On reliability assessment of ship machinery system in different autonomy degree; A Bayesian-based approach

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A B S T R A C T

Analyzing the reliability of autonomous ships has recently attracted attention mainly due to epistemic uncertainty (lack of knowledge) integrated with automatic operations in the maritime sector. The advent of new random failures with unrecognized failure patterns in autonomous ship operations requires a comprehensive reliability assessment specifically aiming at estimating the time in which the ship can be trusted to be left unattended. While the reliability concept is touched upon well through the literature, the operational trustworthiness needs more elaboration to be established for system safety, especially within the maritime sector. Accordingly, in this paper, a probabilistic approach has been established to estimate the trusted operational time of the ship machinery system through different autonomy degrees. The uncertainty associated with ship operation has been quantified using Markov Chain Monte-Carlo simulation from likelihood function in Bayesian inference. To verify the developed framework, a practical example of a machinery plant used in typical short sea merchant ships is taken into account. This study can be exploited by asset managers to estimate the time in which the ship can be left unattended. Keywords: reliability estimation, Bayesian inference, autonomous ship, uncertainty.

1. Introduction

Studies on Maritime Autonomous Surface Ship (MASS) revealed that the more the artificial intelligence and autonomy degree (AD) increases, the more the systemic safety and resilience solution is needed (Felski and Zwolak, 2020). That is mainly due to the advent of new random failures with unrecognized failure patterns in ship operations while approaching a higher degree of autonomy. Recently IMO (2018) introduced four degrees of autonomy through a regulatory scoping exercise for the use of MASS (Goerlandt, 2020). Different researches aiming at predicting the functional capacity (Chaal et al., 2020; Chang et al., 2021), resilience (Zhou et al., 2020; Insaurralde, 2013; Abaei et al., 2022), reliability (Thieme et al., 2018; BahooToroody et al., 2022), availability (Chun et al., 2021) and maintainability (Montewka et al., 2018; Abaei et al., 2020; Liu et al., 2021) of autonomous ship, the application of studies are still traditional ships, though. The studies on MASS can be classified according to two main criteria: (1) type of research (qualitative and quantitative) and (2) application of research (autonomous navigation system, unattended machinery system, etc.). Reviewing the conducted studies revealed that the focus is well balanced in the first category between qualitative and quantitative research. In a recently published

chapter by (Montewka et al., 2021), various qualitative and quantitative models (including Bayesian Network) were presented for the autonomous ship to show the differences in results obtained by applying both types of models. In this context, Utne et al. (2020) Outlined a qualitative methodology based on an integration of STPA and Bayesian Belief Network for online risk modeling of MASS. Valdez Banda, Kannos et al. (2019) highlighted the necessity of enlarging a systemic hazard analysis (i.e. STPA) starting from the earliest design phase of the lifecycle of an autonomous vessel through an application of two autonomous vessel concepts for urban transport. Zhou, Liu et al. (2019) projected a quantitative model of situation awareness based on the system safety control structure of unmanned vessels to propose a probabilistic model for directing the future evaluation of the navigation safety of fully autonomous ships. Recently, Abaei, Hekkenberg et, al. (2021) integrated the multinomial probability distribution and Bayesian inference to predict the safety level of failure-sensitive components operating in the autonomous system. Application of Bayesian inference aid to overcome data limitation for evaluating the reliability of system in the new advanced stage of MASS. The advancement of random-effect models (REM) and specially the advent of Markov Chain Monte Carlo (MCMC) simulation (BahooToroody, De Carlo et al., 2020a; Leoni, BahooToroody et al.,

2021a), makes the application of Bayesian inference extended dramatically in different engineering projects (BahooToroody, Abaei et al., 2019a; Song et al., 2020; Khalaj et al., 2020; Leoni, De Carlo et al., 2021b; Kelly and Smith, 2009; Yazdi et al., 2021; Basnet et al., 2022; BahooToroody et al., 2021).

