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Prognostic health management of repairable ship systems through different autonomy degree; From current condition to fully autonomous ship

Ahmad BahooToroody [a,*], Mohammad Mahdi Abaei [b], Osiris Valdez Banda [a], Pentti Kujala [a], Filippo De Carlo [c], Rouzbeh Abbassi [d]

[a] Marine and Arctic Technology Group, Department of Mechanical Engineering, Aalto University, Espoo 11000, Finland
[b] Department of Marine Technology, Norwegian University of Science and Technology, 7491, Trondheim, Norway
[c] Department of Industrial Engineering (DIEF), University of Florence, Florence 50135, Italy
[d] School of Engineering, Macquarie University, Sydney, NSW 2113, Australia

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ABSTRACT

Maritime characteristics make the progress of automatic operations in ships slow, especially compared to other means of transportation. This caused a great progressive deal of attention for Autonomy Degree (AD) of ships by research centers where the aims are to create a well-structured roadmap through the phased functional maturation approach to autonomous operation. Application of Maritime Autonomous Surface Ship (MASS) requires industries and authorities to think about the trustworthiness of autonomous operation regardless of crew availability on board the ship. Accordingly, this paper aims to prognose the health state of the conventional ships, assuming that it gets through higher ADs. To this end, a comprehensive and structured Hierarchal Bayesian Inference (HBI)-based reliability framework using a machine learning application is proposed. A machinery plant operated in a merchant ship is selected as a case study to indicate the advantages of the developed methodology. Correspondingly, the given main engine in this study can operate for 3, 17, and 47 weeks without human intervention if the ship approaches the autonomy degree of four, three, and two, respectively. Given the deterioration ratio defined in this study, the acceptable transitions from different ADs are specified. The aggregated framework of this study can aid the researchers in gaining online knowledge on safe operational time and Remaining Useful Lifetime (RUL) of the conventional ship while the system is being left unattended with different degrees of autonomy.

1. Introduction

The innovative thinking of Maritime Autonomous Surface Ships (MASS), given all its challenges, has been a prerequisite, specially to secure safety and sustainability. According to Allianz's safety and shipping review [24], human errors lead to 75% up to 96% of maritime accidents. This amount of human error contribution to maritime accidents has been recently challenged through a literature review by Wróbel [69] to be unsubstantiated. However, it is verified that human error constitutes a significant contribution to maritime accidents. Eliminating the crew members on board and introducing novel technologies and state-of-the-art ship design will result in reducing operational cost (up to 36% of total operational cost [23]), energy saving, environmental protection and striking reductions in greenhouse gas emissions, which are all crucial milestones towards sustainability [8].

A great deal of projects has recently been conducted to support the development of MASS such as Advanced Autonomous Waterborne Applications (AAWA) [38], ReVolt [27], The Maritime Unmanned Navigation through Intelligence in Networks (MUNIN) [43], Kongsberg (Konsberg [42]), and most recently, AUTOSHIP [18]. The typical outcome derived from all these studies has been that the more the automation level increased, the more the new random failure with unrecognized failure pattern will be propagated [14]. Safety studies on MASS have been divided into two main categories: (i) risk-based design to recommend the design of safe autonomous ships [44,62]; what design feature of new tools can best mitigate risks? (ii) risk-based asset integrity management to identify the weak and sensitive components in the ship systems once it is operating [17,25]; what are the risks that the new design in MASS should focus on to eliminate/mitigate? Consequently, significant attention has been paid to detect [32,64], isolate [9], identify

* Corresponding author.
E-mail address: ahmad.bahootoroody@aalto.fi (A. BahooToroody).

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the root causes [21,65,67], monitor [56], and predict the downtime of MASS [1–3,76].

Accordingly, system-based approaches such as system theoretic process analysis (STPA), have been applied to recommend the design and operation of safe autonomous ships ([20,35,70]). The considerable research activities based on STPA for such a complex system illustrates its pivotal contribution to the development of preliminary safety management plan of the autonomous ships, e.g., in the recent virtual special issue on autonomous vessels safety [66], more than 25 percent of published articles were based on STPA. STPA as a control-based hazard identification approach proposed and developed based on System Theoretic Accident Model and Processes (STAMP) Leveson [50] and Leveson and Thomas [51]. In another study, Zhou et al. [75] investigated the applicability of 29 hazard analysis methods for autonomous ships and concluded that the traditional hazard analysis approaches could not provide an acceptable safety arrangement for designing autonomous vessels. On the contrary, STPA has been classified as a practical hazard analysis method that is recommended to be integrated with other hazard analysis methods.

The motivation of these initiatives was mainly aimed to identify the hazards. Inevitably, toward securing a practical risk assessment, hazard identification is the baseline. Nevertheless, neither of these studies established a quantifiable approach. Consequently, a collection of ongoing efforts is made to analyze the operational risk and safety of the MASS, quantitatively [22,33,58]. Ellefsen et al. [31] documented four most-celebrated deep learning techniques to support innovation toward the intelligent prognostics and health management (PHM) in semi-autonomous ships. It concluded that deep learning techniques in complex systems deployed in dynamic environments such as MASS would be advantageous mainly due to unsupervised learning features. In another quantitative machine learning-based study, Abaei et al. [7] developed a multinomial process tree to model failures propagated in weak (failure-sensitive) components for evaluating the reliability of an autonomous system under the influence of uncertain disruptions. Bayesian inference was implemented to overcome data scarcity for predicting the number of disruptive events in the new advanced stage of MASS.

The application of hierarchical Bayesian inference (HBI) has been vastly extended in different research areas, from econometrics [40] to phycology [68] and medicine [30]. This extension is principally thanks to two main reasons; first, the development of random-effect models (REM) and specially Markov Chain Monte Carlo (MCMC) simulation [12,46], and second, the capability of HBI in modeling the variability of non-stationary data and the correlation between nonlinear data [10,11,16]. Related literature also set sound examples of MCMC sampling-based HBI for failure modeling of maritime autonomous systems [3,19,53,74].

Aside from qualitative and quantitative analysis of MASS, a significant number of studies have also been carried out on Human-Machine Interaction [26,73], legal and regulatory challenges [15,71], business model development for technological transition [54,59], and system dynamics based robot learning in autonomous systems [45,52,57,61]. Nonetheless, a longstanding gap continues to exist as there is still a lack of unified models to capture the effect of removing crew members on the reliability of ships given the complex time-dependent auto-correlation structure of the uncertainty associated with survival-time of components operating in ships. Satisfying various trustworthiness levels, relying less on the crew member is required upon a vessel moving through each autonomy level (Edge et al., [28]). Therefore, this paper aims to prognose the health state of the conventional ships, assuming that it gets through higher AD. To this end, a comprehensive HBI-based reliability framework using a machine learning application is proposed. There is still a lack of knowledge on the effectiveness of autonomous behaviors of MASS in the execution of risk control strategies such as self-maintenance and self-governing. Therefore, for the purpose of failure specification, these behaviors are not considered in this paper.

As recommended by IMO [37], an autonomous ship should be as safe as a conventional ship regardless of the AD it is operating. As Colon [23] reviewed, the main focus of conducted studies on MASS is to investigate how advanced control systems, navigation software, and online communications could control an unmanned vessel. Although designing a completely unmanned ship arises more problems than navigation and communication, what is often neglected through these studies is the need for reliability estimation within the machinery plant. Therefore, the machinery plant operated in a merchant ship is selected as a case study to indicate the advantages of the developed methodology. The aggregated framework of this study can aid the researchers in gaining online knowledge on weak and failure-sensitive parts of the conventional ship if the system is being left unattended in different stages of its lifecycle and with different degrees of autonomy. These calculations address the involved and, most of the time, unconsidered risk to predict the safety conditions of the operation in the future.

2. Model specification

Given the prognostic aspect of this study, the selected model should be capable of reasoning under uncertainty. Although there are observational data available for conventional ship performance, there is data scarcity on systems behavior in higher autonomy degree. Therefore, the proposed model should also be able to infer under scarcity of data. The nonlinear interactions among different ship systems and stochastic characteristics of the operating environment require both inductive and deductive methods to be integrated. This promising framework is introduced in the ensuing sub-sections.

2.1. Model of the world; hierarchical Bayesian inference

Data acquisition, information processing, knowledge gathering, and making actions based on concluded inference are four steps to estimate and predict the reliability of an autonomous system. Manipulating the information required a model of the world to be framed. Both deterministic and probabilistic models are available for this purpose [41]. Different types of uncertainties (epistemic; also known as state-of-knowledge uncertainty and aleatoric; stochastic) must be incorporated in the model. As an understandable, trusted model, Bayesian statistics can describe these uncertainties with the posterior distribution, $\pi_1(\theta|x)$, [4,13,41] given by Eq. (1).

$$\pi_1(\theta|x) = \frac{f(x|\theta)\pi_0(\theta)}{\int_\theta f(x|\theta)\pi_0(\theta)d\theta} \tag{1}$$

where θ is the unknown parameter of interest, and $f(x|\theta)$ is the likelihood function.

The Bayes theorem utilizes multistage prior distribution to present the population variability through different hierarchy levels. Correspondingly, the first-stage prior denoted as $\pi_1(\theta|\varphi)$ represents the variability between the source of data for the parameter of interest indicated by $\pi_0(\theta)$, as follow:

$$\pi_0(\theta) = \int_{\varnothing} \pi_1(\theta|\varphi)\ \pi_2(\varphi)d\varphi \tag{2}$$

where, φ is a vector of hyper-parameters. Fig. 1 presents this hierarchical structure of Bayesian inference through the parameter of interest, θ, and hyper-parameters. As it can be seen in this figure, two hyper-parameters, φ_1, φ_2, are governing the prior probability distribution of θ. Meanwhile, and through the second stage prior, the uncertainty in hyper-parameters can also be represented by $\pi_2(\varphi)$ as the hyper-prior distribution; (α_1, α_2) are describing φ_1, and (α_3, α_4) are modeling, φ_2.

