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Towards the Development of a Dynamic Reliability Tool for Autonomous Ships: A Bayesian Network Approach

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Autonomous ships developments have been driven by recent advances in smart and digital technologies. As autonomous systems will be responsible for the MASSs' operation, their reliability is of paramount importance. This study aims to develop a Bayesian network (BN) for monitoring the reliability time variation considering subsystem and component levels. The case study of a cargo vessel for short sea shipping operations is employed and its power plant is investigated. The BN is developed based on the power plant's critical components, whilst defining the interconnections between these components. Pertinent data for the component failure rates are derived from multiple sources, including reliability databases and scientific papers. The derived results demonstrate that the ship main engine is identified as the most critical subsystem. This study serves as a foundation for the development of a dynamic reliability tool for autonomous ships which can incorporate sensor measurements to update component reliability in real-time.

Keywords: Autonomous ships, Bayesian network, Power plant, System reliability.

1. Introduction

The maritime industry has faced significant advancements in recent years, owing to the use of smart and digital technologies. One such development is the emergence of autonomous ships, which have the potential to revolutionise maritime transportation (Kobyliński 2018). Several research and industrial projects have initiated to address the development of Maritime Autonomous Surface Ships (MASS) (Chae, Kim, and Kim 2020), (Munim and Haralambides 2022).

Human error, which is the leading cause of accidents at sea, could potentially be mitigated by autonomous ships. Safety levels on board these ships are speculated to be equivalent or better than conventional vessels (Ventikos, Chmurski, and Louzis 2020). Furthermore, autonomous ships have the potential to reduce operational times and costs, as well as maintenance and crew costs (Munim and Haralambides 2022), (Liu et al. 2016). The increased digitalisation and automation of these ships can improve their efficiency, leading to emissions reduction and their environmental footprint improvement (Dantas and Theotokatos 2023).

Nonetheless, technological maturity is yet to be achieved and further developments are required for the deployment of autonomous ships (Bertram 2016). In this respect, a critical aspect for their successful operation pertains to monitoring and assessing the health status of their systems. Autonomous ships will be equipped with advanced sensors that can acquire several operational parameters (Kobyliński 2018). The acquired sensor data can be further processed to enable diagnostic and prognostic functionalities, to monitor and predict the health status of the employed autonomous systems (Heffner and Rødseth 2019). Since, onboard crew will no longer be present shipboard to perform corrective actions, intelligent monitoring systems are essential to provide indications for the safe operation in the case of failures or unexpected events (Utne et al, 2017).

In the existing literature there are various approaches that have been applied to monitor the health state of marine assets. (M. Cheliotis, Lazakis, and Cheliotis 2022) applied a machine learning fault detection technique combined with Bayesian Networks to examine the probability of faults in marine engine subsystems. (Kang et al. 2023) proposed a hierarchical level fault detection and diagnosis method for marine engines. (Tsitsilonis, Theotokatos, and Habens 2020) developed a framework for the health assessment of marine engines using first principles models combined with machine learning tools. (Bolbot et al. 2021) presented a monitoring approach to dynamically estimate the probability of blackout in cruise ships using sensor measurements.

Since few studies focus on the monitoring maritime assets at system level, it is important to estimate the system health state based on the interrelation between system and components. This study aims to develop a Bayesian network to dynamically monitor the time variation of reliability considering subsystem and component levels. The case study of a cargo vessel for short sea shipping operations is selected to investigate its power plant reliability whilst identifying the most critical components.

2. Bayesian Networks for reliability estimation

2.1 Overview of BNs

Monitoring tools require appropriate indicators to characterise the components/systems health condition (Lei et al. 2018). Reliability reflects the degradation of a component/system, hence, it can be used as a health indicator (Zagorowska et al. 2020). The component reliability can be estimated by using its failure rate and operating time.

Nonetheless, for autonomous systems where it is essential to characterise the system health condition based on the components interactions, system-level approaches are required. The most widely used methods to estimate the marine/ship systems reliability include Reliability Block Diagrams (RBD), Fault Trees FT), Markov Models (MM), Petri Nets (PN), Bayesian Networks (BN) (Bolbot et al. 2019).

