

Article

A Stochastic Approach for Evaluating the Reliability of a MASS and Assessing the Compliance with the IMO Regulatory Framework

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Abstract

The introduction of Maritime Autonomous Surface Ships (MASSs) requires reliable engineering methods to demonstrate safety levels comparable to those of conventional manned vessels. This paper presents a mission-based stochastic reliability framework for the comparative assessment of manned and unmanned ship configurations, with a focus on engineering design and verification. The methodology is based on Reliability Block Diagrams (RBDs), where ship missions are decomposed into critical functional subsystems and evaluated over mission-limited operational profiles. To address the uncertainty inherent in component failure data for autonomous systems, Mean Time to Failure (MTTF) values are treated as stochastic variables rather than fixed parameters. A Monte Carlo simulation approach is used to propagate uncertainty from component level to overall mission reliability, producing probability distributions of mission success. The proposed framework is applied to a Search and Rescue Patrol Vessel, comparing manned and unmanned configurations under identical mission scenarios and durations. Results indicate that, for moderate uncertainty levels, the unmanned configuration achieves equal or higher mission reliability, while increasing uncertainty reduces the statistical separation between the two solutions. The approach provides a practical and replicable tool to support reliability-driven design decisions for autonomous marine systems.

Keywords: reliability; autonomous ship; MASS; marine certification; safety; IMO MASS code



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1. Introduction

Two of the main motivations for the development of Maritime Autonomous Surface Ships (MASS) are to enhance safety, and to decrease the environmental risk associated with ships operation.

The reason why the ‘autonomy’ is considered a safer operation is because it should drastically reduce errors associated with the navigation of the vehicle; the absence of the human in command is expected to reduce the risk associated with the most common hazards, for example, the fatigue of the crew, the distractions, and information overload [1].

However, the possibility to have human errors associated with the design of the ship remains, namely “design error”. Furthermore, the increasing reliance on information

systems, and the possible sharing of the conning station among different control systems and/or operators, creates new hazards related to the potential loss of information and leads to new types of “human errors” [2,3].

On the other hand, to make autonomy really safe, ship’s technical systems are required to show very high reliability, given that no one is available onboard for repairs. According to IMO a MASS can operate independently by human intervention with the requisite to have the same safety level of a conventional vessel. Despite the simple definition, MASS deployment presents several challenges that span technical, regulatory and infrastructural domains [4], mainly because the safety assurance is not well established yet.

Several methodologies have been proposed in the literature [5], and the industry generally adopts the safety assurance schemes by the Classification Societies [6,7]. Also, the role of Administrations is becoming strategic in ensuring innovation within the applicable regulatory framework [8,9]. Most of the safety assurance methodologies are based on the risk analysis principles where probability and consequences of undesired events are computed and compared against acceptance levels through an acceptance matrix. The main drawback of this method is that probability and consequence are usually assessed qualitatively, causing difficulties when trying to accurately trace the procedure for future reference.

The approach proposed in this article is based on the mission reliability concept: the new technology is considered acceptable if the achieved mission reliability is at least equal to or greater than the current technology. The idea behind the method is to assess the probability of success of the ship mission, with and without crew, for all types of missions used to design the ship. It is a design-centered approach meant for certification purposes. Reliability modeling offers a structured way to quantify failure risks and system behavior, which is essential for demonstrating compliance with the IMO MASS Code and MASS IACS Class Rules. These frameworks adopt a goal-based approach, requiring autonomous vessels to prove safety levels equivalent to or higher than those of conventional ships. With respect to state-of-the-art mission reliability analysis, the proposed approach handles the inherent uncertainties embedded in the reliability models by using a stochastic Mean Time to Failure (MTTF) for each component, modeled with a normal distribution.

The results of this approach consist of the distribution of the probability of mission success, for both unmanned and manned designs, with the probability of exceedance used as risk KPI.

The novelty of the study lies in the application of a stochastic RBD–Monte Carlo reliability framework to Maritime Autonomous Surface Ships (MASS), explicitly addressing uncertainty in failure data and enabling a quantitative, mission-based comparison between manned and autonomous vessel configurations.

The remainder of the paper is structured as follows. Section 2 discusses the literature review, Section 3 presents the Stochastic reliability method, Section 4 presents a case study where a structured comparison between manned and unmanned vessel configurations under identical operational profiles is shown. Section 5 details the simulation results, followed by the conclusions.

2. Literature Review

The development of Maritime Autonomous Surface Ships (MASSs) represents a transformative step for the global maritime industry, offering improved operational safety, reduced labor dependency, and higher efficiency in logistics chains. This evolution is driven by advances in artificial intelligence, sensor fusion, and control systems which, when integrated with high-availability hardware architectures, support the implementation of autonomous behaviors at sea [1].

2.1. The Regulatory Framework for MASSs

The regulatory framework applicable to MASSs is complex and not unified at the international level. Several countries have published guidelines or issued directives concerning the operation with autonomous ships and at international level; IMO is going to publish the non-mandatory IMO MASS CODE in 2025 [10,11]. This Code defines four degrees of autonomy for MASS operations, ranging from conventional manned vessels with automated systems (Degree 1) to fully autonomous vessels capable of independent decision-making and control (Degree 4). These levels serve as a functional foundation for classification and certification frameworks [12–14],

Despite the conceptual and technological progresses, existing regulatory structures remain under development. The IMO MASS Code, currently non-mandatory and focused on cargo vessels, is expected to become mandatory by 2032, even if military and passenger applications are not addressed.

While MASSs have demonstrated promising capabilities in testbed environments and early deployments [15,16] widespread adoption requires a unified global certification framework that should address technological innovation and actual regulation, particularly in terms of navigation capability in remote operations, collision avoidance strategies, communication and cybersecurity, automation and machinery control system, final testing and validation of all these points. [17–24]

MASS development is further influenced by a variety of national projects and EU initiatives. Examples include the Yara Birkeland [15], the Mayflower [4], and the ReVolt, each demonstrating different degrees of autonomy, energy efficiency, and real-world testing success. The European Union, through programs such as MUNIN, AUTOSHIP, and MOSES, has actively supported both technical innovations and regulatory harmonization for MASSs [9,25–32].

However, a key challenge lies in reconciling fragmented regulations across Flag States especially whenever international navigation is required. While IMO promotes a harmonized international framework, countries like Norway, Japan, and the UK have developed localized approval mechanisms, ranging from goal-based codes of practice to customized certification systems [33–38]. Most of the IACS Classification Societies have anticipated the IMO's roadmap by publishing MASS-specific guidelines (e.g., RINA GUI 35) [7], often emphasizing a risk-based and modular approach. The common approach of these regulations is aimed at demonstrating that an unmanned vessel is at least as safe as its manned equivalent. For this reason it is important to define a scientific methodology for the evaluation of the MASS reliability that can be replicated an unlimited number of times, in order to use it for reducing the risk associated with a specific MASS operational profile, as well as to provide a technical response to the challenge of assessing the reliability between a manned and an unmanned vessel configuration.