Implementation of Bayesian inference is theoretically simple if one can calculate its integrals. While the analytic solution is an option for solving the integrals, it is practical only for elementary models. As an

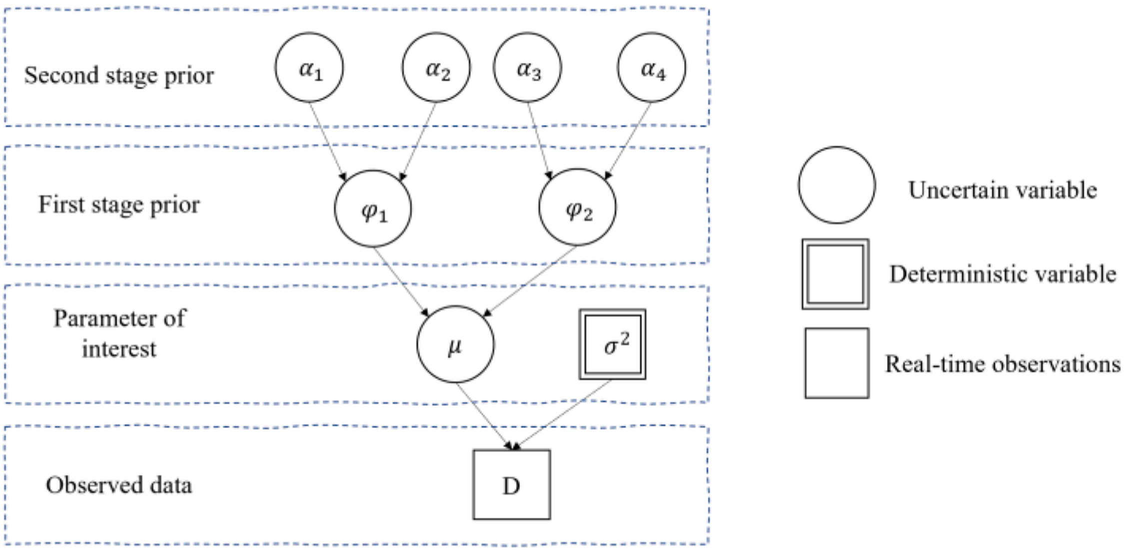


Fig. 1. A schematic directed acyclic graph of Bayesian inference with hierarchical structure.

example of models that have unclean posterior distribution, let consider a one-parameter non-conjugate model. A prior distribution is defined as conjugate whenever its combination with the likelihood will result in a posterior distribution belonging to the same probability distribution of the prior [47]. Assume $y = (y_1, y_2, y_3, \ldots, y_n)$ as a sample of n independent and identically distributed (i.i.d.) observations following a normal distribution with known variance, σ^2, but an unknown mean denoted by μ, i.e., $y_i \sim N(\mu, \sigma^2)$. As stated by [34], The conjugate prior for a normal distribution with random mean and fixed variance is normal distribution; however, it assumes that the prior beliefs about mean are better reflected using a standard t distribution, $\mu \sim t(\mu_0, \sigma_0, \nu_0)$, where μ_0 is location parameter, σ_0 represents scale parameter and ν_0 denotes the degree of freedom. As illustrated by Eq. (1), through the application of Bayes' Theorem, the posterior distribution would be achieved by:

$$P(\mu|y_1, y_2, y_3, \ldots, y_n) \propto \prod_{i=1}^{n}\left[\frac{1}{\sqrt{2\pi}}\exp\left(-\frac{1}{2}(y_i-\mu)^2\right)\right] \frac{1}{\pi(1+\mu^2)}$$

$$\propto \exp\left[-\frac{1}{2}\sum_{i=1}^{n}(y_i-\mu)^2\right] \frac{1}{1+\mu^2}$$

$$\propto \exp\left[-\frac{1}{2}\left(\sum_{i=1}^{n}{y_i}^2 - 2\mu\sum_{i=1}^{n}y_i + n\mu^2\right)\right] \frac{1}{1+\mu^2}$$

$$\propto \frac{\exp[n(\bar{y}\mu-\mu^2/2)]}{1+\mu^2}$$

which is almost proportional to the normal distribution (apart from the denominator $(1 + \mu^2)$), the form of this posterior distribution is not recognizable as a standard distribution, though. Therefore, the model does not have a close-form solution, and it is impossible to integrate or simulate its distribution. As a solution, the computations need to be broken into smaller pieces and transformed into computers through probabilistic programming platforms, including automated computation and inference. MCMC simulation and distributional approximation like Laplace, exaptational propagation, etc., are examples of these frameworks. The advent of computational methods revolutionized and catalyzed the calculations and have proliferated Bayesian inference resulted in its widespread use in probabilistic risk applications ([2], [13,46,48,49]). In this study, MCMC sampling has been incorporated with HBI via open-source simulation software packages, i.e., OpenBUGS [63] to solve the integrals and consequently simulate the likelihood function and prior distribution to obtain the posterior values.

The next challenge is the computers' limitations in terms of memory, speed, and accuracy of calculations. Accordingly, model diagnostics must prove the computations and check whether they are precise or not and whether the data is transformed correctly or not. The present study will establish different chains through MCMC simulation with over-dispersed initial values, providing the opportunity to diagnose the calculations and assess the simulations' convergence.

2.2. AD definition and failure specification

Recently IMO [37] initiated a regulatory scoping exercise (RSE) for the use of MASS outlined in Table 1 [36]. As there is no better definition alternative exists yet in terms of autonomy degree, this RSE is considered to conduct a failure specification for ships with different ADs. The necessity of human availability onboard a ship varies through these distinguished degrees of autonomy. The human can be present onboard a ship regardless of its AD, however, dependency on humans is not following the definition of autonomous ship initiated by RSE. This need for human availability along with observations gathered from the system have been taken into account to recognize the health state of the ship system through different AD (see Fig. 2). As illustrated by Fig. 2(a), observation is divided into two categories of failure and Risk Control Strategy (RCS) (Check (inspection), maintenance, and replacement (unplanned maintenance)). Correspondingly, four levels of health state (safe, reliable, degraded, and unsafe) were considered to describe the safety status of the system and, accordingly, to present the failure perception matrix of the ship system in each AD (Fig. 2(b)).

As still there is not enough knowledge on the effectiveness of autonomous behaviors of MASS (specially for the execution of RCSs) through the operation, in this study, these behaviors have not been considered for failure specification. Accordingly, execution of RCSs is

Table 1
Specified degree of autonomy for Maritime Autonomous Surface Ship (MASS); IMO [37].

ADs	Description; human availability
AD1	Ship with automated process and decision support: human intervention is required
AD2	Remotely controlled ship: seafarers on board, human intervention is partially required
AD3	Remotely controlled ship: no human on board; human intervention is partially required
AD4	Fully autonomous ship: no human intervention is required

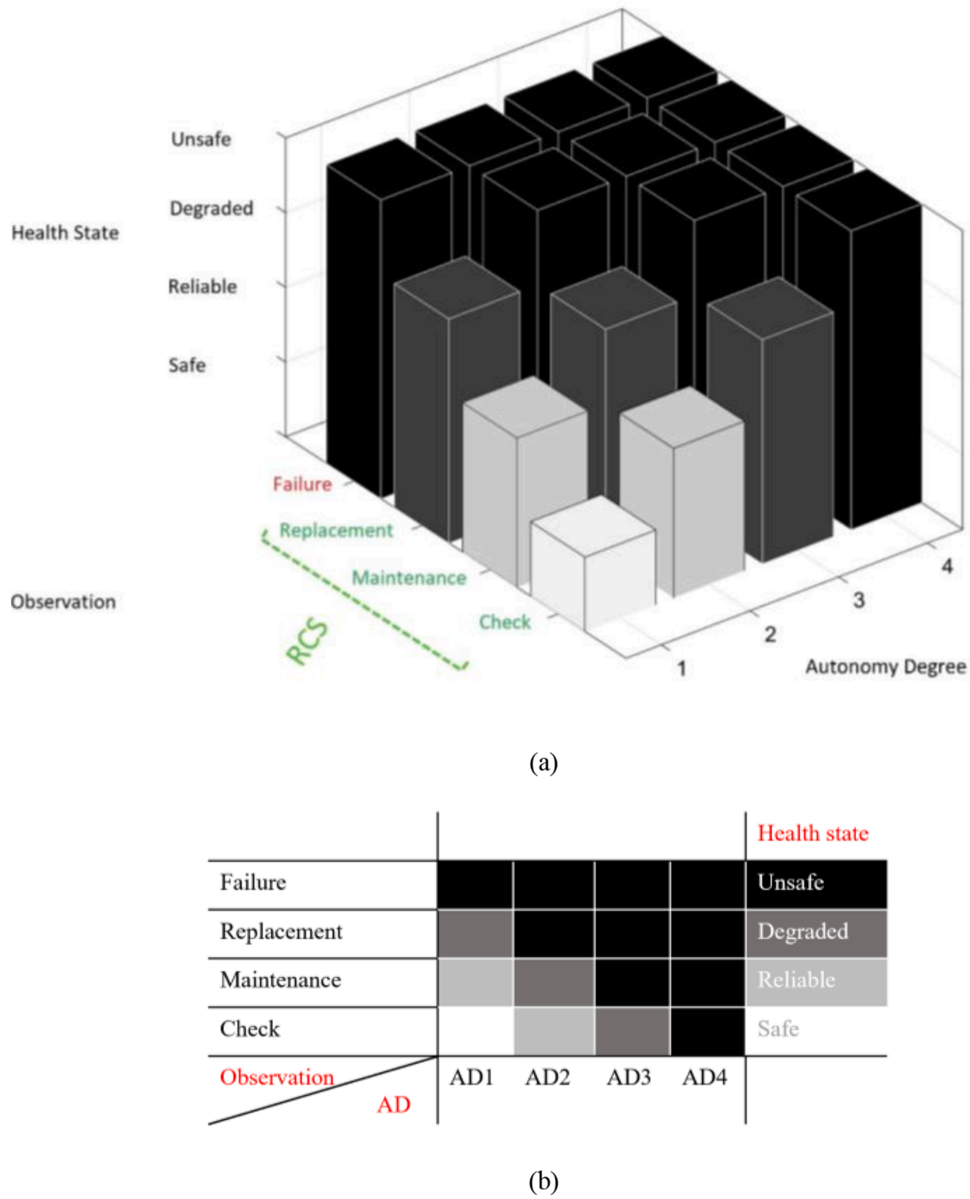


Fig. 2. Health state specification of ship system through different ADs based on observations (a) and the resulted failure perception matrix (b).

genuinely subjected to the availability of humans, meaning that a necessary check or maintenance action cannot be carried out if there is no human on board. No matter how minor the required risk control action is, this dependency to humans availability may not be accepted for ships with specific AD; Refereeing to the IMO definition of AD, humans have the possibility of inspection (onboard or remotely) through the first three AD, maintenance through the first two AD, and Replacement in the first AD. As a result of the execution of these RCSs, the system will not have an unsafe health state through the aforementioned AD. On the contrary, since the system should be able to operate without any need for the RCSs in all remaining conditions (i.e., inspection in AD4, maintenance in AD3 and AD4, replacement in AD2, AD3, and AD4), an unsafe health state will be expected for the system in such cases. As illustrated in Fig. 2, a failure will lead the system to experience an unsafe health state regardless of the AD of the ship. Since the majority of systems inside the conventional ships are not supported by redundancy, it is not taken into account in this failure specification.