In this study, BNs are adopted since they present various benefits. A BN is probabilistic graphical model, which represents the dependencies of the included random variables in the form of a directed acyclic graph (DAG) (Jiang, Zheng, and Liu 2019). BNs are generalisations of RBDs and FTs, employing the Boolean logic, as nodes can take several discrete states in the form of probability distributions (Pan et al. 2019). They can be used to estimate the system reliability as the network arrangement can model the interactions of the components that constitute this system. The joint probability distribution, which represents the system reliability considering all the random variables of the BN can be calculated as (Jiang, Zheng, and Liu 2019):

$$P(X_1, X_2, \dots, X_n) = \prod_{i=1}^{n} P(X_i | Pa(X_i)) \qquad (1)$$

where $Pa(X_i)$ represents the parent set of any variable X_i, and $P(X_i|Pa(X_i))$ is the conditional probability distribution function of variable X_i given its parent set.

2.2 Reliability modelling by BNs

The reliability modelling techniques employ the system decomposition into its components (Verma, Ajit, and Karanki 2015). In the case of BNs, a DAG is constructed where the root nodes represent components, intermediate nodes represent subsystems, and the leaf node represents the system.

In the case of component nodes, the prior probability is provided as an input, and it represents the component reliability. The component reliability R_i is calculated using the corresponding component failure rate λ considering an exponential distribution, using the following equation:

$$R_i(t) = e^{-\lambda t} \qquad (2)$$

In the case of subsystems and system nodes, noisy gates are used to specify the interactions between the component nodes. Noisy gates are a type of conditional probability distribution that takes into account the values of the parent nodes by specifying conditional probability tables (CPT) (Bobbio et al. 2001). They lead to a significant reduction in computational costs by linearly reducing the required parameters for the parents number (Bobbio et al. 2001). Noisy-OR and Noisy-

AND gates are used, which are equivalent to the logical gates employed in FTs (Cai et al. 2012).

The SMILE engine is used to perform the reliability calculations (GeNIe 2020). The C++ wrapper is imported into MATLAB to render the calculations more efficient by providing the input for component reliability.

BNs enable the calculation of importance measures which can be used to identify the most critical components (Rausand, Barros, and Høyland 2021). The criticality importance measure is adopted as it reflects the degree which each component's failure affects the system reliability. It is calculated as the probability that a specific component contributes to system failure, given that the system has already failed.

3. System Description

The power plant of a cargo vessel for short sea shipping operations is considered as a case study. In this case, system reliability refers to the ability of the power plant to provide propulsive power focusing on the autonomous operation.

The existing (conventional) ship has one propeller and two tunnel thrusters, and uses liquefied natural gas as its primary fuel. Depending on the ship operating mode, the main engine can cover the ship propulsion (and electrical via the Power Take-off (PTO) system) power demand, whereas the auxiliary gensets can cover the electric power demand (and may contribute to the propulsion via the power take-in (PTI) system). However, in this case study, the auxiliary gensets are substituted with a battery that is used to cover the power demand fluctuations and avoid operating the main engine in regions with higher brake-specific fuel consumption (BSFC). Figure 1 presents a graphical representation of the power plant components.

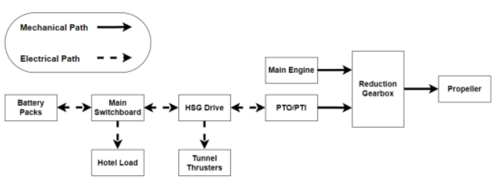

Fig. 1. Power plant layout

The investigated power plant is decomposed into subsystems that consist of various components. Since all the modelled components cannot be shown graphically, only the main subsystems are shown in Figure 2. The main engine consists of the mechanical parts, lubrication, cooling, fuel gas, intake and exhaust subsystems whilst the PTO/PTI and the onboard electronic devices are considered as components.

Fig. 2. Bayesian Network with power plant subsystems

The component failure rates which are used in this study are derived from the pertinent literature as well as reliability databases. The complete list is presented in the appendix.