The Regulatory framework applicable to a MASS is the foundation of [39] where a structured pathway to facilitate the certification and operation of MASSs, addressing technical, operational, and safety considerations is outlined (Figure 1).

In the following paragraph, the state of the art of reliability and availability models applied to marine system and autonomous ships is analyzed.

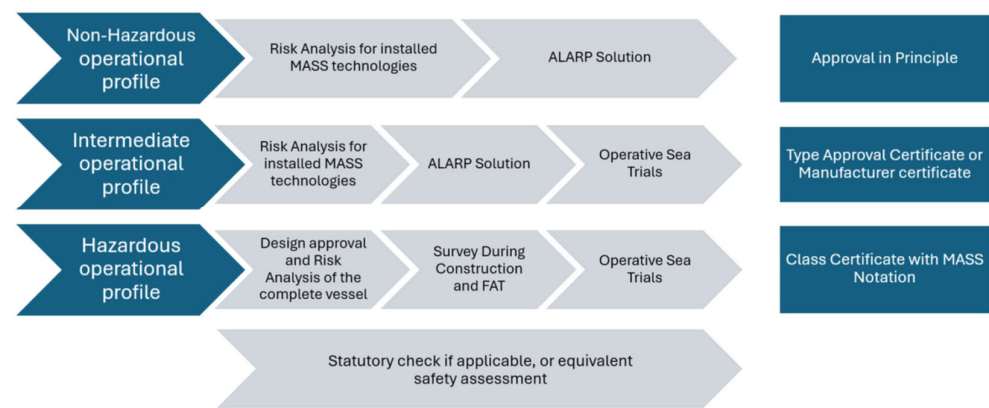


Figure 1. A Pathway for MASS Flag State Authorization as presented in [40].

2.2. Reliability and Availability in MASS Systems

Reliability assessment has become a central pillar in marine engineering, particularly with the increase in automation level, digitalization, and in the last year with the introduction of the autonomous ships. Historically, system reliability in marine and offshore sectors was primarily managed using deterministic, failure-rate-based approaches used in system design and in preventive maintenance policy making. These traditional frameworks—often drawn from aviation and defense sectors, such as Reliability-Centered Maintenance (RCM) developed by the U.S. Navy in the 1970s [40]—provided structured guidelines for managing risk of failure, but have proven insufficient in capturing the multi-dimensional, stochastic, and operational complexities of modern ship systems [41]. The increasing integration of autonomous functionalities, high-speed data acquisition and regulatory pressures has necessitated the evolution toward adaptive, intelligent reliability frameworks capable of supporting proactive and condition-based decision-making under uncertainty.

In any case these traditional methods for the evaluation of reliability could be well applied for the analysis of different system solutions and to compare a traditional vessel with an autonomous one.

In conventional ship systems, particularly those operating without automation, equipment degradation is typically driven by a mix of mechanical wear, material fatigue, environmental exposure and maintenance delays. Studies by Ait Allal et al. [42,43] illustrate how critical systems such as the Sea Water Central Cooling System and Main Engine Lubricating Oil system are subject to failure due to corrosion, pump malfunction and insufficient monitoring, often resulting in costly engine failures and operational downtime. Using classical methods like Fault Tree Analysis (FTA) and Failure Mode and Effects Analysis (FMEA), these works identify system vulnerabilities and suggest design improvements and redundancy strategies that are essential for adaptation to unmanned ship operation.

Edge et al. [44] and Abaei et al. [45] further develop this perspective by considering the requirements of autonomous and optionally manned platforms. In particular, the “Tx Ship” concept and machinery reliability framework for Unattended Machinery Plants (UMPs) underscore that future ship architectures must prioritize availability and fault tolerance over cost or fuel efficiency. Abaei et al. propose a Multinomial Process Tree (MPT) model coupled with Bayesian inference to predict the behavior of critical systems without human intervention, highlighting how systems such as the main engine and gearbox must be continuously monitored for degradation, with real-time diagnostic and prognostic tools supporting remote decisions.

These developments are consistent with trends in system reliability engineering that integrate probabilistic and AI-based models to enhance predictive power and responsiveness [46–48]. As detailed in Chapter 2 of Developing an Advanced Reliability Analysis

Framework by Daya and Lazakis [49], a major paradigm shift is underway: reliability modeling now often relies on hybrid architectures combining Dynamic Fault Tree Analysis (DFTA), Bayesian Belief Networks (BBNs) and FMECA for comprehensive maintenance support. DFTA expands the classical FTA by introducing sequence and time-dependent failure logic through specialized gates, enabling accurate representation of conditional dependencies and repairable component behavior [50,51]. These dynamic gates are especially useful in modeling standby systems or time-delayed failures typical for marine engine rooms.

In parallel, FMECA provides the subjective grounding required to integrate human expertise and operational constraints into reliability evaluation. This is particularly critical where data availability is limited or where failures are influenced by contextual factors such as operator competence, design limitations, and maintenance culture [52]. FMECA allows for component prioritization based on severity, likelihood, and criticality elements that are further refined using structured risk matrices or weighted evaluation mechanisms.

In Daya and Lazakis [53], this hybrid framework was applied to an Offshore Patrol Vessel (OPV) and most of the machinery system have been modeled; through machine learning algorithms the model recommended real-time maintenance strategies—shifting between Planned Maintenance System (PMS), Condition Monitoring (ConMon) or Corrective Action based on operational status and component behavior.

The move toward intelligent reliability frameworks is also aligned with industry efforts to digitalize operations and meet regulatory requirements such as the ISM Code [54] and data standards defined by ISO 19847/19845 [55,56]. Real-time data acquisition from sensors onboard ships, combined with high-throughput analysis can process nonlinear, high-dimensional data to detect anomalies such as overheating, pressure drops, or acoustic irregularities before they evolve into failures.

In addition to technical component reliability, the recent literature has emphasized the growing importance of Human Reliability Analysis (HRA) in autonomous and semi-autonomous operations. Traditional HRA models, originating from nuclear and aerospace sectors, require significant adaptation to be relevant in maritime contexts where human error is filtered through remote interfaces and control centers. These methods are valuable for modeling latent conditions (i.e., hidden problems within the system), procedural failures and oversight challenges that might impact the success of automated or semi-autonomous marine operations.

Pereira de Abreu et al. [57] have called attention to the need for Human Reliability Analysis (HRA), especially in scenarios where MASS are remotely supervised. As Pereira de Abreu et al. [57] discuss, even in systems with minimal crew, human roles persist through remote supervision, decision-making, and response to alarms or automated diagnostics.

