# Ship Machinery Reliability

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Redundancy in ship systems is provided to ensure operational resilience through equipment backups, which ensure system availability and offline repairs of machinery. The electric power generation system of ships provides the most utility of all systems; hence, it is provided with a good level of standby units to ensure reliable operations.

Keywords: marine diesel generator ; reliability importance measures ; fault identification

## 1. Introduction

Ship operators and onboard maintenance managers face the critical challenge of minimising downtime by ensuring the availability of key ship auxiliary systems that are vital to the correct functioning of other main ship systems. A system such as the power generation system plays such a vital role, be it at sea or in harbour, and like any other functioning system, its correct operation depends a lot on the individual subsystems and components that it is made of [1][2]. Considering that the power generation system provides the most utility of all onboard systems, failures underway or extended downtime can result in adverse consequences, including significant economic and operational losses. Hence, to address these challenges, conducting a system-specific analysis that identifies the most critical components and potential causes of delays, whether technical or logistical, becomes imperative [3].

Moreover, shipping decarbonisation is top on the IMO's agenda, and it has put in place regulations and guidelines to address emissions generated by marine diesel engines [4]. This implies that regulations such as the sulphur oxides and particulate matter cap of 2010 and the 2050 GHG emissions would see the world's future fleet having to rely on a broader range of fuels and adopt novel propulsion solutions to efficiently operate [5][6]. Measures in place by the IMO to help ship operators include the Energy Efficiency ship design index (EEXI) and the Ship Energy Efficiency Management plan (SEEMP), as provided in Marine Environment Protection Committee guidelines [5]. The provisions of these guidelines and regulations, such as the Energy Efficiency Existing Ship Index (EEXI) and the Carbon Intensity Index (CII), can only be achieved through more efficient on-board machinery system operations and technology upgrades through retrofits for existing ships and adaptation of new fuels such as ammonia, methanol, and biofuel blends [7][8].

Therefore, it is expected that these new fuels will bring up additional reliability issues [8]. Hence the need to understand how these new fuels and their enabling technologies fit into existing maintenance practises onboard. In this regard, the reliability of systems and failure modes of components will be required to identify which components and failure modes are critical to ship availability going forward. This is especially important considering that machinery failures have been identified as among the major causes of maritime incidents [9]. Moreso, degraded machinery health can be a serious burden on the vessel's owner and operator due to frequent failures and increased consumption of fuel and lubricants [10]. Nonetheless, most of these challenges can be avoided or mitigated with the right understanding of component criticality, which enables more targeted maintenance strategy adaptation [11][12].

Therefore, in order to ensure the availability of equipment and system reliability, operators require an efficient maintenance approach that can minimise failures and reduce downtime through the life cycle of the asset or machinery. In general, ships are supplied with maintenance plan-based schedules drawn from the original equipment manufacturer's (OEM) operating manual. These initial documents can help with routine checks and maintenance, especially when most systems are new. However, operating conditions such as climate, operating profile, technical capacity, and availability of genuine spare parts and other consumables such as fuel and lubricating oil could invalidate the initial as-supplied maintenance plan or approach [13].

## 2. Ship Machinery Reliability

According to Marvin [14], the reliability of a system is equal to the product of the reliability of the individual components that are included in the particular system; thus, the higher the number of components in a system, the more complicated it is to ensure its reliability. On the other hand, a system is defined as a collection of components that interact with each other to achieve a common goal; hence, any dysfunction in one or more components could impact the ability of an equipment or system to operate properly [14][15]. In this regard, calculation methods such as mean time to failure (MTTF), used for discrete events, and mean time between failures (MTBF) for continuous events, as well as failure rates (λ), have been extensively used to calculate equipment reliability or availability for the purpose of maintenance planning [16][17][18]. These measures provide maintenance planners with estimates on machinery reliability but not enough information to understand the course of failure and related impacts [19]. Accordingly, additional tools using failure probability analysis or statistical measurements are employed so that failure and courses of failure can be attributed to particular components in machinery [12][16][20][21].

