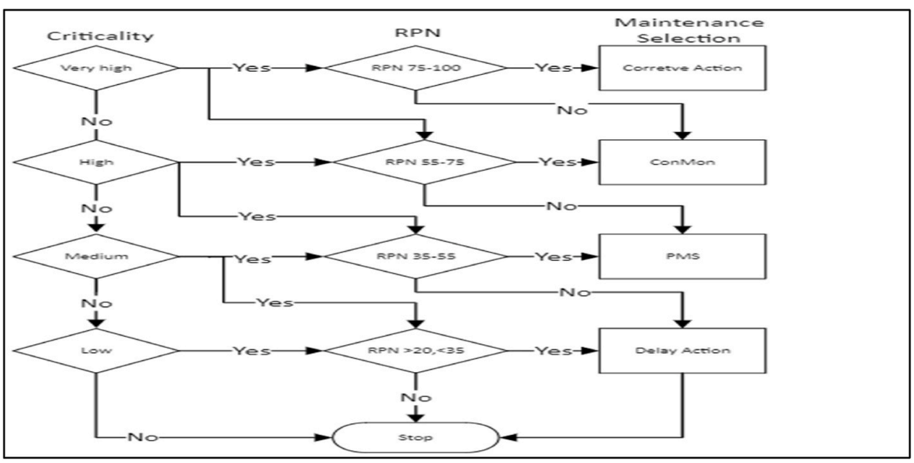

Fig. 6. DSS process schematic.

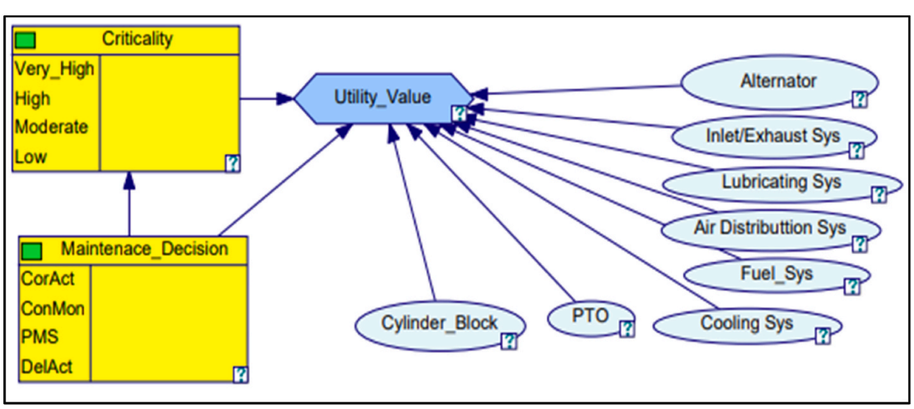

Fig. 7. DSS structure.

power generation system it is usual to have load shading due to high demands from other utilities. Therefore, the power generation system is one system that naval ships cannot afford to compromised.

It is therefore common to have ships undertake repairs while under way to ensure that at least 2 DGs are available, hence any repair that cannot be undertaken by ship's staff while underway is viewed as critical and can affect overall ship availability or deployments. The results of the FMECA highlights these critical failures which may not be seen as

Table 9
FMECA RPN values of Most critical failures.

Subsystem	Component	Failure Mode	Time to repair	RPN
Cylinder Block	Crankcase	1.Cracking	1-3months	65
	Cylinder liner failure	2. Cracks 3. Scuffing 4. Seizure	1wk-3months (depending spare parts availability)	56
	Cylinder head bolts	5. Loose 6. Not tight	1-3hrs	100
	Top Cylinder gasket	7. Burnt 8. Material Failure	10-24hrs	60
	Cylinder head O-ring	9.Deformation	2 wk-2 months	60
Power Take Off	Crank Shaft	10. Surface roughness 11. Misalignment	1 month	58
	Journal Bearing	12.Friction and seizure	6hrs-2 days (with spare availability) 1-2 months (OEM to supply spares)	64
Cooling System	Heat Exchanger Tubes	13. Scale build-up 14. Leakages	30min-6hrs	64
	FW circulation pump	16. No water supply 30. Drop in pressure	2hrs-4weeks	51
	SW pump assembly	32. No SW supply 33 Drop in pressure	2-4hrs	51
	Fuel Quality	46. Loss of power 47. Erratic operation 48.Filter blockage 49. Sludge accumulation in tanks	1-2weeks	56

important by OEMs, but the operator's environment and operational circumstance made it so. Consequently, Table 9 above, is the FMECA RPN values obtained from response of operators, which details how the operators perceive the importance of DGs against the navy's operational demands, maintenance practice and capabilities including environmental conditions.