Traditional HRA methods—such as Human Error Assessment and Reduction Technique (HEART) and Standardized Plant Analysis Risk Human Reliability Analysis (SPARH)—should be applied to the remote-control architectures, human-machine interfaces and cognitive overload under complex supervisory conditions. These methods are essential for identifying latent system conditions, procedural deviations and oversight failures that may not be captured by technical reliability models alone but can have profound implications on system safety and mission success.

Lee, S. M et al. [58] proposes a local route planning algorithm for MASS that integrates fuzzy inference systems, ship domain concepts, and velocity obstacle methods to perform real-time collision avoidance in compliance with COLREGs rules. The study emphasizes the importance of modeling encounter situations and decision-making processes to ensure safe navigation under dynamic operational conditions [58–60]. The same main author developed a collision risk inference system based on COLREGs-compliant rules using an

adaptive neuro-fuzzy approach, incorporating multiple navigational parameters such as CPA, ship domain and encounter dynamics. The proposed framework enables a more comprehensive assessment of collision risk by explicitly modeling decision-making processes and regulatory constraints [61].

2.3. Stochastic Reliability Modeling

Deterministic models such as RBD, FTA, FMEA and FMECA have long been the standard in marine engineering to identify potential failure paths. In MASS application, these models are essential for early design-stage analysis and for satisfying IMO MASS Code or IACS Class Society requirements like RINA GUI 35 [7] or CCS “i-Ship” frameworks [6]. However, their applicability is inherently limited by simplifying assumptions, most notably the hypothesis of stochastic independence between components and the use of constant, deterministic failure rates.

As system complexity increases, particularly in highly automated and autonomous architectures, dynamic and dependent behaviors become non-negligible. Components may interact through load-sharing mechanisms, standby redundancy, on-demand activation, failure propagation or common-cause failures, while system configurations may change due to maintenance policies or phased-mission characteristics. Under these conditions, classical static RBDs and FTs may lead to oversimplified or optimistic reliability estimates. To overcome these limitations, Distefano and Puliafito proposed Dynamic Reliability Block Diagrams as an extension of conventional RBDs, enabling the modeling of dependent and time-varying failure behaviors and configuration changes driven by repair, maintenance and mission-phase effects [58].

Their work demonstrates that dynamic reliability formalisms are necessary whenever the assumption of independence between system elements is violated.

In parallel, state-based and probabilistic approaches have been increasingly adopted to address uncertainty and data scarcity, which are particularly critical in autonomous ship applications. Abaei et al. proposed a reliability assessment framework for unattended machinery plants based on a Multinomial Process Tree coupled with Hierarchical Bayesian Inference, explicitly designed to cope with limited historical data and uncertain disruptive events in autonomous ship operations [61]. Their results highlight that uncertainty in failure behavior and the absence of onboard human intervention significantly affect system reliability and must be explicitly represented in quantitative models.

More recent studies in reliability engineering have further emphasized the importance of accounting for multisource uncertainty and performance degradation. Reliability degradation models show that variability in manufacturing tolerances, material properties, environmental conditions and operational stresses can substantially influence system-level reliability outcomes, even when nominal design parameters remain unchanged [39,62,63].

These findings reinforce the need to treat failure parameters as stochastic quantities and to propagate uncertainty from component level to system level rather than relying on single-point estimates.

Simulation-based stochastic frameworks, including Monte Carlo techniques, offer a practical compromise between analytical tractability and modeling fidelity [58,64,65].

Such approaches allow analysts to relax strict assumptions on failure rate determinism, to incorporate heterogeneous probability distributions, and to evaluate the sensitivity of mission success to uncertainty in reliability data [61].

Stochastic programming formulations have shown that reliability can be quantified for complex system topologies and arbitrary failure distributions, where closed-form analytical solutions are no longer feasible [59].

Within this context, the stochastic reliability approach adopted in the present work aims to preserve the transparency and design-oriented structure of RBD modeling while explicitly addressing uncertainty in input failure data. By treating component Mean Time to Failure (MTTF) values as random variables and propagating their variability through Monte Carlo simulations, the proposed method enables a probabilistic comparison between manned and unmanned vessel configurations under identical mission profiles. This approach is consistent with the goal-based safety philosophy underpinning the IMO MASS Code, allowing compliance to be demonstrated in terms of mission success probability rather than through deterministic or purely qualitative risk metrics.

From a certification perspective, (Figure 1) recent studies emphasize that the approval of Maritime Autonomous Surface Ships increasingly relies on risk-informed and goal-based approaches, where compliance is demonstrated through quantitative evidence of reliability, availability, and fault tolerance rather than prescriptive design solutions [40]. This highlights the importance of probabilistic reliability models capable of addressing uncertainty and limited operational experience when demonstrating safety equivalence between manned and unmanned vessel configurations.

3. Material and Methods

In this section the methodology and data taken into account in the calculation applied for the analysis are presented.

The ship mission is decomposed hierarchically into a number of critical functions/subsystems—Navigation Control, Situation Awareness, Propulsion, Maneuver, Stability, (Figure 1). Each function/subsystem is further divided into sub-modules down to the last single components/units. The reliability of the subsystems and of the mission itself is computed using Reliability Block Diagrams (RBDs), assuming exponential failure distribution, where the reliability (R) and the Main Time To Failure (MTTF) of the i -th element are expressed as

$$R_i(t) = e^{-\lambda_i t}$$

where λ_i is the constant failure rate of the component and (t) is the mission time. The MTTF is defined as the expected value of the time to failure and for an exponential distribution is given by

$$\lambda_i = \frac{1}{MTTF_i}$$

This formulation enables a direct link between failure rate data and reliability evaluation within the Reliability Block Diagram (RBD) framework. Series and parallel configurations are then used to compute subsystem and system-level reliability according to standard RBD rules, assuming statistical independence between component failures.

The analysis assumes independence between component's failures and is limited to mission-based time horizons, rather than the full life cycle of the vessel.

The analysis requires a scenario definition, i.e., mission type and mission duration, used to compute the RBD model.

Input data $MTTF_i$ represents a major challenge; multiple sources, including OREDA database (Offshore & Onshore Reliability Data) [66,67], other reliability databases, classification society documentation and manufacturer manuals, have been considered. The MTTF implemented in the model are reported in Appendix C.

To describe the "MTTF" of the crew element in the RBD, an alternative approach has been considered. EMSA (European Maritime Safety Agency) publishes annual overviews of marine casualties and incidents in EU waters; these reports classify events into categories such as "human error," "technical failure," "external causes," etc. For the 6 years from 2014 to 2020, EMSA consistently showed that a large share of accidents (about 80.7%) are directly

attributable to human error. To translate this into a failure rate (λ) suitable for reliability analysis, the following approach is applied:

- Consider the total exposure time of crews at sea (approximated via the number of ships, average crew sizes, and operating hours).
- Relate the number of accidents involving human error per year to this exposure time.
- The ratio gives a failure frequency, which can be interpreted as an effective human-related failure rate.