As it can be seen in Fig. 2(a), a degraded state is assumed for a conventional ship (a ship with AD1) if any system, subsystem, or component requires to undergo unplanned maintenance (replacement) action. Given the acceptable level of human intervention in a ship with AD of two and three any required maintenance in AD2 and necessary check in AD3 will degrade the system through its life cycle. Finally, any required maintenance activities reported through AD1 and inspection in AD2 illustrate that the system's health state lost its safe state. Although, thanks to the availability of humans and the possibility of intervention, the system will have a reliable health state.

3. Methodology; prognostic health assessment

The sequence of the developed model is outlined in Fig. 3.

The preliminary step is to determine the scope of study via specification of the system to be involved in this PHM model. It is aimed to divide the given system into its most relevant components. Later, an operational limit should be considered to preserve the process in a safe condition. For this purpose, different acceptable health thresholds can be assigned for the system based on the proposed matrix (Fig. 2). This threshold will be determined according to the stakeholders' risk management strategies and priorities (one company may not operate while the ship system is degraded, contrary to the other company that accepts

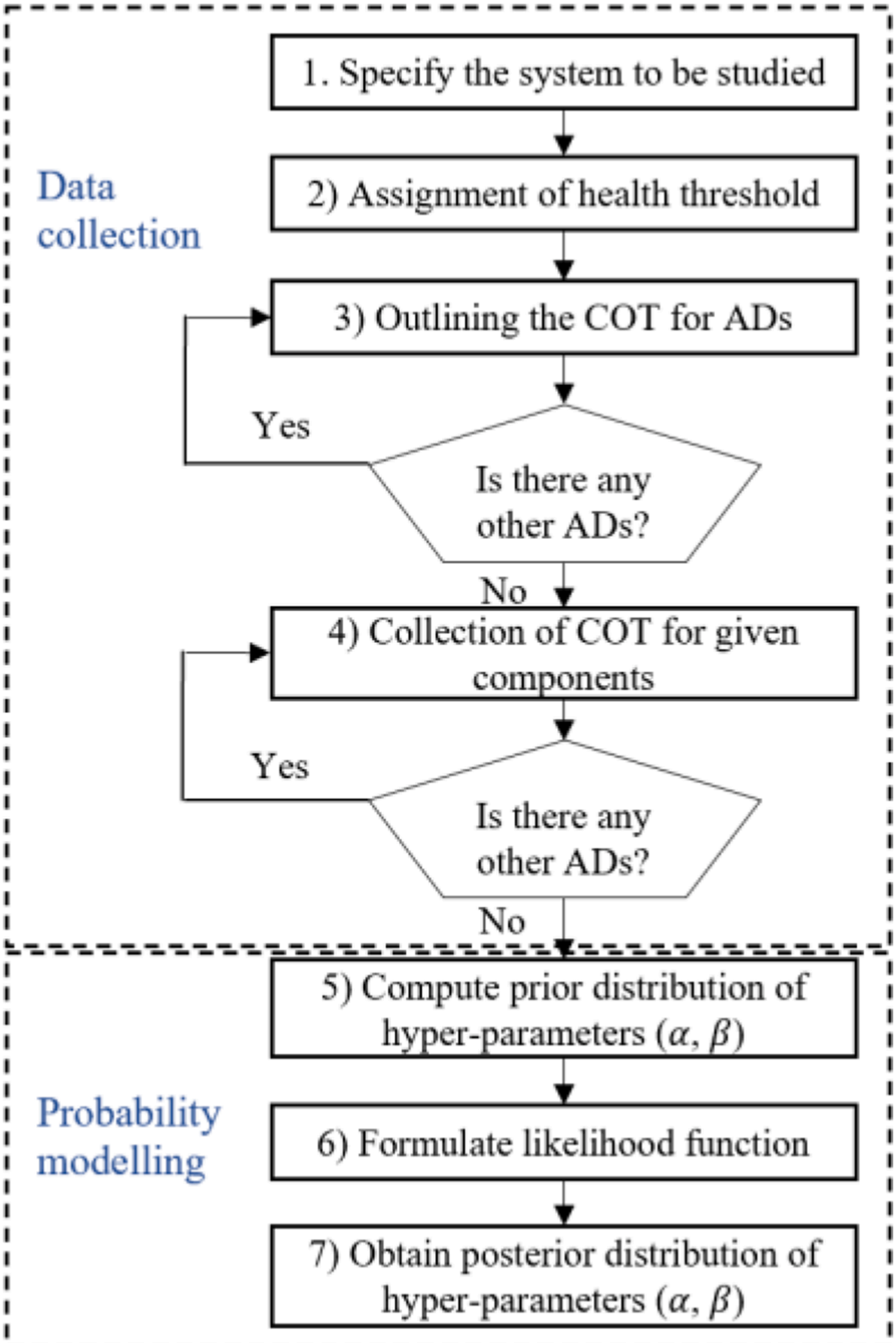


Fig. 3. Sequence of proposed statistical-based PHM model for ships with different ADs.

the risk of operating in a degraded condition). Upon specification of the health threshold, the interarrival time between observations (ones leading the system to exceed the recognized threshold) should be recorded as an input to predict the likelihood of health threshold exceedance through the target AD. In this study, a threshold is set to accept all health states but unsafe conditions. Table 2 outlines the critical operational times (COT) for different ADs.

Therefore, the prognostic health management of the ship system can be modeled through different ADs, given its associated COT, e.g., in AD3, the TTFRM should be captured. The interarrival times between RCSs and failures should be presented in time series to incorporate the

Table 2
Description of critical operational times for different ADs.

Autonomy Degree	Critical operational times (COT)
One (current situation)	Time to Failure (TTF)
Two	Time to Failures and Replacement (TTFR)
Three	Time to Failures, Replacement, and Maintenance (TTFRM)
Four	Time to Failures, Replacement, Maintenance, and Check (TTFRMC)

uncertainties associated with data via indicating the correlation of monitoring data. Different statistical inferences and probability assumptions have been adopted to model the interarrival observation times. The division of modeling categories is made based on several factors, including whether the observation interarrival times are dependent over the asset operational time or not [13]. While as one of the two most utilized assumptions, Homogenous Poisson Process (HPP) presumes that the inter-arrival times of an observation data are independently and identically distributed (*iid*), the other widely used assumption, Nonhomogeneous Poisson Process (NHPP) assumes that ith time-step (t_i) is dependent on the value in the previous time-step, t_{i-1}. As recognized by BahooToroody et al. [13], discounting the time dependency by HPP assumption often yields improper results and subjects to a significant level of uncertainty. Therefore, in this study, NHPP assumption is given to model the exceedance rate of safety limit, $\lambda(t)$, through the specific time interval $[t_n, t_{n+1}]$, as presented by Eq. (3) [13];

$$E(NE) = \int_{t_n}^{t_{n+1}} \lambda(t)dt \tag{3}$$

where $E(NE)$ denotes the expected number of exceedances. As an appropriate function for representing the exceedance rate of safety limit, Power-law, log-linear, and linear models are suggested in [5,41]. Compared to linear models, the power-law model can predict the nonlinearity of $\lambda(t)$, as a stochastic trend, with reasonable precision, and therefore with the relationship expressed by Eq. (4) [60], this model is established herein;

$$\lambda(t) = \frac{\alpha}{\beta}\left(\frac{t}{\beta}\right)^{\alpha-1} \tag{4}$$

A two-parameter Weibull distribution, (t,β,α), with shape parameter, α, and scale parameter, β, is generated through modeling the inter-arrival times between successive observations by power-law ([11]b) given by Eq. (5);

$$f(t,\beta,\alpha) = \frac{\alpha}{\beta}\left(\frac{t_1}{\beta}\right)^{\alpha-1}\exp\left[-\left(\frac{t_1}{\beta}\right)^{\alpha}\right] \tag{5}$$

A conditional probability must be defined in order not to relax the dependency of observational times, T_i, for each desired time interval $[t_{i-1}, t_i]$ as expressed by Eq. (6) [29];

$$f(t_i|t_{i-1}) = f(t_i|T_i > t_{i-1}) = \frac{f(t_i)}{\Pr(T_i > t_{i-1})} \tag{6}$$

Accordingly, the Weibull distribution would be achieved by Eq. (7) as;

$$f(t_i|t_{i-1}) = \frac{\alpha}{\beta^{\alpha}}(t_i)^{\alpha-1}\exp\left[-\left(\frac{t_i}{\beta}\right)^{\alpha} + \left(\frac{t_{i-1}}{\beta}\right)^{\alpha}\right] \tag{7}$$

where, $i = 2, \ldots, n$. To quantify the uncertainty associated with the parameter of interest of formulated Weibull distribution, Bayesian inference is established. Contrary to frequentist approaches such as Maximum Likelihood Estimation (MLE) and Least Square Estimation (LSE), in estimating the parameters, Bayesian inference assumes that α, β are uncertain values following a distribution with a prior probability as stated by Eq. (2). Given this equation, a vector of hyperparameters should be sampled from a particular parametric form to model the uncertainty integrated with population variability existing in the data source of prior distribution of shape and scale parameters. To this end, a non-informative prior distribution is considered for the hyper-parameter to support MCMC simulation to generate data within any range without any primary preference. This model of prior distribution can also lead to a better reflection of the nature of data, including the uncertainties by the posterior distribution since there is no impact from prior probability distribution on posterior probability distribution through the Bayesian updating [12,72]. A typical choice of non-informative distribution for hyper-parameter is a gamma distribution with independent diffuse hyperpriors, assuming to be the prior distribution of hyperparameters in this study as suggested by Abaei et al. [6,41] to formulate the first-stage prior, $\pi_1(\theta|\varphi)$;

$$\begin{cases} \alpha \sim Gamma(\alpha_\alpha,\ \beta_\alpha) \\ \beta \sim Gamma(\alpha_\beta,\ \beta_\beta) \end{cases} \tag{8}$$

where$(\alpha_\alpha,\ \beta_\alpha)$ and $(\alpha_\beta,\ \beta_\beta)$ are the vector of hyperprior employed to describe the uncertainty integrated in hyperparameters. The prior distribution of shape and scale parameter would be expressed by Eqs. (9) and (10), respectively:

$$\pi_0(\alpha) = \int_{t_n}^{t_{n+1}}\int_{t_n}^{t_{n+1}} \frac{{\beta_\alpha}^{\alpha_\alpha} t^{\alpha_\alpha-1} e^{-\beta_\alpha t}}{\Gamma(\alpha_\alpha)}\ \pi_1(\alpha_\alpha,\ \beta_\alpha)d\alpha_\alpha,\ d\beta_\alpha \tag{9}$$

$$\pi_0(\beta) = \int_{t_n}^{t_{n+1}}\int_{t_n}^{t_{n+1}} \frac{{\beta_\beta}^{\alpha_\beta} t^{\alpha_\beta-1} e^{-\beta_\beta t}}{\Gamma(\alpha_\beta)}\ \pi_1(\alpha_\beta,\ \beta_\beta)d\alpha_\beta, d\beta_\beta \tag{10}$$