A look at the table indicates majority of faults with low likelihood have high criticality and severity values. Therefore, taking from the definition of these 2 factors the operators are more concern with failures that affects ship availability. This is not to say safety is not of concern, in fact the threat to safety as regards loss in power generation output could be in 2 folds. First is safety and security both external and internal to the ship. The second is operational external safety to do with threats to national assets and safety of navigation which is equally a safety concern to personnel onboard. Hence, faults that can be fixed while underway or which do not expose the ship to danger i.e. loss of 2 out of the 4 DGs is within acceptable limits. Therefore, consideration for the maintenance strategy selection needs to be dynamic to reflect the prevailing operational and health condition of the DGs. Hence the need to consider the interaction between objective and subjective data sources to provide balance in the DSS analysis.

5.2. DFTA

MCS obtained through DFTA for individual sub systems were used as inputs to build the BN probability analysis. MCS being a combination of events or failures that leads to the system or subsystem failure can be efficiently utilised to improve system availability. Nonetheless, some failures can be triggered by a fault in another system, especially in marine diesel generators where many faults are interrelated due to system dependencies. For instance, one of the most important failures on the DGs was crank case failure but influenced by multiple factors from other subsystem such as the lubricating system and the cooling freshwater system as well as the air distribution system. This makes it difficult to isolate failure to faults, so the approach in this research is to identify the MCS, and link the components and their probability of occurrence, as shown in Table 10. This way the operators will be able prioritise maintenance and identify spare parts shortages as necessary.

Moreover, another important factor with MCS is that events are considered based on their contribution to failure not only occurrence. In some cases, failure occurrence may not necessarily be the reason why a component becomes critical to maintenance. In most cases factors such as down time, cost of repairs and repair capability could be major

Table 10
Top 10 cut set and probability of occurrence.

DG1	Probability	DG 2	Probability	DG3	Probability	DG4	Probability
Crankshaft journal failure	0.49	Fuel Injection pump Mechanical failure	0.82	Crankshaft journal failure	0.78	HP fuel pipe leakages	0.85
Fuel Filter (1&2)	0.87	FW Heat Exchanger Fouling	0.67	FW Heat Exchanger Fouling	0.94	FW Heat exchanger tube fouling	0.7
Sea Chest blockage	0.71	Tappet clearance (In&Ex)	0.82	RW impeller Damage	0.84	Rocker arm and Tappets clearance	0.86
Tappet clearance (In&Ex)	0.52	Burnt top cylinder gasket	0.86	Turbo charger lub failure	0.75	Governor drive	0.77
Cylinder Head sealing	0.75	Clogged Air filter	0.75	Cylinder head gasket damage	0.72	intercooler fins fouling	0.53
Fuel Lift pump defects	0.82	Injector Nozzle faults	0.74	Injector nozzles cylinder	0.72	Turbo charger	0.52
Turbo Charger leakages	0.54	Clogged Air filter	0.76	blacked fuel filter	0.76	Cylinder Head gasket damage	0.73
Cylinder jacket cracks	0.5	Oil filter	0.46	Piston crown damage	0.87	Loose cylinder head bolts	0.64
Low fuel pressure	0.63	No Fuel Supply	0.78	Tappet clearance	0.8	Clogged air filter	
RW water impeller	0.84	Defective fuel pump	0.82	Loose cylinder head bolts	0.68	Injector camshaft failure	0.54

concerns for operators. For Instance, overheating related failures are dominated by sea water heat exchanger scale build-up and are mainly of concern because of the envisaged operational interruption. However, lubrication system failures or losing alternator exciter which seldom happens but their occurrence could lead to serious consequence. These types of faults are well captured by MCS formation in DFT analysis, however the DFTA structure does not support the modelling of MCS that can develop to CCF covering more than one subsystem. Hence BBN was adopted to overcome the challenge of CCF, while accommodating course effect analysis considering multiple operational factors.