System reliability analysis has historically aided maintenance planning since the advent of organised maintenance approaches that evolved from the breakdown of simple machines to condition monitoring-based predictive analysis [22][23]. In this regard, the evolution of maintenance strategies to prioritise certain maintenance actions can partly be attributed to advances in reliability analysis that enable an understanding of how component failure contributes to equipment availability [24][25]. On the other hand, risk and criticality are increasingly taking centre stage in equipment maintenance, especially in industries where human casualties or environmental pollution are priorities; hence, more focus is placed on the safety of operations and system reliability [26][27]. Consequently, authors have provided in-depth research regarding the application of reliability analysis tools in various industries. A criticality-based maintenance plan for coal power plants using Failure Mode Effect and Criticality Analysis (FMECA) to drive Risk Priority Number (RPN) aimed at identifying critical components in the plant to help with spare parts sourcing and reduce unscheduled shutdown was presented in [28]. System reliability analysis using tools such as Fault Tree Analysis (FTA) and Failure Mode Effect and Criticality Analysis (FMECA) has found wide application in the nuclear industry, especially in the energy sector [29]. Similarly, a great deal of research has been performed in the maritime sector on the use of reliability tools to improve safety, reduce risk, and achieve reliability for ships and offshore wind turbines [18][20][30].

The adoption of new technologies by ship operators, such as onboard diagnostics, intelligent sensors, and the internet of things (IoT), has enabled the implementation of remote monitoring and digital twin technologies. These technologies greatly help in system maintenance delivery and planning through automation and remote sensing, enabling real-time condition monitoring and possible early intervention. Consequently, this helps reduce crewing levels, reduce maintenance costs, and improve climate-friendly ship operations [31]. Moreover, the ISM code as contained in IMO [32] mandates operators develop processes to identify ship equipment whose sudden failure could lead to hazardous situations. Furthermore, industry regulations have initiated the introduction of advanced technologies that would require ship operators to adopt additional reliability measures [33][34]. Likewise, Classification Societies require ships to have standard maintenance documentation and strategies prior to acquiring Class qualification [35][36]. Hence, the adoption of tools such as FTA, Reliability Block Diagrams (RBD), Event Tree Analysis (ETA), Failure Mode Effect Analysis (FMEA), and other variants has been proposed to ensure the establishment of robust maintenance regimes.

It is therefore critical that researchers adopt hybrid approaches that combine a number of reliability tools in order to overcome some of the inherent deficiencies of individual tools or take advantage of other tools flexibility and depth of application, as shown in [16][37][38]. Establishing component criticality to aid maintenance planning is a key aspect of maintenance strategy implementation. For instance, [39] presented a combination of FMEA and FTA tools for critical component identification in order to increase ship machinery availability. A combination of reliability tools and ANN was used to develop predictive condition monitoring [40][41], which shows the competitive flexibility that can be driven due to the use of reliability tools and numerical methods in system reliability analysis. The criticality of a system, component, or event in FMEA is derived by the use of RPN [14][42]. Reliability analysis tools examine the risks of failures by considering quantitative and qualitative aspects. In this case, the selection of tools for reliability analysis depends on factors such as the depth of analysis intended, the system to be analysed, the type of data (qualitative or quantitative), the objective of the analysis, tool availability, the availability of computing resources, and the interaction between systems and/or components. Other factors include tool characteristics, i.e., inductive or deductive-based analysis [14][43]. Additionally, research gaps in the literature provide another important factor in the selection of tools for reliability analysis; therefore, additional research work is needed to identify a better or more efficient way of conducting similar analysis. In doing so, tools are assessed based on their strength or compatibility with the research at hand. Some of the notable reliability analysis tools include ETA, FTA, Dynamic FTA (DFTA), FMEA, FMECA, and Bayes' Theorem presenting the Bayesian Belief Networks (BBNs) [16].