Accordingly, the likelihood function would be achieved by Eq. (11);

$$f(T_1, T_2, \ldots, T_n|\alpha,\beta) = f(T_1)\prod_{i-2}^{n} f(t_i|t_{i-1})$$

$$= \frac{\alpha^n}{\beta^{n\alpha}}\left(\prod_{i=1}^{n} {t_i}^{\alpha-1}\right) exp\left[-\left(\frac{t_n}{\beta}\right)^{\alpha}\right] \tag{11}$$

where $T_1$and T_n are the times of first and nth observation (RCS and failure) events. This function is required to perform the MCMC simulation from the joint posterior distribution of hyper-parameters via open-source simulation software packages, i.e., OpenBUGS [63]. Given Bayes' Theorem, the posterior probability distribution of shape and scale parameters can be expressed by Eqs. (12) and (13) as;

$$\pi(\alpha|\ T_1, T_2, \ldots, T_n) = \frac{\frac{\alpha^n}{\beta^{n\alpha}}\left(\prod_{i=1}^{n} {t_i}^{\alpha-1}\right) exp\left[-\left(\frac{t_n}{\beta}\right)^{\alpha}\right]\int_{t_n}^{t_{n+1}}\int_{t_n}^{t_{n+1}} \frac{{\beta_\alpha}^{\alpha_\alpha} t^{\alpha_\alpha-1} e^{-\beta_\alpha t}}{\Gamma(\alpha_\alpha)}\ \pi_2(\alpha_\alpha,\ \beta_\alpha)d\alpha_\alpha,\ d\beta_\alpha}{\int_{\alpha}\int_{t_n}^{t_{n+1}}\int_{t_n}^{t_{n+1}} \frac{\alpha^n}{\beta^{n\alpha}}\left(\prod_{i=1}^{n} {t_i}^{\alpha-1}\right) exp\left[-\left(\frac{t_n}{\beta}\right)^{\alpha}\right] \frac{{\beta_\alpha}^{\alpha_\alpha} t^{\alpha_\alpha-1} e^{-\beta_\alpha t}}{\Gamma(\alpha_\alpha)}\ \pi_2(\alpha_\alpha,\ \beta_\alpha)d\alpha_\alpha,\ d\beta_\alpha,\ d\alpha} \tag{12}$$

$$\pi(\beta|\ T_1, T_2, \dots, T_n) = \frac{\frac{\alpha^n}{\beta^{n\alpha}} \left(\prod_{i=1}^{n} t_i^{\alpha-1}\right) exp\left[-\left(\frac{t_n}{\beta}\right)^{\alpha}\right] \int_{t_n}^{t_{n+1}}\int_{t_n}^{t_{n+1}} \frac{\beta_\beta^{\alpha_\beta} t^{\alpha_\beta-1} e^{-\beta_\beta t}}{\Gamma(\alpha_\beta)}\ \pi_2(\alpha_\beta,\ \beta_\beta) d\alpha_\beta,\ d\beta_\beta}{\int_\alpha \int_{t_n}^{t_{n+1}}\int_{t_n}^{t_{n+1}} \frac{\alpha^n}{\beta^{n\alpha}} \left(\prod_{i=1}^{n} t_i^{\alpha-1}\right) exp\left[-\left(\frac{t_n}{\beta}\right)^{\alpha}\right] \frac{\beta_\beta^{\alpha_\beta} t^{\alpha_\beta-1} e^{-\beta_\beta t}}{\Gamma(\alpha_\beta)}\ \pi_2(\alpha_\beta,\ \beta_\beta) d\alpha_\beta,\ d\beta_\beta,\ d\beta} \tag{13}$$

The derived directed acyclic graph (DAG) model for the developed Bayesian model is illustrated in Fig. 4, where P is the posterior Weibull function by which the exceedances time from the health threshold through different ADs in operation can be predicted. Since the likelihood function formulated in this study is not pre-programmed into Openbugs software, a vector of n array is created to assign a generic distribution with parameter Φ as Φ= log(likelihood), (recommended by Abaei et al. [5,11,41]) given by Eq. (14);

$$\varphi = \log(\alpha) - \alpha \times \log(\beta) + (\alpha - 1)\log(t_i) - (t_n/\beta)^{\alpha}/n \tag{14}$$

where t_i and t_n are the last and i^{th} observation of the exceedances event from health threshold in the simulation, respectively [6,11]. This will allow Openbugs to perform the simulation through Bayesian updating via likelihood function and specify the marginal posterior distribution as outlined by Eq. (15).

$$\pi(\alpha,\beta|\ T_1, T_2, \dots, T_n) = \int_{t_n}^{t_{n+1}}\int_{t_n}^{t_{n+1}}\int_{t_n}^{t_{n+1}}\int_{t_n}^{t_{n+1}} \pi(\alpha,\beta|\alpha_\alpha,\ \beta_\alpha,\ \alpha_\beta,\ \beta_\beta)\ \pi\big((\alpha_\alpha,\ \beta_\alpha,\ \alpha_\beta,\ \beta_\beta)\big|T_1, T_2, \dots, T_n\big) d\alpha_\alpha,\ d\beta_\alpha, d\alpha_\beta,\ d\beta_\beta \tag{15}$$

Through the presented Bayesian network in Fig. 4, α and β as the hyper-parameters are independent before observing the data. Once an

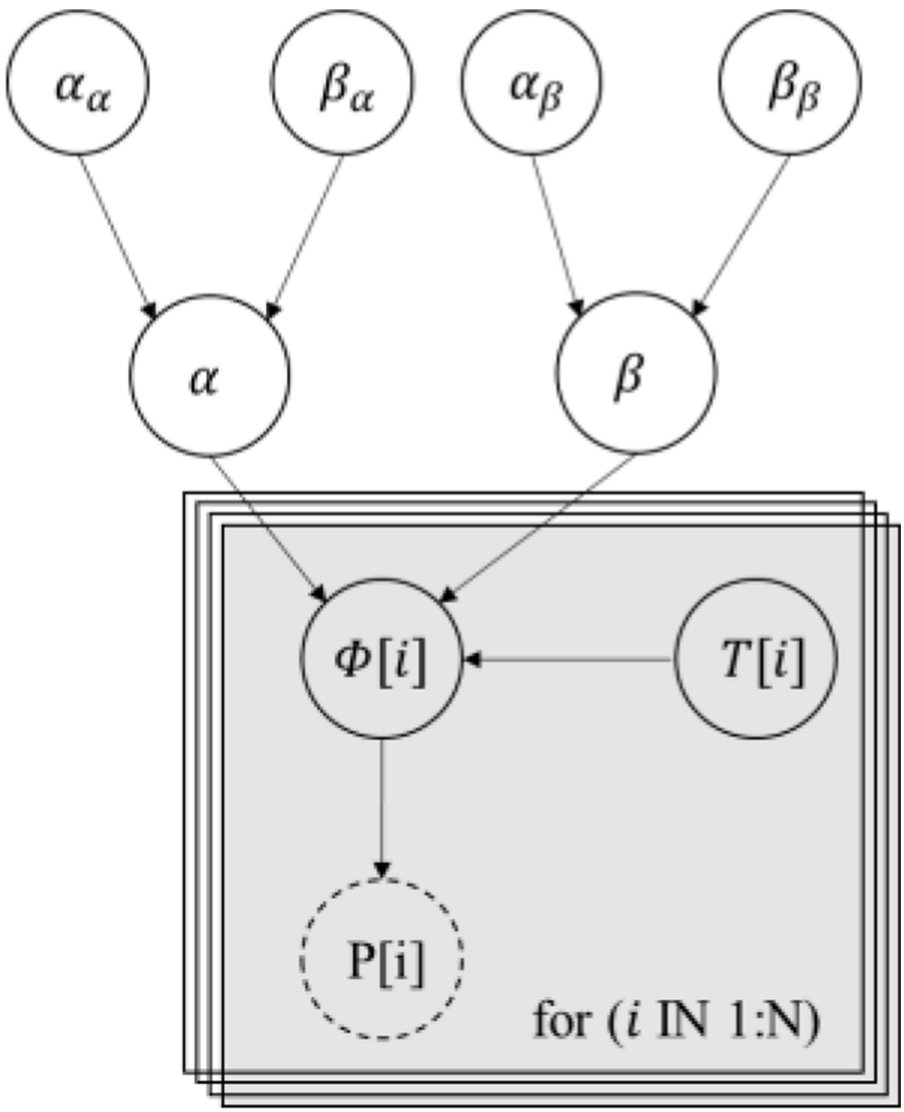


Fig. 4. Derived directed acyclic graph (DAG) for the developed Bayesian-based PHM model.