5.3. BBN and maintenance DSS

Power generations system reliability is of great concern for all ship operators irrespective of sector, as it provides the highest utility and ensures collective safety of operators, passengers, equipment and cargo. In this regard the BBN model investigated multiple failure types and their impact on components and DG availability. Modelled components were from DFTA MCS and their failure probability from the collected MRO data. This input was used to obtain the availability for individual DGs as well as the main subsystems modelled, as shown in Table 11. The results shows that all 4 DGs had varying degrees of availability with DG2 being slightly more available as compared to the rest. The subsystem availability particularly that of the lubricating system of DG2 at 75% is an important pointer. Moreover, the lubricating subsystem is one of the most reliable subsystems in most DGs, this can be attributed to the centrality of its function particularly to the moving parts and heat transfer. On the other hand, a very critical situation is presented in the cooling system with availability values below 40% which is far below the expected availability of the operator. The low availability values could be linked to the sea chest blockages which can be very frequent and rapid due to scale build-up on the cooling fins. Nonetheless, the cooling system for the ships in question has at least 4 redundant sources of water supply in addition to the inline source, while this design helps reduce the risk of overheating due to delays in switching water sources. It is important that an early warning system is provided to ensure that watch keepers are adequately alerted at the onset of any pressure reduction in water supply or temperature increase for at least 10 min with no corresponding increase in demands or beyond normal threshold.

Furthermore, the DG availability can be used independently to aid maintenance planning, in that the subsystem availability indicates where maintenance effort should be directed. However, to improve maintenance decision making additional issues that influence delivery and quality of maintenance needs to be considered. In this regard the FMECA provides a solution, and it was used for building the DSS with other inputs from the availability and maintenance strategy choices. Overall, the 4 maintenance strategy options namely Corrective Action, ConMon, PMS and Delay Action. The first 2 options are meant for high critical failures or component with severe failure consequences while the last 2 are to address failures with time dependent pattern or equipment with high redundancy and low criticality. The maintenance criticality also has 4 levels which are, Very High, High, Medium and Low and these conforms' with the maintenance strategy in order of hierarchy. The same also applies to the RPN values against the maintenance strategy options.

The approach compares the criticality in decreasing priority from very high to low based on RPN numerical values where 100 represent the highest possible outcome and 0 lowest possible outcome. The RPN values provide an iterative procedure using the linear scale ranges to place components to certain maintenance strategy group. Therefore, this helps ease some of the restriction of the component criticality Likert scale, hence providing a flexible procedure to prioritise system maintenance. Accordingly, the inputs for the overall BBN DSS comprise of the subsystem RPN, critical components and their cut set as well as the relevant CCF as shown in Table 12. Consequently, using these values, the DSS was built based on the structure shown in Fig. 8 representing DG 2, showing the 3 additional nodes, 2 decision nodes on orange and 1 utility node in yellow. The decision node 'Maintenance Decision' is defined by independent variables of maintenance strategy choices and is a parent to Utility node which is a dependent variable and child to another decision node 'RPN'. The decision node 'RPN' takes information representing the maintenance decision arrangements and matched with RPN criticality hierarchy based on RPN scale.

Following from the above, the DSS allocates percentage values between 0 and 100 to each of the 4-maintenance strategy choice for the DG based on the input data. The allocated percentage for each of the strategy determines how the maintenance action, planning and monitoring should be prioritised. This allows for flexibility regarding distribution of resources such as personnel, spare parts, logistic support and operational deployment. Furthermore, high criticality ranking for ConMon indicates the need for additional monitoring approach which can be addition of sensors, increased inspection frequency or watchkeeping attention.

The overall outcome for the maintenance strategy selection DSS of the DGs is presented in Fig. 9. The analysis indicates how each of the DGs fit to a certain maintenance strategy regime as a reflection of the main variables i.e utility and RPN. In all, Corrective Action and ConMon appear to be the most preferred choice for all the DGs except for DG1 with relatively low figures in ConMon but high in PMS.