4. Results & Discussion

This section presents the results obtained from the developed BN to evaluate the system reliability of the considered hybrid power plant and identify the most critical components.

System reliability is estimated at different time intervals. As per MUNIN project guidelines, the unmanned engine room is expected to perform reliably without human intervention for a period of 500 hours (Abaei et al. 2021). Figure 3 presents the system reliability time variations obtained by the BN for an operating time of 500 hours considering time intervals of 50 hours. As expected, the system reliability decreased with time, with a final reliability value of 0.2 at 500 hours of operation. Notably, engine reliability (Figure 4) had a significant impact on the overall system reliability, decreasing rapidly compared to the electrical subsystems present in the considered power plant.

Figure 4 illustrates the engine reliability time variation (considering 500 hour of operation). The decrease in system reliability can be attributed to several components and subsystems of the engine. Based on the obtained results, it is inferred that the engine cannot be reliably operated for 500 hours, as values lower than 0.7 indicate a high probability of critical failure. Furthermore, the results indicate that a human operator onboard the vessel may be necessary to monitor and intervene in the event of engine failure.

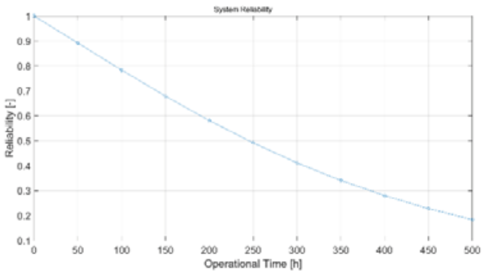

Fig. 3. System reliability time variation

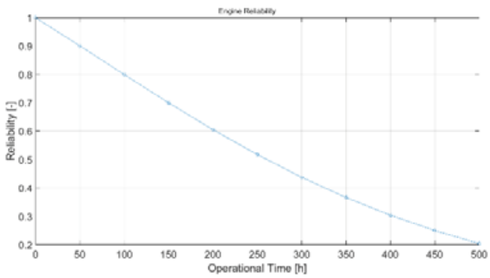

Fig. 4. Engine Reliability time variation

Figure 5 presents the criticality importance measure for the 10 most critical components at an operating of 500 hours. Most of the components belong to engine subsystems. This highlights the importance of monitoring and maintaining these critical components to ensure safe and reliable operation of the power plant. Improving the reliability of these components can significantly affect overall system reliability.

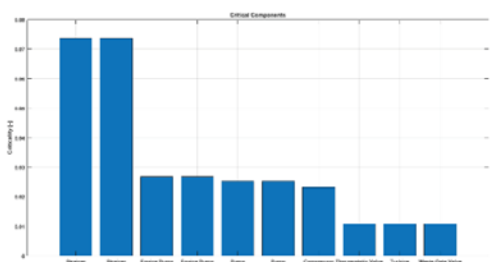

Fig. 5. Critical components based on criticality measure

This study presented an important first step towards the dynamic reliability estimation of autonomous ship power systems. In the case of autonomous operations, intelligent monitoring capabilities are essential to assess the systems and components; health state, providing information into the decision support systems for potential failures and their effect on system performance (Ellefsen et al. 2019).

Nonetheless, to ensure the effectiveness of advanced monitoring systems in autonomous ship operations, it is essential that these systems receive input from real-time measurements. A limitation of this study is that the BN calculations are static since component reliability is calculated based on historical failure rates, without considering evidence from the actual operating conditions. Future research is recommended to employ shipboard sensor measurements to improve the estimation of system/component reliability and consequently update their health state.

Additionally, the investigated power plant was decomposed into subsystems and components in a certain way which is susceptible to epistemic uncertainty. Epistemic uncertainty arises due to various factors that contribute to a lack of complete knowledge or information about the system. Potential causes of epistemic uncertainty include lack of adequate or precise data, incomplete understanding of underlying system structure and assumptions made during the analysis (Mi et al. 2016).