## 2.1. Dynamic Fault Tree Analysis (DFTA)

Dynamic fault trees use all the structure and logic of the static fault tree except for the addition of dynamic gates such as the Priority And (PAND), Functional Dependency (FDEP), Sequence Enforcing (SEQ), and Spare gate [44][45]. The PAND gate models a system failure or an undesirable event in order of occurrence from left to right, such that the left-most event occurs before the next event can take place. An example can be seen in the series of fuel filters in that a secondary filter downstream of the primary filter gets clogged only when the primary filter malfunctions. The SEQ gate, as the name suggests, models events in a constrained manner from left to right, such that an event occurs only if the event before it has occurred. In this regard, the SEQ differs from the PAND gate due to the constrained nature of failure occurrence and can be especially useful for modelling close-loop systems with feedback failure, such as in the bilge eductor in the bilge system, whereby pressure drop at any point in the system affects the entire piping network. The FDEP behaves in a slightly different manner compared to PAND and SEQ gates in that it takes into consideration the function of the system or component and resulting failure, for instance, the failure of a thermostatic valve that results in overheating of a heat exchanger that can be caused by a leakage in the system.

The Spare gate has some special futures, unlike the other gates, especially in modelling redundancy in system reliability or failed standby equipment. Spare gates consider only spare events as input, with the left-most events being the active or primary events [25]. All other spare events after the primary events are alternative inputs and have a varying degree of influence based on the dormancy factor, which is between 0 and 1 [44]. The dormancy factor indicates how active the spare event is, with 0 being a cold spare and 0.1 to 0.9 being a warm spare. In this regard, a failed spare is replaced by the next most active spare from left to right; a spare gate fails only when all the spare events have occurred, i.e., failed. Therefore, this makes it very relevant in analysing system improvements as presented in [13][46]. Therefore, these additional gates have provided more scope for DFT analysis [45][47], which can be used to factor repairs or improvements due to routine maintenance. Moreover, additional outputs such as reliability importance measures and minimal cut sets in the DFTA are equally influenced by the logic structure of the developed model. In that case, the output of a static FT and a dynamic FT would be significantly different and reflective of whatever dependencies exist in the model when considering functional dependencies and the sequence of failures or events.

## 2.2. Reliability Importance Measures (IMs)

Reliability Importance measures assist in identifying the event that, if improved, is most likely to produce a significant improvement in equipment or system performance [18][48]. In essence, the evaluation of IMs helps the operators, maintenance crew, and administrators, including regulatory agencies, prioritise actions that could result in improvements in equipment/system reliability. Among the commonly used IMs are the Birnbaum (Bir), Fussell-Vesely (F-V), and Criticality (Cri) ones. The Bir IM evaluates the occurrence of the top events based on the probability of basic events occurring or not occurring; hence, the higher the probability of basic events, the higher the opportunity for a top event to occur [49]. Criticality (Cri) IM is calculated in a similar way to Bir IM except that it compares the probability of the occurrence of the basic event to the probability of the occurrence of the top event. On the other hand, 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 IM considers the contribution of the basic event to the occurrence of the top event, irrespective of how it contributes to the failure. The Bir IM and Cri IM were considered in this research; however, comparing the two measures, the Bir IM is more reflective of the component’s criticality as modelled.

System reliability analysis using a combination of tools, including DFTA, was conducted on a set of four marine DGs, where the reliability IMs were used to identify critical components on marine DGs to improve maintenance delivery [39]. Reliability IMs are equally used for analysis, especially on safety-critical systems where components are critical to the safe operation of such systems [50][51]. Using Risk Achievement Worth (RAW) and Risk Reduction Worth (RRW) [29] introduced a methodology that can be applied to measure power distribution network criticality. Similarly, importance measures can be used to help improve overall understanding of either the weakest component or the most reliable component in a system so that maintenance planners are able to balance their efforts. Moreover, when components have been identified as critical or related to a failure that can be high-risk, maintenance planners are able to provide remedial plans against sudden failures or ensure sufficient quantities of spare parts are held in stock [52]. The Bir IM, as highlighted earlier, measures the contribution of the most critical component to the occurrence of the top event, thereby helping to clearly identify what component needs improvement. In this regard, researchers have adopted Bir IM to enable the identification of critical system failures to avoid catastrophic failures like crankcase explosions in diesel engines [53][54]. DFTA has equally been combined with other tools to achieve additional research goals, such as decision support or analysis requiring some level of subjective input [55][56]. Moreover, scrutiny in machinery health condition monitoring due to emission regulations and improved sensor capability, including autonomous shipping, has led to the application of machine learning-based tools for diagnostics and prognosis analysis [40][57], combining in some cases DFTA and other tools [13][58].