The failure rate of a technical component is itself an aggregate representation derived from multiple underlying failure mechanisms and operational conditions. In a similar way, the human-related failure rate adopted in this study is interpreted as an equivalent aggregate failure frequency derived from accident statistics. While maritime accident data represent complex events involving multiple contributing factors, the conversion is intended to provide an effective, system-level estimate of human-induced failure likelihood over a given exposure time. This approach does not aim to model individual human error mechanisms in detail, but rather to ensure consistency with the system-level reliability framework used for technical components. The limitation of this approximation is acknowledged and the resulting human failure rate should be interpreted as a simplified, order-of-magnitude representation suitable for comparative analysis between manned and autonomous configurations.

EMSA's figure "80.7% of accidents in the marine sector (19,300) are caused by human error," and a statistical average value of 13,098 ships in Europe with the hypothesis of 5000 h/year of motion per ship computes a human-error failure rate as

$$\lambda_{crew} = \frac{N^{\circ} \text{ of human_error accidents}}{\text{Total crew exposure time}}; \quad \text{MTTF}_{crew} = \frac{1}{\lambda_{crew}} = 3.4 \times 10^3$$

This formulation provides an order-of-magnitude estimate of the frequency of human-induced failures at system level. It should be noted that this approach does not model individual human error mechanisms, but rather aggregates their overall impact into a single equivalent failure rate, consistent with the level of abstraction adopted for technical components in the RBD model.

The reliability model adopted in this study is based on a hierarchical Reliability Block Diagram (RBD) representation of the ship system, in which the mission is decomposed into critical subsystems and further into individual components. Each element is characterized by a Mean Time To Failure (MTTF), which is used to derive the corresponding failure rate under the assumption of exponential failure behavior. A detailed description of the stochastic modeling approach is provided in Section 4, while the complete RBD structure for both manned and unmanned configurations is reported in Appendix A as a hierarchy table and in Appendix B as a graphic way.

It is to be considered that these sources, even if authoritative, may provide failure data for contexts not directly transferable to MASS applications, thereby introducing significant uncertainty.

To account for the limited availability and heterogeneity of failure data, the model is extended to a stochastic formulation in which MTTF values are treated as random variables rather than deterministic inputs. The resulting framework enables the propagation of uncertainty from component-level to mission-level reliability through simulation-based techniques.

To address the limitation of having the proper MTTF value, an alternative solution modeled through a stochastic framework has been adopted.

The standard deviation of the MTTF distributions has been varied between 10% and 40% of the nominal value in order to investigate the sensitivity of the model to uncertainty

in failure data. This range is not intended to represent a precise statistical characterization of all components, but rather to provide a structured exploration of uncertainty levels typically encountered in early-stage design and in contexts where heterogeneous data sources are used.

Lower values (10–20%) represent scenarios with relatively high confidence in failure data, such as well-documented components, while higher values (30–40%) represent conservative conditions where data uncertainty, variability in operating conditions, or limited empirical evidence may significantly affect reliability estimates (Figure 2a,b).

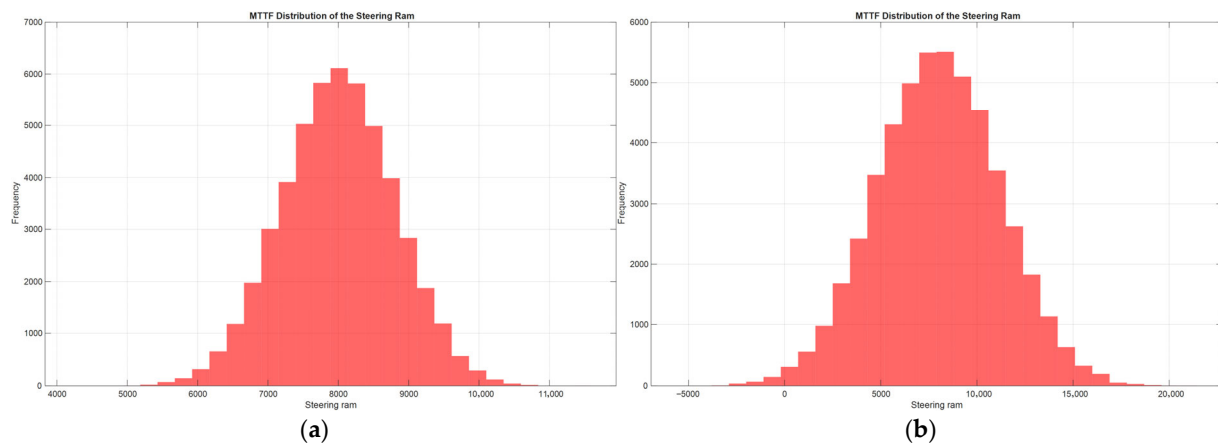


Figure 2. (a): Standard deviation 10% MTTF; (b): standard deviation 20% MTTF.

This sensitivity-based approach allows the robustness of the comparative results to be assessed and highlights the impact of uncertainty propagation on system-level reliability outcomes.

This approach allows us to consider the variability and limited confidence associated with failure rate data derived from heterogeneous sources. The stochastic simulations, performed in MATLAB R2022b, generated multiple iterations of perturbed MTTF datasets, with each cycle recalculating subsystem and mission reliability. The output of this process provides a probability distribution of reliability, from which confidence intervals and probabilistic comparisons between manned and unmanned configurations can be derived.

The developed code is structured in the following way:

- Definition of the component MTTF;
- Definition of the selected Standard Deviation;
- Random number generation between -1 and $+1$;
- Random MTTF generation for each component;
- Calculation of the reliability of the various subsystems (n iterations);
- Calculation of the n mission reliability;
- Calculation of the average reliability of the mission;
- Graphical representation of the distributions.

4. Stochastic Reliability Modeling for a SAR Autonomous Vessel

The reliability model implemented in this study is designed with the aim of providing a robust and realistic evaluation of the operational probability of success of a MASS compared to its manned counterpart: a Search and Rescue (SAR) fast patrol vessel. The reliability assessment is developed in two phases: a deterministic evaluation and a stochastic evaluation. The motivation behind this dual approach lies in the inherent uncertainties that characterize the estimation of component reliability parameters, in particular the mean time

to failure (MTTF), which are rarely available with the precision and consistency required for a purely deterministic model.