While, the focus on second category is not as balanced as the first one; meaning that greater attention is devoted to autonomous navigation system than other applications such as machinery set up onboard the MASS. An intelligent guidance is presented by Perera et al. (2014) to support safe autonomous navigation and avoid collision of ship maneuvers. Ozturk and Cicek (2019) presented an extensive literature review on methods of collision risk assessment to ensure navigational safety in MASS. Bolbot et al. (2021) developed a novel hybrid process to comprehensively assess the safety of an autonomous inland waterways ship at design phase. In this study, autonomous navigation and communication were touched upon. Lee et al. (2021) applied Fault Tree Analysis to estimate the availability of autonomous navigation function of a short sea shipping vessel. Bolbot et al. (2020) proposed a novel cybersecurity risk assessment targeting the increased connectivity of systems as a result of enhanced autonomy of ship systems. Recently, a probabilistic machine learning based resilience study is proposed by Abaei., et al. (2022) on machinery system considering unexpected perturbations, disruptions, and operational degradations.

Considering the conducted studies, neither of reviewed studies considered the change in autonomy degree while the ship is operating through their proposed framework. A question still needs to be touched upon is how the performance of a ship system may change while the ship moves through the phased functional maturation approach to higher ADs. To enhance safety, the AD of ship might change during the voyage depending on the environmental situation and the level of ship self-awareness. To this end, this paper considers the limit state concept for studying the reliability of MASS. With a fundamental phenomenon of comparing the present condition of a given system with its critical threshold, the limit state concept has been widely applied to define the failure function of different operations probabilistically (Abaei, Arzaghi et al., 2018c; Khalaj et al., 2022; Arzaghi et al., 2018; Chen et al., 2018; Leoni et al., 2019).

In this paper, executed risk control strategies onboard a ship (any maintenance, check, or replacement) and reported failures are specified as potential disturbances and disruptions through the operations. The interarrival times between failures and executed risk control strategies are appointed as an input to form a system reliability distribution through the application of Bayesian inference. Up to now different models and approaches have been trained to estimate the reliability function of repairable systems (Islam et al., 2017; Abaei et al., 2019; Keshtegar et al., 2019; Yazdi et al., 2020; Zarei et al., 2021). The novelty of these studies mainly relies on the level of quantified uncertainties. The more the uncertainty is quantified, the more the reliability function can be righthand. Establishment of Bayesian inference herein aimed at representing the fluctuations that come with operational data, such as the variability between the source of data, and the correlation between data.

To demonstrate the applicability of the developed methodology a case study of machinery plant of a typical short sea merchant ship is offered. The proposed framework can be exploited as a tool to assess the reliability of ship systems given that the vessel is independent of any human intervention.

2. Methodology

The proposed method is presented in two subsections; first a brief discussion on Bayesian modeling with hierarchical structure, and then, model specification aimed at covering the branded research gap.

2.1. Model of the world; Bayesian inference

Apart from the *motivation* of being an intelligent system, the real-time operational data (*raw data*) from the health condition of the system and perceived *value* of the asset are accounted for the development of the *model* of the world. Upon establishing the model, there are three crucial steps to estimate and predict the reliability of an autonomous system; information processing, knowledge gathering, and finally making actions based on concluded inference to achieve a safe and resilient design (Aven, 2013). A summary of the process for performing inference using data and a probabilistic model is presented in Fig. 1. A model of the world should be framed to manipulate the information. Both deterministic or probabilistic models are available for this purpose (Kelly and Smith, 2009). Different types of uncertainties (epistemic; also known as state-of-knowledge uncertainty, and aleatoric; stochastic) must be incorporated into the model if the efficiency is important (Paté-Cornell, 1996). To this end several methods and models can be applied (Aven, Baraldi et al., 2013b; Ferdous et al., 2013; Bhandari et al., 2015; Abbassi et al., 2017; Yazdi et al., 2019). As an understandable model, Bayesian statistics can be applied to describe aleatoric uncertainties, including the fluctuations associated with variability between the source of data and the correlation of observations. The resulting posterior distribution can properly represent these uncertainties (Kelly and Smith, 2009; Leoni, BahooToroody et al., 2021c) given by Equation (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, $\pi_0(\theta)$ represents the prior knowledge, $f(x|\theta)$ is the likelihood function, and $\pi_1(\theta|x)$ is the posterior distribution.