Only DG1 and 2 seem to have some values for Delay Action and present high figures both Corrective Action and ConMon. This suggests that the 2 generators are highly maintenance intensive, moreover DG1 has about 54% to corrective action and DG2 is about 58% in ConMon. On the other hand, DG3 and DG4 fall in relatively similar level of priority levels except in PMS where DG4 numbers appear much higher than that of DG3. A likely reason for this could be that DG1 and 2 are located in the same engine room likewise DG 3 and 4. As such due to shared resources such as sea chest, ventilation, fuel line and local stress such vibration, the generators tend to present similar pattern of failure. Though some of these findings were not apparent to the operators prior to this research, however were consistent with similar research findings within the shipping industry (Goossens and Basten, 2015; Lazakis and Ölçer, 2015; Lazakis et al., 2018) and others with focus on Naval ship platforms (Berghout et al., 2021; Tomlinson, 2015).Moreover, the FMECA findings also provide additional evidence as to the acceptability of the research findings and relevance of the methodology.

Table 11
BBN DG and Component availability.

DG	DG1	DG2	DG3	DG4
Availability	50%	53%	48%	47%
Subsystem Availability				
Cylinder Block	47%	43%	44%	44%
PTO	60%	56%	50%	60%
Cooling	37%	39%	39%	37%
Fuel System	43%	45%	44%	44%
Air Distribution	50%	52%	52%	42%
Lubrication	62%	75%	56%	55%
Inlet and Exhaust	60%	63%	62%	58%
Alternator	59%	52%	59%	57%

6. Conclusions

The maintenance department in large organisations help to ensure platform availability through the implementation of a maintenance strategy which fits best to organisational roles. In this regard the effort of the maintenance department is to utilise the strategy within its disposal to ensure that failures are not only minimised but are managed in an economical and timely manner. Maintenance efforts onboard also ensures that ship operators meet the IMO and ISM code provision on emission reduction and safety respectively. In this regard this research paper presented a novel methodology through the combination of

Table 12
Summary of BN DSS inputs.

Sub-System	RPN	Components	MSC	CCF	Mode	Causes
Cylinder Block	65%	7	6	1	Overheating	No cooling water, lubrication oil failure, vibration, gasket damage, seizure
PTO	58%	3	2	2	Seizure, Overheating	Missed timing, Overheating,
Cooling	64%	6	2	3	Reduced Cooling, No cooling	Sea chest blockages, scaling, thermostat fault, Pump failure
Fuel System	34%	5	4	3	Low Pressure, No supply, contamination	Air log, dirty tanks, filter blockage, fuel quality
Air Distribution	33%	2	2	0	Low supply, Hot air	Air filter blockage, air cooler fouling
Lubrication	3%	3	2	0	Low pressure, No supply, contamination	Filter blockage, Pump failure Seal failure
Inlet and Exhaust	0%	4	4	3	Missed timing, valve clearance, poor scavenge	Valve setting/tappet clearance, weak spring, valve seat, bent valve stem
Alternator	14%	4	10	5	Overheating, rubbing, load shedding, no output, degraded performance (low voltage/frequency)	Bearing failure. Miss alignment (lose of air gap), defective AVR, defective exciter, vibration.

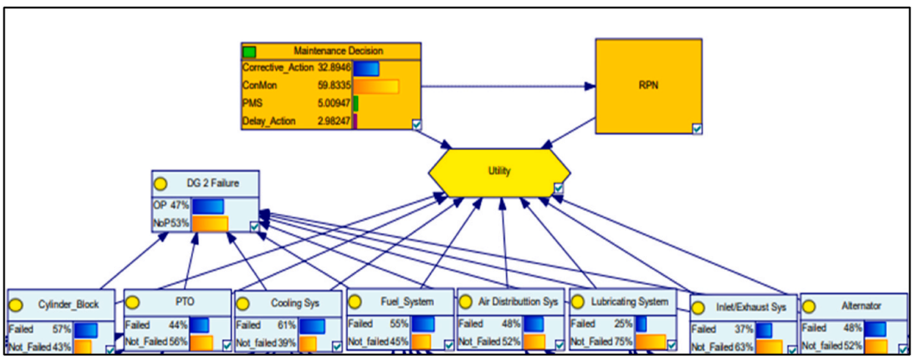

Fig. 8. BBN component availability and RPN.