In the deterministic study, the system is decomposed hierarchically into five critical subsystems—Navigation Control, Situation Awareness, Propulsion, Maneuver, and Buoyancy/Stability—(Figure 3) each of which is further divided into sub-modules up to the last single components/units. The complete model is reported in Appendix A for the manned and unmanned configurations. The reliability of the subsystems and of the mission itself is computed using Reliability Block Diagrams (RBDs) with exponential failure laws. Two missions of different duration and operative profile are considered: a 8 h SAR mission and a patrol 100 h mission scenario. Input data for the deterministic model were obtained from multiple sources and presented in the following.

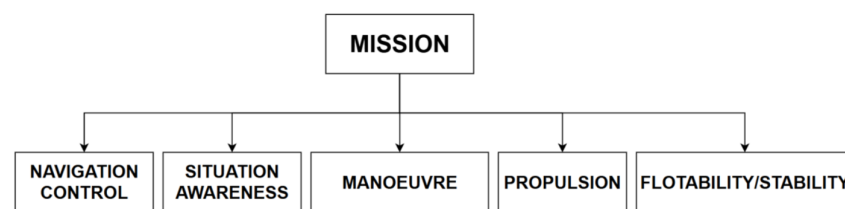


Figure 3. Hierarchical structure Level 2 system for manned Ship.

Down to the second level the manned and unmanned configuration are equivalent; the differences start from level 3 as detailed in Appendix A.

For the SAR mission both shaft lines are required, and the mission is modeled with a series of blocks in the RBD (Figure 4).

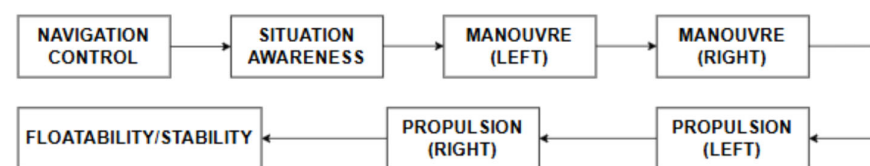


Figure 4. RBD scheme of the SAR Mission.

For the patrolling operational profile the hypothesis that the mission is accomplished with at least one shaft line has been assumed. The shaft line modules are set as a parallel in the RBD scheme (Figure 5).

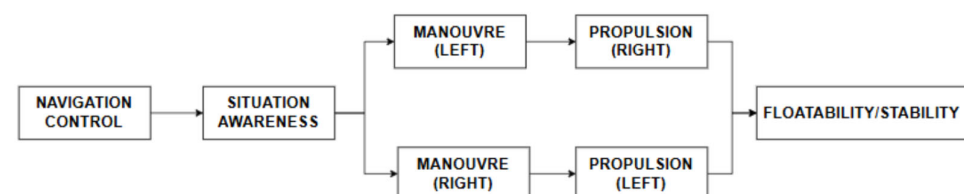


Figure 5. RBD scheme of the Patrol Mission.

Two different mission duration are considered: 8 h and 100 h.

5. Results

This section presents the simulation results of the stochastic reliability model applied to the two ship configurations: manned and unmanned for the two different mission profiles. The model uses a continuous-time Markov chain (CTMC) framework, based on the system architecture and component-level failure data, to estimate system availability, failure probability and mission success likelihood for both rescue and patrol missions.

5.1. Manned Ship Configuration—Deterministic Model

In the manned vessel configuration, systems are subdivided according to traditional operational layers—propulsion, navigation, auxiliary and command/control—as explained in Appendix A. The failure rate for each component is a fixed value and it is not considered in this approach a possible human intervention that can mitigate certain failure modes (Table 1).

Table 1. Reliability model result for the manned vessel.

Mission Duration	Rescue Mission	Patrol Mission
8 h	0.958	0.988
100 h	0.614	0.856

5.2. Unmanned Ship Configuration—Deterministic Model

The results of the same simulation with the unmanned vessel model are presented in the following (Table 2).

Table 2. Reliability model result for the unmanned vessel.

Mission Duration	Rescue Mission	Patrol Mission
8 h	0.970	0.992
100 h	0.730	0.895

The results are obtained applying the methodology presented in paragraph 3, assigning MTTF data available in the literature or declared by the manufacturer of specific components used in the preliminary design of the vessel systems.

5.3. Comparative Preliminary Analysis of the Deterministic Model Results

One of the goals of this paragraph is the verification that the results of the model (Table 3) are coherent with the good practice and the experience of these kind of vessels and missions. The single main modules (level 2) reliability results are presented in order to better understand the importance of the single modules and how they affect the final result.

In the Reliability Block Diagrams reported in this section, the *Propulsion*, *Maneuverability*, *Floatability* blocks represent distinct functional capabilities required for mission completion to the vessel platform. The *Propulsion* block refers to the vessel's ability to generate and maintain thrust through the main propulsion system and its essential auxiliaries, while the *Maneuver* block represents the capability to control heading and trajectory, including steering and control-related functions necessary to safely execute course changes.

The Navigation Control and situational awareness are the two key elements of the MASS technology or crew function.

All the RBDs are presented in Appendix B.

The results obtained represent the probability that the single module will positively conclude the mission (Table 3). In a second step the mission successful probability is calculated as the product of this Reliability Block.

5.4. Stochastic Modeling of Failure Scenarios Results

The results of the stochastic reliability modeling applied to the failure behavior of critical onboard systems are presented hereafter. The reliability of components is described by a Gaussian function with mean value MTTF and standard deviation ranging from 10% of MTTF to 40% of MTTF (Figures 6–9). Several computations have been carried out

iteratively in MATLAB environment to calculate in a stochastic way the reliability value of the various configurations, providing a graphical result histogram for each considered range of standard deviation.

Table 3. Comparative analysis of the reliability results obtained for each block.

Mission Type	Reliability Manned	Reliability Unmanned	Difference (%)
NAVIGATION CONTROL			
8 h—SAR	0.995	0.996	0.10%
100 h—Patrol	0.941	0.95	0.96%
SITUATION AWARENESS			
8 h—SAR	0.996	0.997	0.10%
100 h—Patrol	0.953	0.956	0.31%
PROPULSION			
8 h—SAR	0.976	0.98	0.41%
100 h—Patrol	0.779	0.827	6.16%
MANEUVRABILITY			
8 h—SAR	0.993	0.998	0.50%
100 h—Patrol	0.915	0.97	6.01%
FLOATABILITY			
8 h—SAR	0.997	0.999	0.20%
100 h—Patrol	0.959	0.987	2.92%