The Bayes theorem utilizes multistage prior distribution to present the population variability through different hierarchy levels. Correspondingly, the first-stage prior denoted as $\pi_1(\theta|\varphi)$ is accounted to denote the variability between the source of data for the parameter of interest indicated by $\pi_0(\theta)$, as follow (BahooToroody, Abaei et al., 2019b):

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

where, φ is a vector of hyper-parameters.

2.2. Model specification

A machine learning based framework is developed in this study to propose a reliability function for ship machinery systems through different ADs. The sequence of the proposed model incorporating the key element of Bayesian inference establishment is plotted in Fig. 2.

Predicting the reliability of a system is mainly based on the interarrival times between successive breaks or stops during the operation. Therefore, the first step is to collect the time of occurred interruptions; disturbances (any maintenance, check or replacement) and disruptions (failures). In order to estimate the reliability of a ship system, the AD in which the operation is on the go and its associated human availability onboard the ship must be specified. These two variables can be defined based on the regulatory scoping exercise for the use of MASS initiated by IMO (2018) (outlined in Table 1).

Then based on the specified degree of autonomy, human availability, and type of captured interruptions, a limit state concept is considered to specify the event time for studying the health state of MASS. That is when any unplanned interruptions such as disturbances or disruptions cannot be managed in the voyage operation. The limit state G, is adopted as follows here;
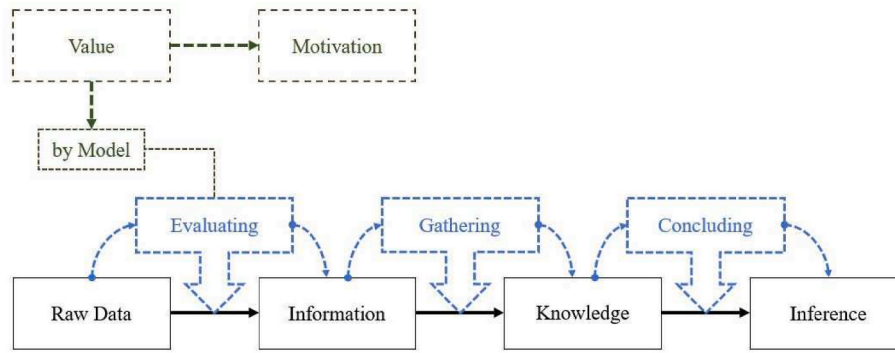
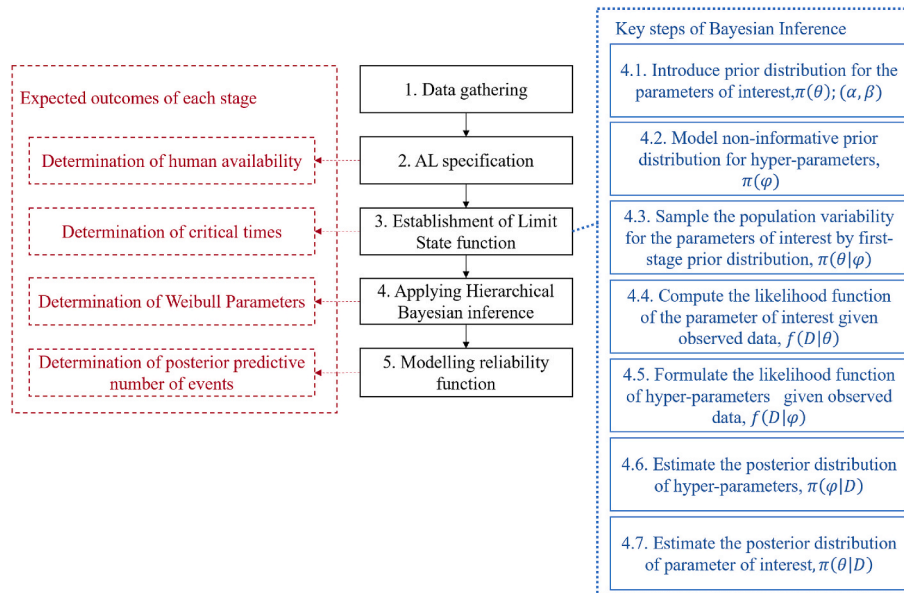**Fig. 1.** An overview of the knowledge engineering process and its key elements.