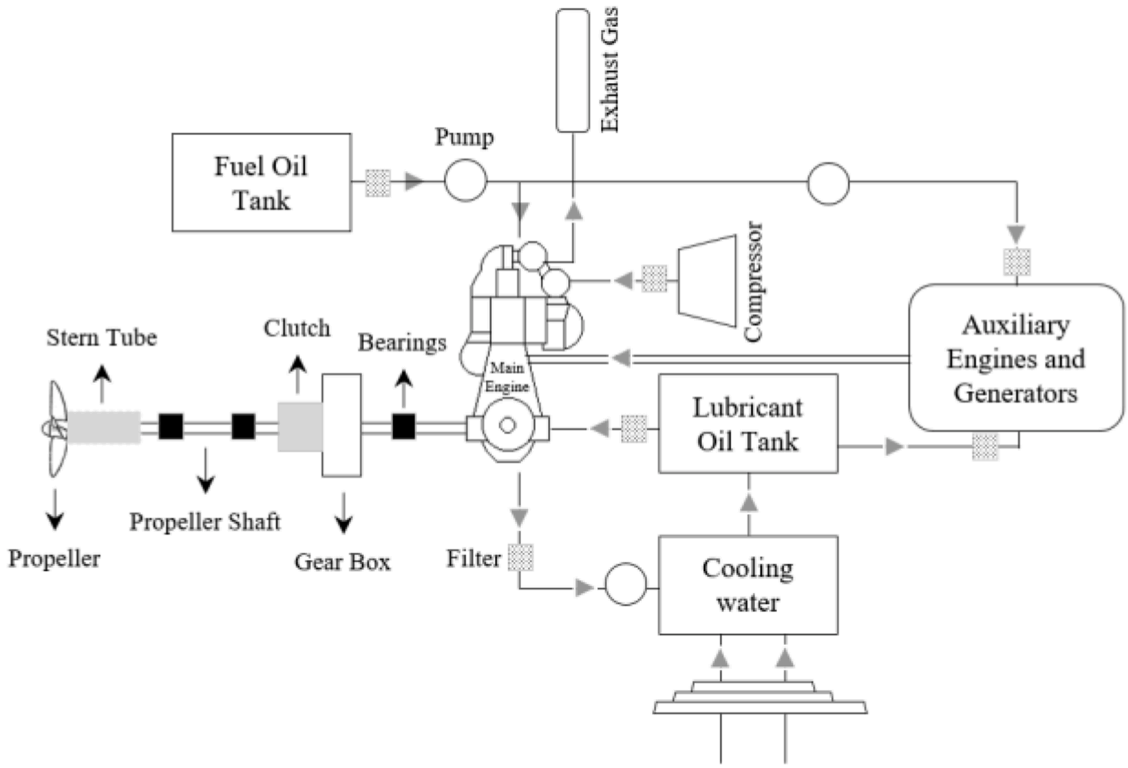


Fig. 5. General overview of Machinery Plant onboard.

RCS or a failure is observed, these parameters will be dependent.

4. Application of methodology

The presented framework in this study can be applied to different ship systems. As the machinery plant has been less studied compared to autonomous navigation and communication [3,7,23], a practical example of the machinery plant of three cargo RoRo (Roll-on/Roll-off) ships is considered to verify the presented framework. The following sub-sections deliver a comprehensive discussion on the application of the proposed methodology to the case study.

4.1. Case study; setup of the machinery plant

A machinery plant used in typical short sea merchant ships is offered to demonstrate the applicability of the developed methodology. A schematic arrangement of the machinery plant is illustrated in Fig. 5. As a prime mover of the ship, the main engine is either a two or four-stroke diesel engine connected to the propeller to produce the power necessary for the desired ship speed of advance. The engine output power is transmitted from the engine turning gear to the propeller shaft via the clutch and reduction gearbox. The clutch engages and disengages the engine from the propeller shaft, and the reduction gearbox reduces the rotation speed to the operating speed of the propeller. The control (maneuvering) system regulates engine speed by acting on the quantity of fuel injected into the cylinder for combustion. The cylinder cover holds the injection valve, the inlet valves, and the exhaust valves and connects the lubrication oil circuit and cooling water circuit to the cylinder. The piston is the central moving part inside the cylinder during the combustion cycle. The linear movement of all pistons generated the rotative movement of the engine crankshaft and turning wheel. The attached lube oil pump is necessary for circulating the lubrication oil under pressure through the moving parts of the engine to avoid wear and overheating. The tail shaft propeller is carried by the stern tube, which connects the shaft to the propeller out at sea and assures water tightness.

The type of merchant ship considered in this study is cargo RoRo (Roll-on/Roll-off) ship. The data is collected from three ships with the same machinery set up, as shown in Fig. 5. The three ships are fitted with four-stroke diesel engines and have a close age ranging from 14 to 18 years. The ships are also operating in the same sea region; the Mediterranean Sea. The observational data outlined in Fig. 6 was adopted from ship alarm system records, maintenance records, and engine logbooks. Survey analysis and interviews with the ship machinery crew were conducted to understand the data and structure it for this study. Failure times as well as the time intervals of the check, maintenance, and replacement operations, are touched upon through this data. The crew also provided the definition of different types of observations (RCSs and failure) in the context of the considered case study (see Table 3).

Accordingly, the COT for all observations was pointed out based on instructions reported in Table 2.

4.2. HBI; sampling the Weibull parameters with NHPP assumption

Upon specifying the COT for different ADs, the Bayesian inference paradigm can be applied to simulate from likelihood function and prior distribution, and finally obtain the posterior values of Weibull parameters, α, and β. As stated by Section 3, an independent diffusive Gamma distribution is applied for the prior distribution of hyper-parameters, α, and β as;

$$\begin{cases} \alpha \sim Gamma(0.0001, 0.0001) \\ \beta \sim Gamma(0.0001, 0.0001) \end{cases} \tag{16}$$

Accordingly, using MCMC simulation, 1000 burn-in iterations followed by 3×10^5 iterations have been sampled through three chains with an over-dispersed initial value of α and β for all ADs to estimate the posterior distribution of hyper-parameters and to check the convergence. As a model diagnosis, the convergence of applied chains (depicted by different colors) was checked by presenting the treatment of chains through the simulation via trace plot and history of iterations of hyper-parameters. The statistical summary of hyper-parameters is

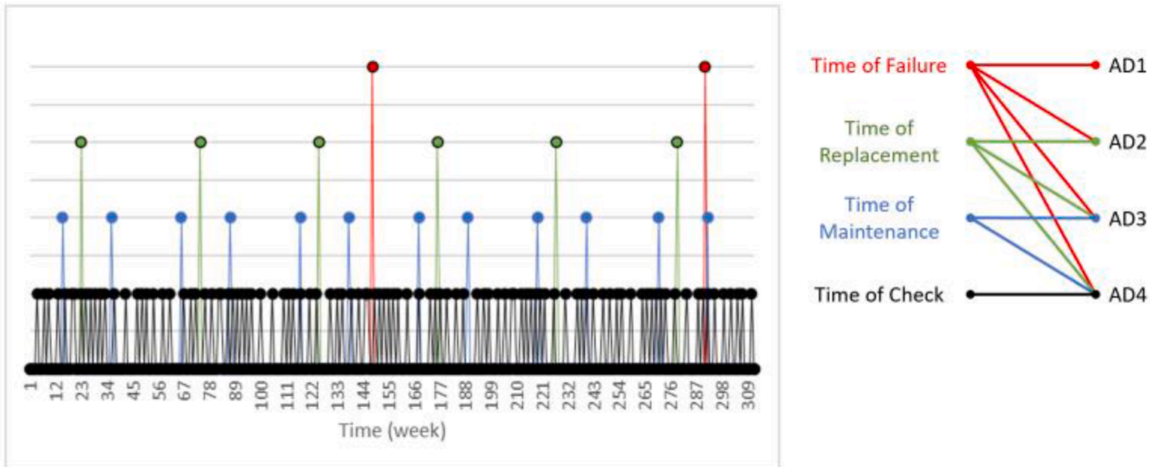


Fig. 6. Observational data as well as considered COT through different ADs.

Table 3
Definition of different types of observations in the context of the considered case study.

Type of observation	Explanation/Definition
Check	The principal components of the engine are inspected (visually or with a dedicated tool).
Maintenance	The maintenance is pre-scheduled actions according to the prescription given by the manufacturer.
Replacement	The replacement is an unplanned operation conducted due to an abnormal performance.
Failure	The operation is interrupted due to a failure of one of the engine components.

outlined in Table 4, though due to limited space, the posterior probability density function, and trace plot of α and β and history of iteration of α for only one AD (AD3) are illustrated in Fig. 7.

This model diagnosis is followed by monitoring the correlation of simulated value of α and β through the sampling process. The resulting scatter plots (shown in Fig. 8) validate that the convergence has been well reached through the developed HBI script for all ADs.

According to Table 4, the shape parameters of the probability model through all ADs are higher than 1, confirming that the number of exceedance events is dependent upon time. The obtained posterior value of hyper-parameters can be incorporated in Weibull distribution to predict the System Health Index (SHI) and the cumulative number of exceedances from health threshold through the time for different ADs. SHI can be modeled according to survival function as expressed by Eq. (17) as;

$$S(t) = 1 - F(t) = e^{-(\beta t)^{\alpha}} \quad \text{for } t > 0 \tag{17}$$

where $F(t)$ is the cumulative density function of a two-parameter Weibull distribution, (t, β, α) With shape parameter, α, and scale parameter, β. $S(t)$ as SHI function represents the probability that the exceedance from a predefined health threshold has not yet occurred by a given time t if T denotes the lifetime of the system. Fig. 9 depicts the SHI function for a conventional ship, given that it would be left unattended at different stages and with different ADs. In this figure, the time was presented in logarithm. The SHI function will be elaborated more later in the discussion section to establish the Reliability Centered Maintenance (RCM) strategy, predict Remaining Useful Lifetime (RUL), and model the degradation trend.

The cumulative exceedance number, $H(t)$, can also be achieved by Eq. (18) as;

$$H(t) = -\ln[1 - F(t)] = -\ln S(t) = (\beta t)^{\alpha} \tag{18}$$

Fig. 10 presents the predicted cumulative exceedance number (CEN) for all ADs, with a confidence interval of 95 percent. Similar to the SHI function, the time is in logarithmic format. Given this prediction, the safe operational time of the ship through different ADs can be specified (see Table 5). Correspondingly, the given main engine in this study can operate for 3, 17, and 47 weeks if the ship gets through the phased functional maturation approach to autonomy levels of four, three, and two, respectively.

5. Results and discussions

According to the presented model, here in this study, two discussions of SHI-based and exceedance modeling-based applications are presented. Later, the limitations of the framework as well as different types of uncertainties integrated with the proposed model are discussed.