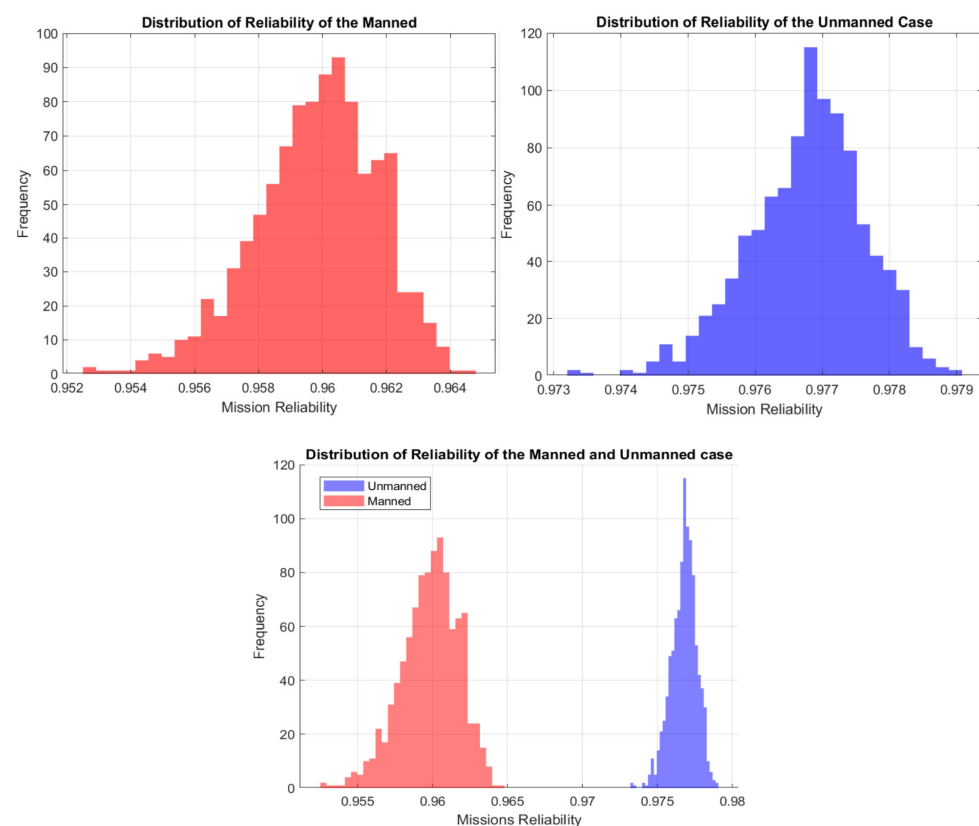


Figure 6. Distribution Reliability for a 8 h Rescue mission, 10% of std. deviation, manned and unmanned configuration.

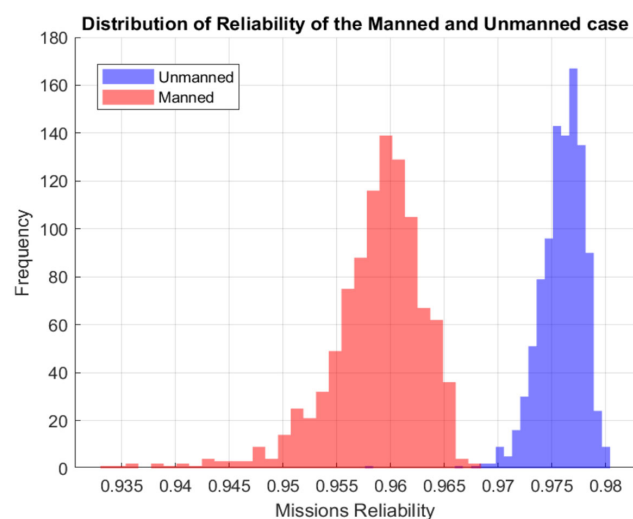


Figure 7. Distribution Reliability for a 8 h Rescue mission, 20% of std. deviation, manned and unmanned configuration.

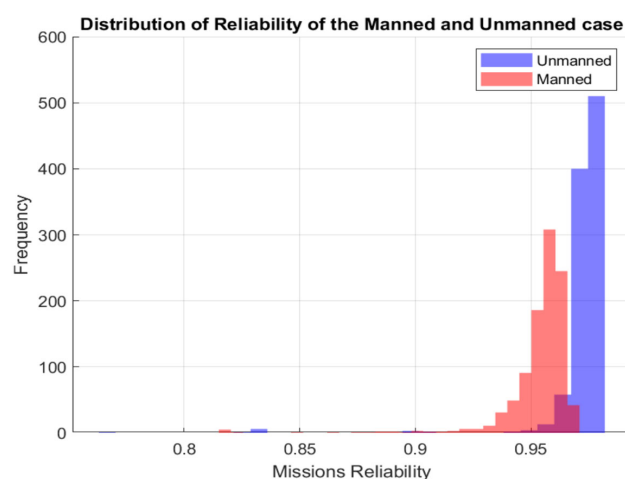


Figure 8. Distribution Reliability for a 8 h Rescue mission, 30% of std. deviation, manned and unmanned configuration.

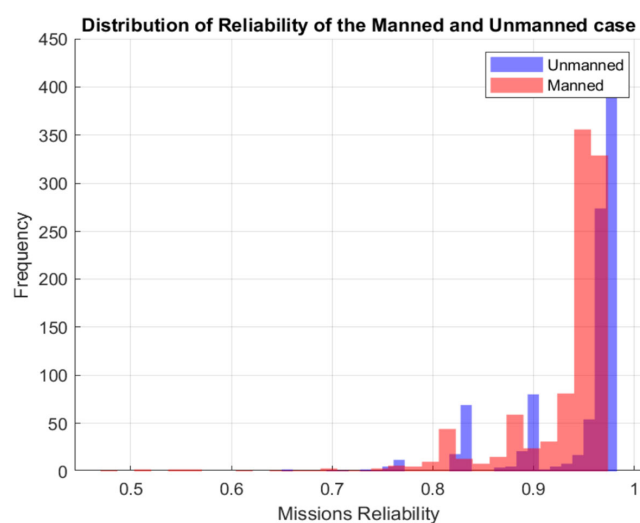


Figure 9. Distribution Reliability for a 8 h Rescue mission, 40% of std. deviation, manned and unmanned configuration.

With the distribution results it is possible to calculate the probability of overlapping of the two distributions, and the results obtained are presented in the following (Table 4):

Table 4. Distribution overlap results.

% STD DEV	$P(R_{manned} > R_{unmanned})$
10	0%
20	0.3%
25	5.2%
30	13.4%
35	27.7%
40	50.8%

Up to an uncertainty of the MTTF value related to a STD DEV equal to 20%, the probability that the manned configuration is more reliable is very low (0.30%). As the uncertainty on the MTTF increases, the variability of the reliability distributions also increases, leading to a larger overlap between the manned and unmanned configurations. Consequently, the statistical advantage of the unmanned configuration progressively reduces, and the likelihood that the manned configuration attains equal or higher reliability becomes non-negligible.