Furthermore, the developed BN decomposes the subsystems into components without considering the likelihood of unexpected events that can affect system reliability. Even if the components function properly, system operation can potentially be interrupted. One notable example is the Viking Sky incident, where a blackout was caused by a signal indicating a low level of lubrication oil in the generator sets due to adverse weather conditions (Johansen et al. 2023). Future studies could potentially capture the effects of these events to provide more accurate estimations.

4. Conclusions

In this study, a Bayesian network (BN) was developed to monitor the time variation of reliability at both subsystem and component levels for the case of a cargo vessel for short sea shipping operations. The results demonstrated that the critical components of the power plant concern mainly the main engine, which significantly affects the overall system reliability. At 500 hours of operation without crew intervention, the estimated system reliability dropped to unacceptable levels to be considered for autonomous operations. In addition, the investigated power plant was investigated without considering the effect of unexpected events, which can further reduce the overall system reliability.

This study can serve as the foundation towards building a dynamic reliability tool for autonomous ships that can potentially incorporate real-time sensor measurements to update the component reliability. It can support the monitoring of safety and reliability metrics for autonomous ships, and ultimately render them a viable solution for the shipping industry. Further research is necessary to explore the feasibility and potential benefits of this approach in real-world scenarios.

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Appendix
The failure rates (λ) used as input to this study are provided in Table 1.

Table 1. Component failure rates

Component	λ [$\times 10^{-6}$ h^{-1}]	Source
	Engine Components	
Centrifugal pump	769.62	(SINTEF and NTNU 2015)
Lubricating oil filter	457.00	(Dionysiou and Bolbot 2021)
Heat exchanger	53.89	(SINTEF and NTNU 2015)
Pump motor	36.51	(SINTEF and NTNU 2015)
Pressure relief valve	10.85	(SINTEF and NTNU 2015)
Sump tank	12.70	(Dionysiou and Bolbot 2021)
Thermostatic valve	39.60	(SINTEF and NTNU 2015)
Strainer	1370.00	(Dionysiou and Bolbot 2021)
Pressure sensor	0.62	(Hauge and Onshus 2010)
Flow control valve	39.60	(SINTEF and NTNU 2015)
Temperature sensor	0.30	(Hauge and Onshus 2010)
Bleedoff valve	10.85	(SINTEF and NTNU 2015)
Flowmeter	2.00	(Hauge and Onshus 2010)
Gas filter	0.42	(Milioulis et al. 2022)
Gas regulator	39.60	(SINTEF and NTNU 2015)
Shut-off valve	26.43	(SINTEF and NTNU 2015)
Solenoid valve	39.60	(SINTEF and NTNU 2015)
Throttle valve	39.60	(SINTEF and NTNU 2015)
Compressor	196.00	(Milioulis et al. 2022)
Turbine	93.85	(SINTEF and NTNU 2015)
Pressure built up unit	28.83	(SINTEF and NTNU 2015)
Heat exchanger LNG	42.75	(Milioulis et al. 2022)
Evaporator	4.51	(Bolbot 2020)
LNG tank	77.80	(Milioulis et al. 2022)
Piston rod	16.31	(Cheliotis 2020)
Piston	32.62	(Cheliotis 2020)
Cylinder liner	16.31	(Cheliotis 2020)
Cylinder head	16.31	(Cheliotis 2020)
Igniter	14.85	(SINTEF and NTNU 2015)
Camshaft	11.85	(SINTEF and NTNU 2015)
Crankshaft	11.85	(SINTEF and NTNU 2015)
Bearing	16.31	(Cheliotis 2020)
Engine valve outlet	83.10	(SINTEF and NTNU 2015)
Engine valve Inlet	83.10	(SINTEF and NTNU 2015)
	PTO/PTI	
Motor	43.76	(SINTEF and NTNU 2015)
	Switchboard components	

Hardware	17.60	(Hauge and Onshus 2010)
Software	6.18	(SINTEF and NTNU 2015)
Electronic components		
Circuit breaker	0.80	(Hauge and Onshus 2010)
Inverter	21.31	(Gao et al. 2021)
Bus bar	0.41	(Vedachalam and Ramadass 2017)
Battery components		
Battery	63.57	(Hauge and Onshus 2010)
BMS	4.54	(SINTEF and NTNU 2015)

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