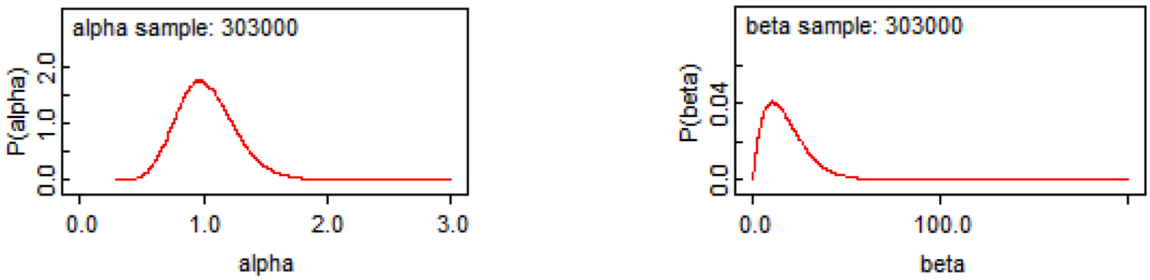
5.1. Exceedance modeling-based application

5.1.1. Exceedance rate function

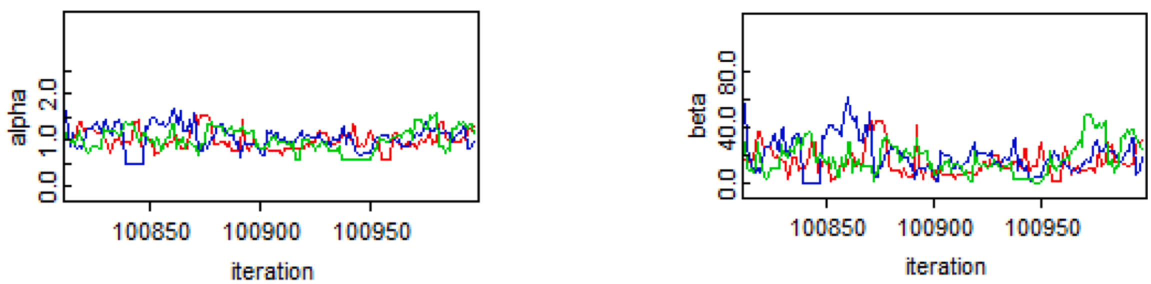
In addition to the CEN, estimated Weibull parameters can be incorporated into the functions explained in Section 3 to obtain exceedance models. As an applicable model for risk mitigation programs, the exceedance rate function (ERF) within different ADs can be determined for the presented case study using Eq. (3). As illustrated by Fig. 11, the uncertainty quantification through shape and scale parameters with gamma distribution resulted in the integration of uncertainties with the ERF over time. The more time and ADs are progressing, the more the

Table 4
Statistical summary of predicted hyper-parameters for different ADs.

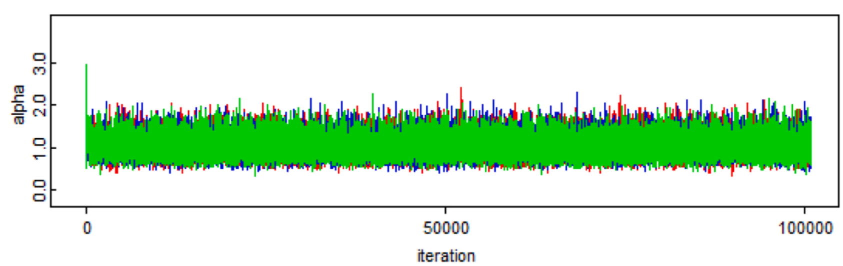
hyper-parameters	α			β		
ADs	mean	2.5 percentile	97.5 percentile	Mean	2.5 percentile	97.5 percentile
AD1	1.573	0.122	5.519	262.5	0.4233	1142.0
AD2	1.123	0.4492	2.093	50.07	2.634	126.8
AD3	1.025	0.6169	1.536	17.46	2.168	44.6
AD4	1.019	0.8406	1.212	3.071	1.052	6.165



(a)



(b)



(c)

Fig. 7. (a) Posterior probability density function, and (b) trace plot of α and β, and (c) history of iteration of α for the third level of autonomy.

uncertainties are integrated. A subplot of ERF against density is presented to describe the quality of association between ERF and uncertainties through different ADs. The time is in logarithmic format. As it can be viewed, the ERF intervals become wider as the ADs are growing in the system.

5.2. SHI-based applications

Here in this study, the predicted SHI function is employed for three main applications of Remaining Useful Lifetime (RUL) prediction, Reliability Centered Maintenance (RCM) strategy, and degradation modeling.

5.2.1. RUL prediction

RUL is the operational time in which a system can offer its functionality before it fails. Two thresholds of deterioration start-point and endpoint are considered by Okoh et al. [55] to determine the RUL. Fig. 12 depicts the SHI against time, including the RUL specification for different ADs of the main engine. As recommended by engineering knowledge and crew experts, an SHI threshold of 0.8 was assigned in this model-based RUL method as the starting point of deterioration. Moreover, the predicted MTTF outlined in Table 5 was considered as the endpoint of deterioration for the main engine through different ADs.

Based on the predicted RUL reported in Table 6, the RUL reduces dramatically when the ship approaches higher ADs; RUL of 134 weeks for the main engine in AD1 will decrease to 34 weeks in AD2, 13 weeks in AD3, and only two weeks in AD4. The proposed method can be exploited by maintenance engineers, asset managers, and policymakers to figure out the operability of the system in different ADs.

5.2.2. RCM strategy

RCM method has a primary objective of maintenance optimization (time and cost-wise) based on the system's inherent reliability values [39]. The development of RCM in this study aims to identify the maintainable operational time representing the time through which the system can operate safely and by which the crew's intervention must be scheduled. Since crews are fully available on board a ship through AD1, this AD was excluded from this estimation. To this end, an SHI threshold needs to be incorporated to determine the intervention time. The SHI values of exceedance time, reported in Table 5, remarks that an SHI of at least 0.5 must be secured upon time. Fig. 13 presents how the SHI function for different ADs might change by potential interventions leading to an operational time extension. The type of intervention for different ADs varies based on the human availability on board the ship, e.g., in AD2, the intervention targets only the replacement of deteriorated subsystems or components since, as stated in Section 2.2, the

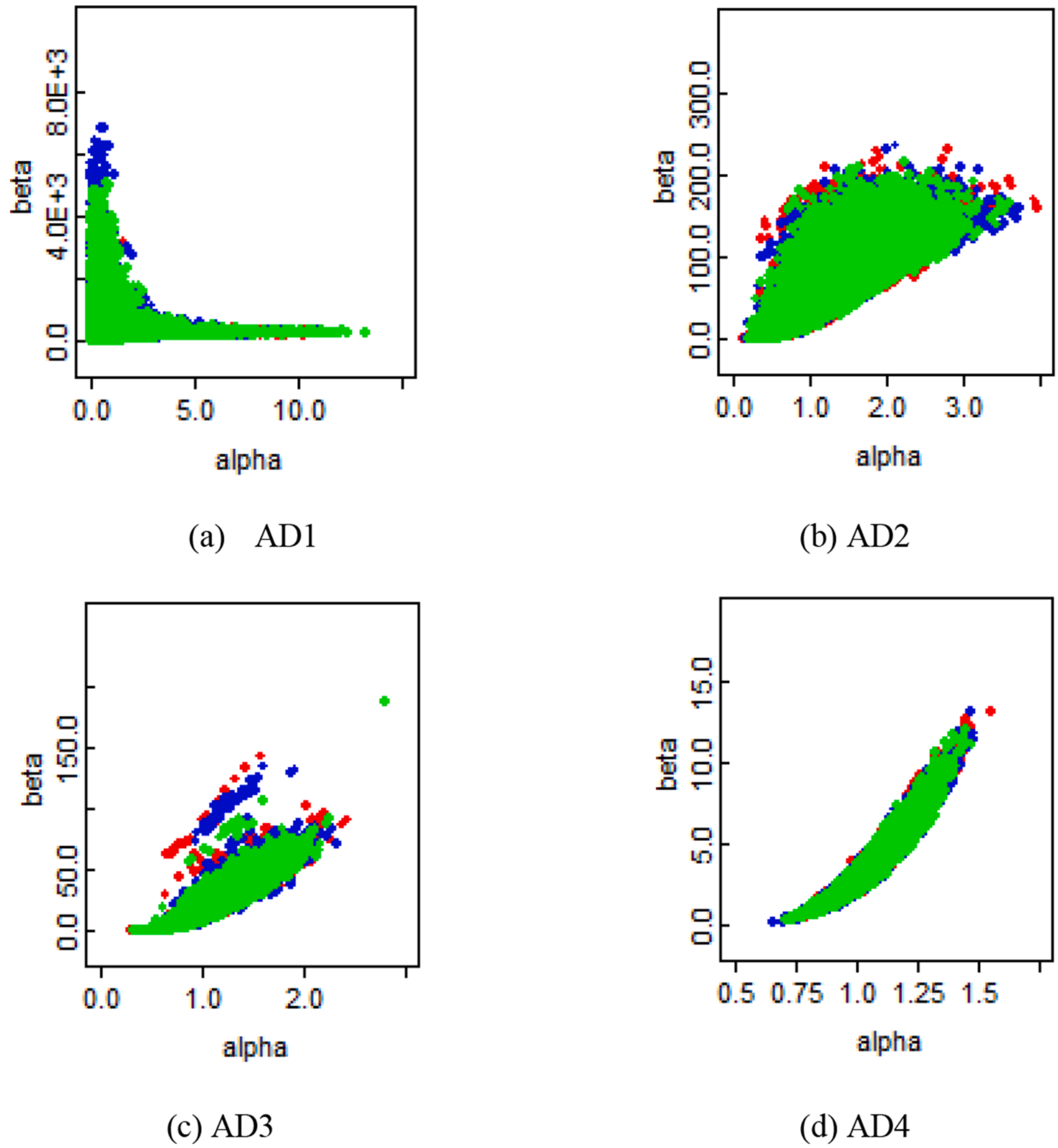


Fig. 8. Scatter plot of the individual simulated values of hyper-parameters for all ADs.

maintenance and check actions can already be taken by crews.