5.5. Comparison of Stochastic vs. Deterministic Reliability Models

The hypotheses underpinning the model include the memoryless property of the exponential failure distribution, the independence of component failures and the assumption that Gaussian distributions adequately represent the variability in MTTF values. While these assumptions are standard in reliability engineering, they introduce limitations when applied to complex MASS architectures. In real operational environments, failures may be correlated due to shared subsystems, environmental conditions or common-cause events, and system behavior may exhibit time-dependent degradation rather than memoryless characteristics [68–74]. As a result, the model may underestimate or oversimplify certain failure propagation mechanisms. In particular, the Markovian nature of the model does not account for degradation mechanisms with memory effects, which are relevant in long-term operations (i.e., the vessel is considered a New Building in each simulation). Furthermore, the mission-limited focus excludes life-cycle phenomena and the Gaussian approximation may not capture the skewed nature of real-world failure distributions.

The proposed framework focuses on hardware subsystems and does not explicitly model higher-level navigational decision-making processes. Therefore, the results reflect mission-level hardware reliability rather than the full operational safety process. This limitation is acknowledged and will be addressed in future developments.

The results demonstrated that with moderate levels of uncertainty of the failure rate (10–20% variability in MTTF), the unmanned vessel consistently exhibited higher reliability than the manned configuration. This outcome reflects the elimination of human-related failure rates, which are statistically non-negligible in traditional vessels, even if the result reflects some important hypothesis, including the decision to exclude the possible failure of the software in the above-described model. However, when the variability of the MTTF data increases beyond approximately 30%, the uncertainty introduced at the component level propagates through the reliability model, leading to a significant widening of the resulting reliability distributions. Under these conditions, the separation between the manned and unmanned configurations is reduced and the relative ranking of the two solutions is no longer statistically robust. As a consequence, the stochastic realizations may

yield scenarios in which the manned configuration attains reliability values comparable to, or higher than, those of the unmanned vessel. This behavior does not indicate systematic superiority of the manned configuration, but rather reflects the loss of model stability and discriminative power caused by highly uncertain input data.

One of the main results is the demonstration that for this case study, a small variance of the MTTF data does not impair the final result, allowing us to compare different design solutions even if exact data are not available.

6. Conclusions

This study has presented a stochastic reliability framework tailored for MASSs, using Markov chains to model the dynamic failure and repair behavior of critical systems of a MASS compared to a traditional vessel. Unlike conventional deterministic methodologies, the proposed approach captures the probabilistic evolution of system states allowing them to manage the problem of MTTF data availability.

The simulation results reveal that reliability outcomes are highly sensitive to architectural choices and component repair assumptions. This reinforces the necessity of adopting stochastic processes during the early design and verification phases of MASS development. Furthermore, the model enables direct comparison between manned and unmanned configurations, providing a quantitative basis for verifying functional equivalence in line with the IMO MASS Code and emerging goal-based Class Society requirements. In particular, the ability to evaluate how redundancy, repair latency and mission duration affect operational resilience is crucial for meeting the safety assurance obligations of autonomous systems.

The use of a stochastic approach was not merely a methodological enhancement but a practical response to the inherent variability and uncertainty in MASS reliability data. By incorporating probabilistic transitions, the model offers a more realistic and flexible representation of system behavior under imperfect operational conditions. It also allows critical analyses, helping to identify critical design parameters and operational thresholds beyond which the expected performance of autonomous configurations may degrade below acceptable levels.

Ultimately, the integration of Markov-based stochastic modeling within a broader reliability assessment framework contributes to a more rigorous, transparent and regulation-aligned evaluation of MASS safety based on a scientific methodology.

Future research will focus on extending the presented Markov modeling framework toward real-time, adaptive reliability assessment. One promising direction involves the development of non-homogeneous Markov models whose transition rates are dynamically updated based on sensor feedback and operational context. Coupling these models with condition-based maintenance (CBM) policies and AI-based diagnostics may significantly improve the responsiveness of autonomous vessels to incipient failures. Additionally, the integration of stochastic reliability results into holistic digital twin environments would enable continuous risk assessment throughout the vessel's lifecycle.

A future improvement of the analysis should also include the evaluation of the reliability of the software, not limited to the hardware as presented in this work.

Experimental validation of the models using sea trials or high-fidelity simulation platforms is also envisaged to refine parameter estimates and ensure alignment with actual system behavior. Finally, interdisciplinary collaboration between naval architects, control engineers and classification societies will be essential to embed these methodologies into practical safety assurance and regulatory frameworks for future MASS operations.

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Appendix A

Table A1. System Hierarchy for the manned and unmanned vessel.

Abbreviation	Description	Manned Level	Unmanned Level
Mission	Mission to be carried out by the vessel, such as patrolling or rescue	1	1
Navigation Control	Allows control of the unit's motion in mode automatic	2	2
Track Keeping	Control system to maintain the long-term course	3	3
Course Control and Speed	Control system to maintain the instant course and speed	3	3
Collision Avoidance	Reactive maneuver planning system following obstacle detection	NA	3
GNSS	Global Navigation Satellite System	4	4
AES	Action Execution System	4	4
DMS	Decision-Making System	4	4
INS	Inertial Navigation System	4	4
SAS	Situation Awareness System	4	4
Situation Awareness	Manages, controls the on-board systems and sensors to enable navigation functionalities	2	2
Weather Sensors	Sensors that detect environmental conditions, such as wind intensity and wave height	3	3
Surveillance	Remote surveillance of the external spaces with cameras	NA	3
IR	Provides infrared night vision	NA	4
Server Video	Collects and integrates the information from the cameras	NA	4
Surveillance Camera	Provides external vision in visible light	NA	4
Surveillance Communications	Transfers the information from camers to servers	NA	4
Communication towards the base	Manages communications towards the remote control station	NA	3
Main Link	Ensures the transfer of navigation and patrolling data to the remote station	NA	4
Emergency Link	Receives the minimum set of return information unit safety in case of emergency	NA	4
Transmitter	Transmits information to the remote location	NA	4
Receiver	Receives information from the remote location	NA	4
HMI	The Human–Machine Interface allows operators to interact with on-board systems and machines	3	3
Radar	Identifies obstacles in the surrounding space	4	4