### 2.3. Artificial Neural Networks (ANNs)

In general, there are two types of machine learning approaches: supervised and unsupervised learning [59][60]. The supervised machine learning is used to train a model using labelled data; that is, the features to be looked out are already known, and the algorithm is trained to look out those features in the input data [10]. On the other hand, unsupervised learning deals with unlabelled data, which means the algorithm will identify the unique features in the data and partition it accordingly [61][62]. Unsupervised learning is useful for exploring data in order to understand the natural pattern of the data, especially when there is no specific information about significant incidents in the data that can easily point to fault indicators [63].

ANNs have been applied in the field of maintenance for machinery health analysis and prediction of machinery conditions by various authors. Therefore, following on the existing success and procedures in the use of ANN for machinery data analysis, this research will employ ANN for fault classification and detection, fault/condition prediction, and machinery remaining useful life analysis. In a research paper presented by [48], an ANN approach for fault detection is combined with FTA to identify critical components of diesel generators. In some cases, machinery fault data are recorded without identifying the fault signals; therefore, this requires data clustering [64]. Clustering is a form of unclassified machine learning that is applied to machinery diagnostics [10]. The advantages of using clustering models are that they help identify possible clusters as well as the most influential clusters in the data. In research, ANN Self-Organising Maps were used for clustering of machinery log data from DG. SOM consists of a competitive layer that can classify a dataset of vectors with any number of dimensions as the number of neurons in the layer and is good for dimensionality reduction, as presented in [41].

Accordingly, ANNs are widely employed for multiple tasks such as clustering, forecasting, prediction, pattern recognition, classification, and feature engineering [65]. The use of ANN and Regression techniques was employed to estimate vessel power and fuel consumption, and the model was able to predict the actual vessel fuel consumption in real time [66]. The use of ANN for fault classification has been employed by [41][67][68]. Using a self-organising map, an ANN clustering algorithm analyses the health parameters of a marine diesel engine, looking at exhaust gas temperature, piston cooling outlet temperature, and piston cooling inlet pressure. Therefore, the performance of ANN in prediction and classification, as reviewed in [69][70][71], was presented as good in handling nonlinear high-dimensional data with fewer data sets [71]. In this regard, to build on the success of ANN, this work will apply the use of ANN to labelled data for diagnostic analysis on four sets of marine diesel generators. Therefore, the feedback from the ANN is used in combination with the reliability analysis output to identify the dominant faults and most affected components.

In view of the foregoing, several authors and researchers have made efforts in the application of DFTA, ANN, and other data-driven approaches for reliability and fault identification [40][41][72]. Nonetheless, there still exist some gaps in the application of DFTA for criticality analysis, especially when using the Bir IM to identify critical component failures. On the other hand, ANN and other machine learning approaches have been widely used in system diagnostics and fault identification [62][68][71], but their combination with DFTA criticality analysis with a view to identifying fault-related component failures requires further investigation. Moreover, in this research, a methodology was developed to apply the combination of DFTA and ANN fault identification to MDGs based on component criticality to improve ship operational availability. Furthermore, future engineering based on correlation analysis using power output as an independent variable to identify the most sensitive variables to performance alterations was presented. Therefore, this methodology presents an efficient approach to system reliability and fault detection analysis with the potential to be applied to an individual ship or fleet of ships.

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