5.2.3. Deterioration ratio

A ratio of deterioration, ν_{ij}, is proposed in this study for the desired time interval $[t_n, t_{n+1}]$, as expressed by Eq. (19) to characterize the potential degradation progress when the system moves into higher AD, e.g., from AD1 to AD2.

$$\nu_{ij} = \frac{\int_{t_n}^{t_{n+1}} S_i(t) - \int_{t_n}^{t_{n+1}} S_j(t)}{\int_{t_n}^{t_{n+1}} S_i(t)} \; ; for\ i > j \tag{19}$$

where $S_i(t)$ and $S_j(t)$ are the SHI functions of the system through the i^{th} and j^{th} AD, respectively. Three-time intervals of 3 weeks (500 h; the aimed operational time of unmanned vessel through MUNIN project), 13 weeks (3 months), and 26 weeks (6 months) were accounted to model the deterioration ratio of the main engine. As outlined in Table 7, through the first 500 h of operational time, the transition to AD4 will significantly deteriorate the main engine, regardless of which AD the transition is making. Similarly, in three weeks, the system is predicted to experience a deterioration of 0.04 and 0.1509 if it approaches AD2 and AD3 from AD1, respectively.

Furthermore, the estimation highlights that the growth of one AD, from AD1 to AD2 for three months, will lead to degradation of the main engine for 19.03 percent. The estimated deterioration ratio for six months depicts that the system cannot secure the least required functional capacity to continue operating if it moves to AD4.

Reviewing the SHI threshold of 0.5 assigned in Section 5.1.2 for the development of RCM strategies, the acceptable transitions of ADs are those by which $\nu_{ij} < 0.5$ (the system would not experience a deterioration ratio of more than 0.5). This will include the transitions from AD1 to AD2 for all given time intervals, to AD3 for only three weeks, and finally from AD2 to AD3 for three months.

The proposed deterioration model can be applied by ship designers to determine to what extent the given system is ready to approach higher ADs. This outcome can later be employed to rank the systems, subsystems, and components of a ship with respect to their maturation to be independent of human availability onboard the vessel.

5.3. Limitations and uncertainties

In prognostic studies, different types of uncertainties are encountered. Therefore, to be verified and practically applied in real-world

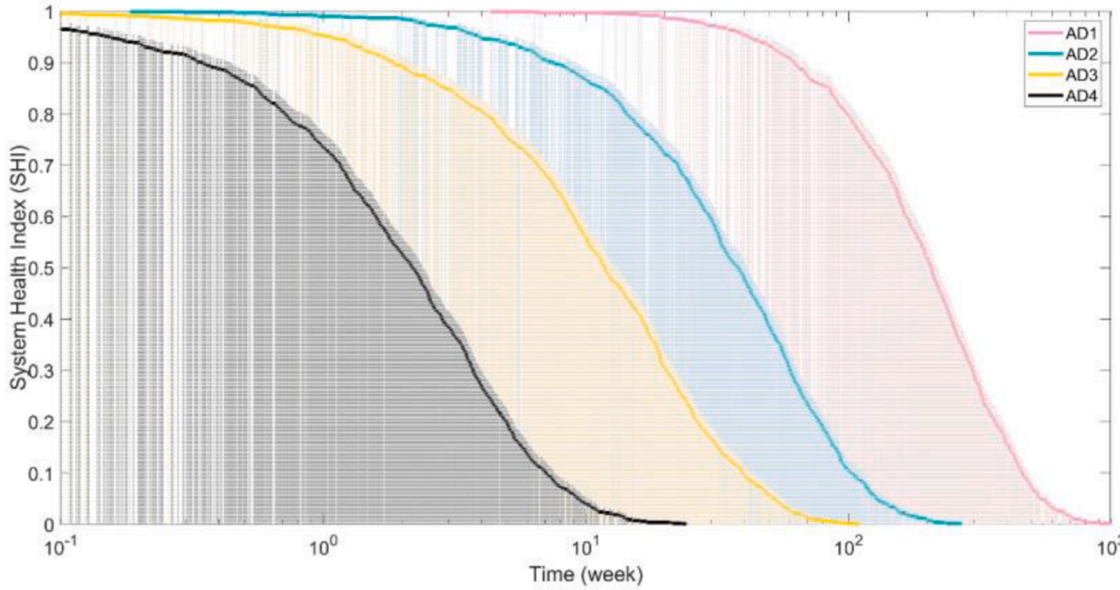


Fig. 9. Estimated System Health Index of the main engine through different ADs.

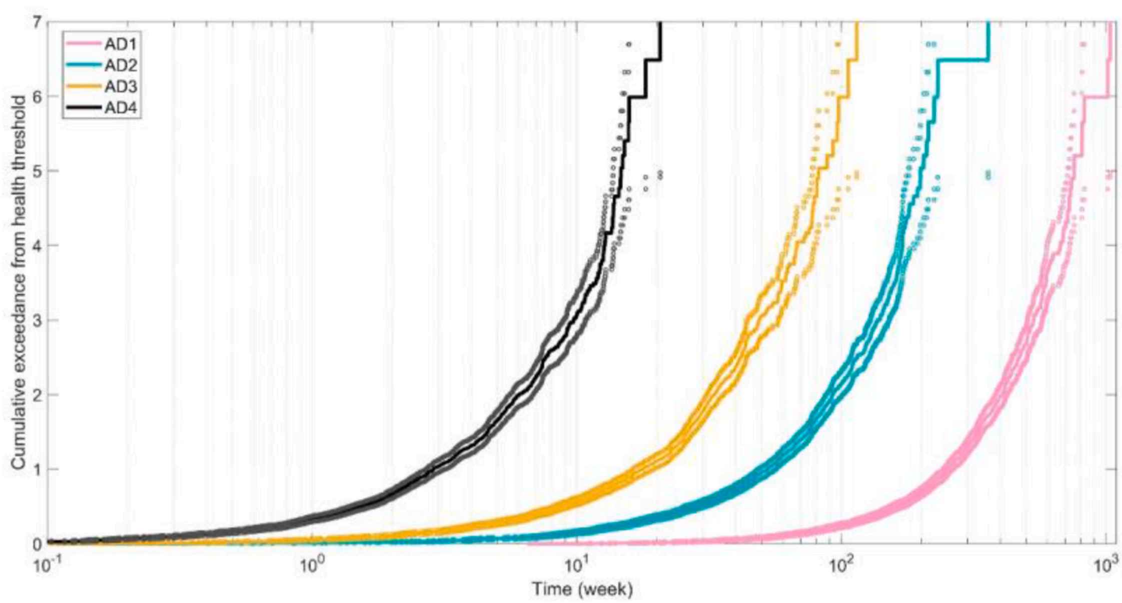


Fig. 10. Predicted cumulative number of exceedances from predefined health threshold for different ADs.

Table 5
Mean Time to Failure of main engine for different ADs (expressed in weeks).

ADs/Time	AD1	AD2	AD3	AD4
Mean Time to Failure (MTTF)	235.7343	47.9940	17.2842	3.0214

problems, these models are required to have sound uncertainty quantification capabilities. The integrated uncertainties modeled in the proposed framework comprise; (i) uncertainties integrated with estimating the Weibull parameters, (ii) uncertainties associated with population variability existing in the data source of the prior distribution, (iii) uncertainties associated with the correlation of monitoring data, (iv) uncertainties associated with modeling the dependency of interarrival time between failure. Considering the limited available failure data, the precision of conducted estimation can be increased by establishing non-parametric approaches such as Kernel-based models, leading to increased data dimensionality. This will help to propagate better the uncertainty integrated with limited data. Checking the convergence of sampled MCMC for different ADs in this study proved that the fewer data fed into the model, the less effective sample size the MCMC produces. Therefore, more sampling iterations will be required for the chains to be converged. In such a situation, increasing the data points' dimension will overcome this limitation and secure higher precision of calculations.

6. Conclusion

In this study, a Machine Learning-based model was proposed to deliver the PHM of the main engine operating in a merchant ship given that it is moving through the phased functional maturation approach to higher ADs. The priority of this study was to capture the effect of removing crew members on the reliability of ships from the current situation to fully autonomous. To this end, the COT was introduced. The

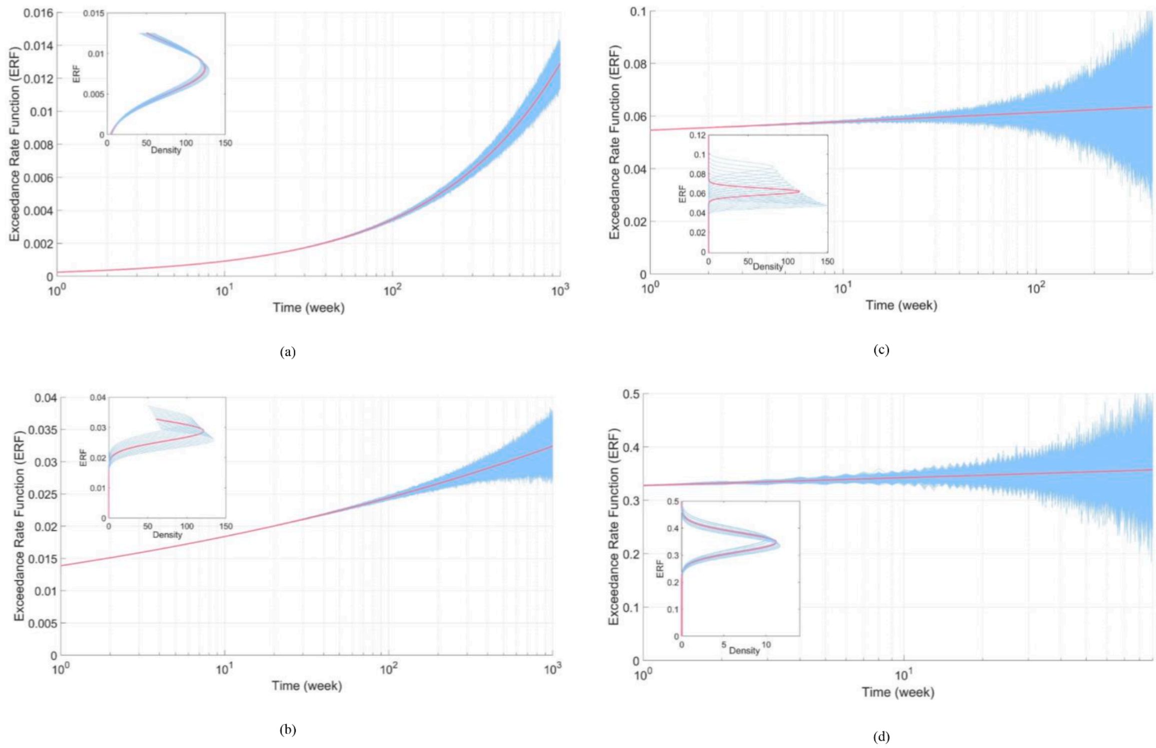


Fig. 11. ERF of the main engine in AD1 (a), AD2 (b), AD3 (c), AD4 (d); red lines represent ERF while blue surrounded areas represent integrated uncertainties.