Table A1. *Cont.*

Abbreviation	Description	Manned Level	Unmanned Level
AIS	Tracking system of surrounding vessels, standard device installed also on crewed ships	4	4
Integrated Bridge	Integrate images with navigation information	4	4
Multifunctional Video	Display images on board	4	4
Maneuver	Allows for course change and directional control of the ship	2	2
Maneuverability Control	Closed loop verification of correct execution of the steering command	3	3
PLC Maneuverability	Generates control signals for the implementation of the nozzle	4	4
Hydraulic Power Pack	Power the manoeuvre nozzle hydraulic ram	3	3
Maneuver Nozzle Hydraulic Ram	Piston for handling the nozzle	3	3
Propulsion	Allows for variation and control of the speed of the ship	2	2
Control of the Propulsion	Control and adjust propulsion engines	3	3
PLC Propulsion	Process the set point and determine the control signal for the fuel valve	4	4
Telegraph	Generate the speed setpoint	4	4
Encoder	Measure engine rpm	4	4
Can. Bus	Transmits the information	4	4
Main Engine	Main engine of the ship	3	3
Transmission	Transmits the torque required by the propeller	3	3
Gearbox	Reduces engine speeds to a speed compatible with the propulsor	4	4
Stern tube	Prevents water from entering the hull by the slow axis	4	4
Joint	Allows the connection of misaligned shafts	4	4
Propulsor	Allows the generation of thrust	3	3
Impeller	Hydrojet component that accelerates water flow	4	4
Hydraulic Power Pack	Power the reversing bucket hydraulic ram	4	4
Reversing Hydraulic Ram	Piston for handling the bucket	4	4
Flotability/Stability	Ability of the vessel to ensure floatability and stability	2	2
Bilge Pumping System	System ensuring that the engine room remains dry	3	3
Main Pump	The bilge system main pump removes water from the ship's bilge	4	4
Emergency Pump	Pump that is activated in the case of failure of the main pump	4	4
PLC Bilge System	Control the bilge system	NA	4

Appendix B

In the figure below the colors represent:

- GREEN: System added for the unmanned ship;
- RED: System removed for the unmanned ship;
- GREEN and RED: System modified for the unmanned ship;

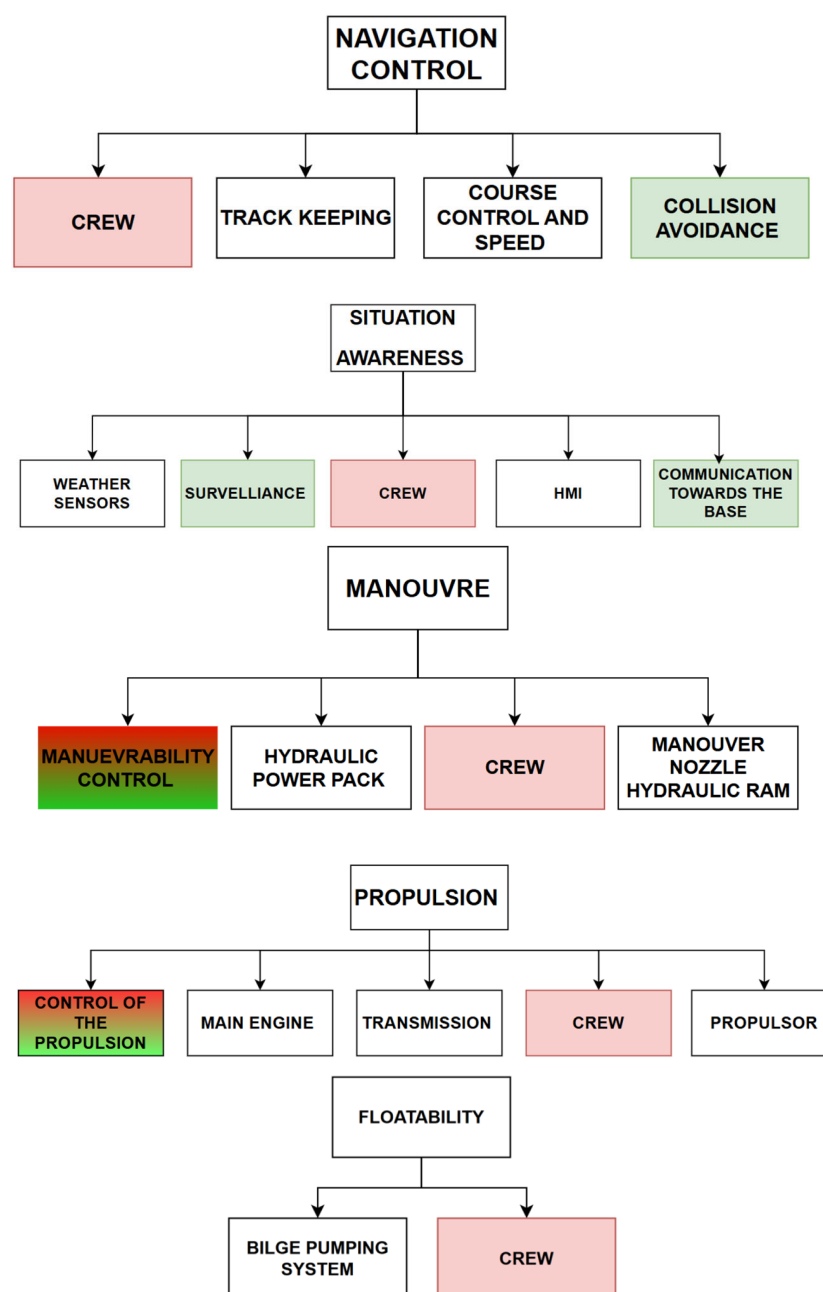


Figure A1. Hierarchical structure of the main RBD modules (Level 2/3) for unmanned ship.

Appendix C

Table A2. Main time to failure of the components integrated in the reliability model.

Type of Component	λ	MTTF
NAVIGATION CONTROL		
GNSS	6.12×10^{-6}	163,312
INS	2.22×10^{-5}	44,976
AES	2.37×10^{-6}	421,625
DMS	8.73×10^{-7}	1,145,632

Table A2. Cont.

Type of Component	λ	MTTF
SITUATIONAL AWARENESS		
Weather Sensor	4.57×10^{-5}	21,893
Radar	9.82×10^{-6}	101,788
AIS	1.12×10^{-5}	89,157
Integrated Bridge	3.74×10^{-6}	267,148
Multifunctional Video	1.17×10^{-4}	8555
MANEUVER		
Manuevrability Control/PLC	1.18×10^{-5}	85,000
Hydraulic Power Pack	1.00×10^{-5}	100,000
Maneuver Nozzle Hydraulic Ram	1.25×10^{-4}	8000
PROPULSION		
PLC Propulsion	1.18×10^{-5}	85,000
Telegraph	3.18×10^{-5}	31,400
Encoder	1.61×10^{-5}	62,150
Can. Bus	1.00×10^{-7}	9,999,999
Main Engine	2.24×10^{-4}	5804
Gearbox	3.47×10^{-4}	3744
SternTube	6.67×10^{-5}	15,000
Joint	3.61×10^{-4}	2770
Impeller	6.67×10^{-5}	15,000
Hydraulic Power pack	1.00×10^{-5}	100,000
Reversing Hydraulic Ram	1.25×10^{-4}	8000
Crew	2.95×10^{-5}	33,932
FLOATABILITY—STABILITY		
Main Bilge Pump	6.00×10^{-5}	16,667
Emergency Bilge Pump	6.00×10^{-5}	16,667

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