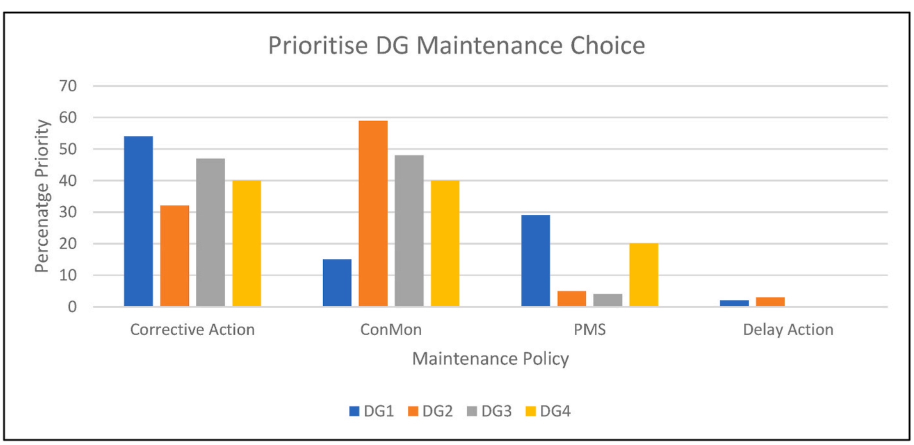

Fig. 9. Maintenance DSS choice for all DGs.

reliability analysis and decision support system to help provide the most efficient maintenance strategy option for a given system and components by combining DFTA, FMECA and BBN. The methodology was implemented in the presented case study of an OPV power generation system consisting of 4 marine diesel generators. Modelled components originated from MCS obtained through DFTA and their failure probability from the collected MRO data. This input was used to obtain the availability for individual DGs as well as the main subsystems modelled. The RPN from the FMECA was generic to all generators, but the MCS from the DFTA was not, hence the DFTA cut set output was the source for the component inputs that form the child nodes in the BBN for each of the 4 DGs, while failure rates were used as inputs for the CPT. The inputs provided analytical data for ships availability analysis in BN model. The maintenance DSS was built on the existing BN with additional influence diagrams nodes taking inputs from RPN and maintenance strategy choice.

Overall, the results show that all 4 DGs had varying degrees of availability with DG2 being slightly more available as compared to the rest. The subsystem availability particularly that of the lubricating system of DG2 at 75% is an important pointer. On the other hand, a very critical situation is presented in the cooling system with availability values below 40% which is far below the expected availability of the operator pegged at 80%. The results overall indicates' that Corrective Action and ConMon appear to be the most preferred choice for all the DGs except for the DG1 with relatively low figures in ConMon but high in PMS. Only DG1 and 2 seem to have some values for Delay Action and presented high figures both Corrective Action and ConMon. This suggests that the two generators are highly maintenance intensive, moreover DG1 has about 54% to corrective action and DG2 is about 58% in ConMon. On the other hand, DG3 and DG4 fall in relatively similar level of priority levels this except in PMS where DG4 numbers appear much higher than that of DG3. One of the major reasons for this could be that DG1 and 2 are located in the same engine room likewise DG 3 and 4, hence are affected by the same factors. Consequently, based on the outcome of the case study especially on subsystems with low availability values such as the cooling system, which can be linked to the sea chest blockages and scale built-up on the cooling fins. This is despite a relatively high redundancy in the cooling water sources, but delays in switch water sources could still lead to overheating. Therefore based on the results the following are recommended.

- Early warning system be provided to ensure that watch keepers are adequately alerted at the onset of any pressure reduction in water supply or temperature increase for at least 10 min with no corresponding increase in demands or beyond normal threshold.
- Provision of additional online pressure sensors on the sea water line.
- Consider use of cooling water additives and increased flushing frequency of the cooling water tubes.

Moreover, further research efforts to extend the presented work could include the use and application of artificial neural networks for fault detection and the development of a methodology for estimating the remaining useful life of ship system components, along with a spare parts estimation process. Furthermore, in light of shipping decarbonization, the application of the aforementioned methodology and tools can be extended to ship system reliability analysis on the impact of the use of biofuels and alternative fuels on the reliability assessment of engine system components.

CRediT authorship contribution statement

Abdullahi Abdulkarim Daya: Conceptualization, Methodology, Data Collection, Software, Validation, Formal analysis, Investigation, Writing – original draft, Visualization. **Iraklis Lazakis:** Conceptualization, Validation, Resources, Writing - review, Supervision.

Declaration of competing interest

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

Data availability

Data will be made available on request.

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