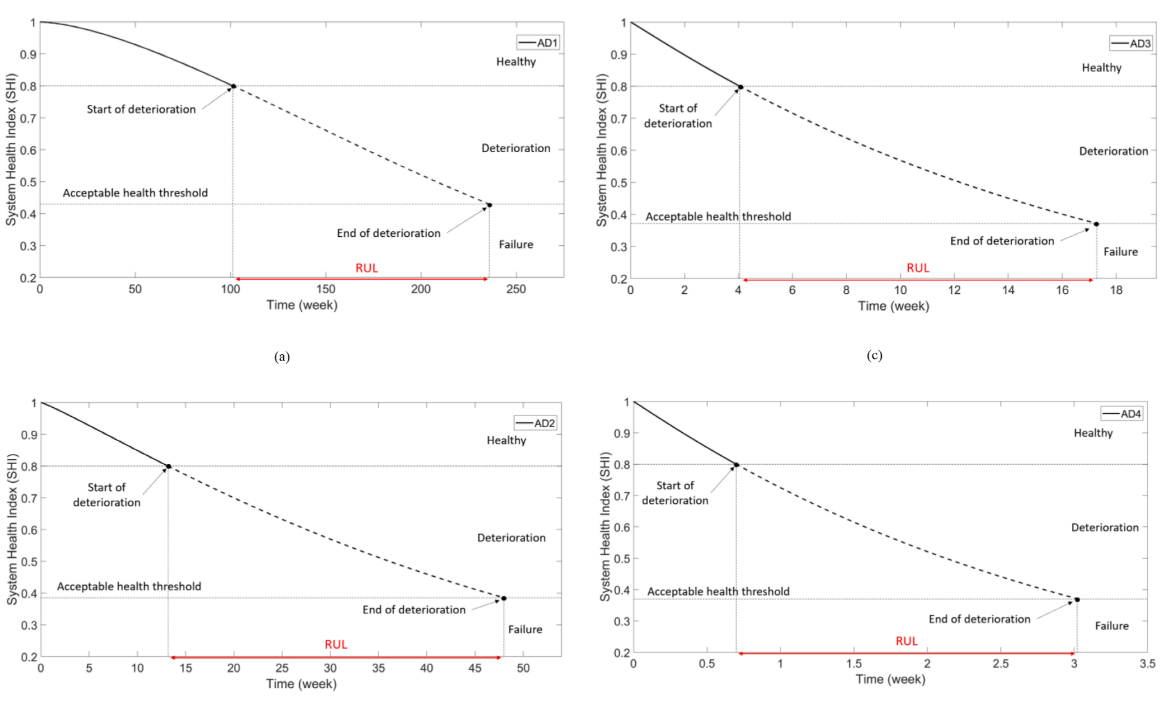


Fig. 12. SHI against time, including the RUL specification for AD1 (a) AD2 (b) AD3 (c) AD4 (d) of the main engine.

Table 6
Predicted Remaining Useful Lifetime (RUL) of Main engine through different ADs.

ADs/Time	AD1	AD2	AD3	AD4
RUL	134.59	34.82	13.24	2.32

NHPP assumption confirming that the number of exceedance events is dependent upon a time is established. The Bayesian inference with hierarchical structure was later employed to obtain a regulated prediction of interarrival time between exceedances, while both aletoric and epistemic uncertainties associated with observations were integrated. Weibull parameters were then sampled based on operational observations by MCMC simulation to predict their posterior distribution. The

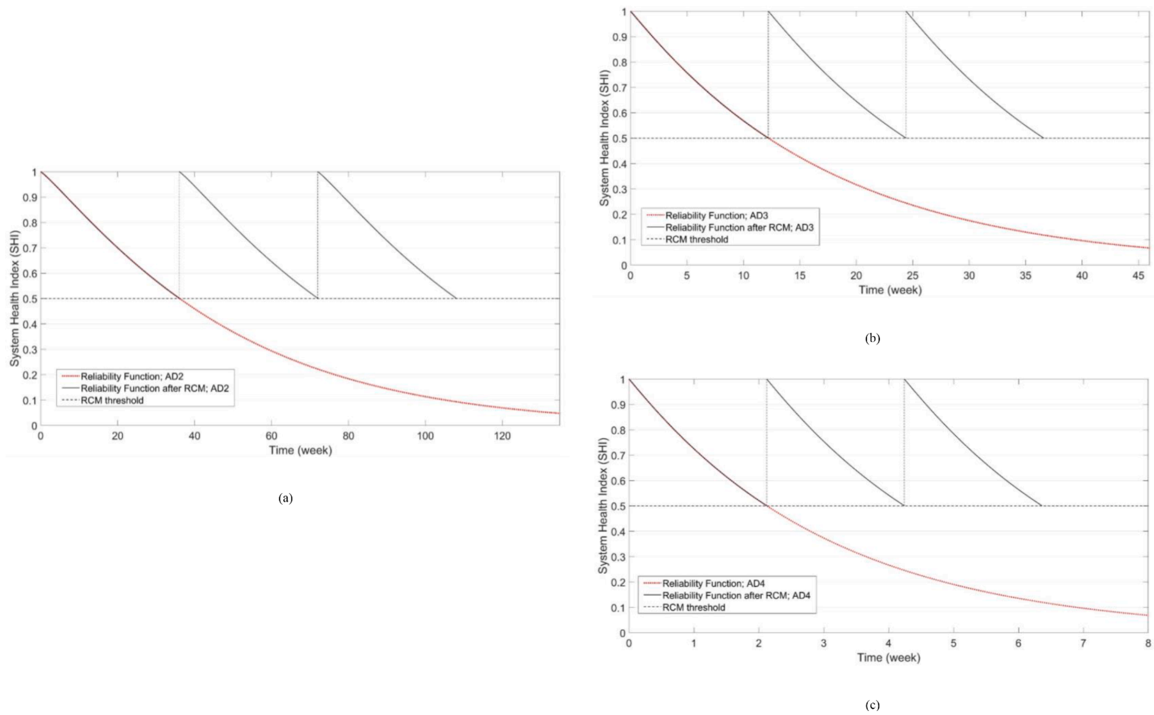


Fig. 13. Developed RCM method for the main engine in AD2 (a), AD3 (b) AD4 (c); black and red dotted lines represent the SHI function with and without human intervention, respectively.

Table 7
Deterioration ratio of the main engine for different possible growth of ADs.

ADs (Deterioration ratio)/Time interval	AD1		AD2		AD3	
	ν_{12}	ν_{13}	ν_{14}	ν_{23}	ν_{24}	ν_{34}
3 weeks (500 h)	0.0407	0.1509	0.6262	0.1149	0.6104	0.5598
13 weeks (3 months)	0.1903	0.5182	0.9875	0.4050	0.9845	0.9740
26 weeks (6 months)	0.3641	0.7718	0.9999	0.6412	0.9998	0.9994

obtained posterior distribution of these parameters was then considered as an input for two categories of applications; SHI-based and exceedance-based. Accordingly, Exceedance rate function (ERF) including the associated uncertainties, Cumulative exceedance number, posterior predictive probability of exceedances per week, System Health Index (SHI), Remaining Useful Life-time, deterioration modeling, Reliability Centered Maintenance (RCM), and its impact on safe operational time was presented for the given main engine through different Autonomy Degrees. Each of these estimations can deliver a road map to achieve a higher level of trustworthiness while the ship moves to higher ADs. Correspondingly, the given main engine in this study can operate safely for 3, 17, and 47 weeks if the ship approaches to autonomy degree of four, three, and two, respectively. Given the deterioration ratio defined in this study, the transitions from AD1 to AD2 for all considered time intervals, AD1 to AD3 for three weeks, and finally from AD2 to AD3 for three months are highlighted as the acceptable transitions in which the system would not experience a deterioration ratio of more than 0.5.

Further research is recommended to conduct an ML-based investigation of the resilience solutions aiming to increase the safe operational time. The proposed research path can be further developed by comparing the functional capacity with and without implementing resilience solutions through different ADs.

Authorship statement

We the undersigned declare that this manuscript is original, has not been published before and is not currently being considered for publication elsewhere before its appearance in the Journal of Reliability Engineering and System Safety. We confirm that the manuscript has been read and approved by all named authors and that there are no other persons who satisfied the criteria for authorship but are not listed. We further confirm that the order of authors listed in the manuscript has been approved by all of us. We understand that the Corresponding Author (**Ahmad BahooToroody**) is the sole contact for the Editorial process. He is responsible for communicating with the other authors about progress, submissions of revisions and final approval of proofs Signed by all authors as follows:

Authorship contributions

Here it is indicated the specific contributions made by each author (list the authors' initials followed by their surnames).

Category 1

Conception and design of study: **A. BahooToroody, M. M. Abaei , O.V Banda, P. Kujala, F. De Carlo, R. Abbassi**

Acquisition of data: **A. BahooToroody, M. M. Abaei , O.V Banda, P. Kujala, F. De Carlo, R. Abbassi**

Analysis and/or interpretation of data: **A. BahooToroody, M. M. Abaei , O.V Banda, P. Kujala, F. De Carlo, R. Abbassi**

Category 2

Drafting the manuscript: **A. BahooToroody, M. M. Abaei , O.V Banda, P. Kujala, F. De Carlo, R. Abbassi**

Revising the manuscript critically for important intellectual content: **A. BahooToroody, M. M. Abaei , O.V Banda, P. Kujala, F. De Carlo, R. Abbassi**

Category 3

Approval of the version of the manuscript to be published (the full names of all authors are listed):

A. BahooToroody, M. M. Abaei , O.V Banda, P. Kujala, F. De Carlo, R. Abbassi

Declaration of Competing Interest

The authors have no conflicts of interest to disclose. These include all financial and non-financial interests and relationships, direct employment with a private sector entity (whether full or part-time), and service on the private sector and non-profit boards and advisory panels, whether paid or unpaid. Authors would also disclose that there is not any conflict of interest that may have influenced either the conduct or the presentation of the research to the editors, including but not limited to close relationships with those who might be helped or hurt by the publication, academic interests, and any personal, religious or political convictions relevant to the topic at hand. Please address all correspondence concerning this manuscript to me at ahmad.bahootoroody@aalto.fi.

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