Fig. 2. Developed framework for reliability estimation.

Table 1

Description of autonomy degree for MASS and its associated human availability; IMO (2018).

ADs	Description	Human availability
AD1	Ship with automated process and decision support	Human on board
AD2	Remotely controlled ship	Seafarers on board
AD3	Remotely controlled ship	No human on board
AD4	Fully autonomous ship	No human on board

$$G = a_h - a_r \tag{3}$$

where a_h, is actual human availability according to AD specification reported by IMO (2018) and can be expressed as;

$$a_h = \begin{cases} 3 & for \quad AD_1 \\ 2 & for \quad AD_2 \\ 1 & for \quad AD_3 \\ 0 & for \quad AD_4 \end{cases} \tag{4}$$

Meanwhile, a_r represents the required human intervention for different unplanned interruptions classified as below;

$$a_r = \begin{cases} 1 & for \quad check \\ 2 & for \quad Maintenance \\ 3 & for \quad Replacement \\ 4 & for \quad Failure \end{cases} \tag{5}$$

Consequently, any interruption represents an event if $G < 0$. The resulted event time for different ADs is outlined in Table 2.

Next is to form a probabilistic distribution for determined event times. There are two common assumptions; either the event times are assumed to be dependent (resulting in an occurrence rate following a Non-Homogeneous Poisson Process (NHPP) (Sheu et al., 2018; Abbassi et al., 2021; Li, Zhang et al., 2021a, Seghier, Keshtegar et al. 2021)) or independent (occurrence rate will be constant in time and follows Homogeneous Poisson Process (Barabadi et al., 2014; BahooToroody et al., 2016; Toroody et al., 2016; Li, Zhang et al., 2021b)). BahooToroody et al. (2020b) explained both assumptions' differences, advantages, and weaknesses, concluding that relaxing the HPP assumption (constant failure rate) and considering the time dependency between the failure times results in a more accurate reliability function. Accordingly, given that the time between successive events of the system is not independent

Table 2

Event times specification according to human availability for different AL.

ADs	Event times (ET)
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)

and identically distributed (iid), the Bayesian inference with hierarchical structure is developed. To model the nonlinearity of $\lambda(t)$ including the integrated stochastic trend, the power-law model is adopted herein with the relationship expressed by Equation (6) (Ross et al., 2004) as suggested by Kelly and Smith (2009) and Abaei, Arzaghi et al. (2018a);

$$\lambda(t) = \frac{\alpha}{\beta}\left(\frac{t}{\beta}\right)^{\alpha-1} \tag{6}$$

Upon modeling the time to first observations by power-law function, a two-parameter Weibull distribution, (t, β, α) is generated (Leoni, Cantini et al., 2021d). Different types of prior distribution can be assigned for generated shape parameter, α, and scale parameter, β. In this study, a non-informative gamma distribution with independent diffuse hyperpriors, assumed as the prior distribution of hyperparameters (Kelly and Smith, 2009; Abaei, Arzaghi et al., 2018b). Given 'Bayes' Theorem, to obtain the posterior probability distribution, in addition to prior distribution, a likelihood function must be formulated. Considering the dependency of observational times, T_i, for any operational time interval $[t_{i-1}, t_i]$, a conditional probability must be defined as an appropriate likelihood function expressed by Equation (7) (El-Gheriani et al., 2017);

$$f(t_i|t_{i-1}) = f(t_i|T_i > t_{i-1}) = \frac{f(t_i)}{\Pr(T_i > t_{i-1})} \tag{7}$$

The Markov Chain Monte-Carlo simulation via open-source simulation software packages, i.e., OpenBUGS (Spiegelhalter et al., 2007) is proposed to obtain the joint posterior distribution of hyper-parameters. The mean time to events, then estimated from the predicted value of hyperparameters.

3. Model and results

The application of the proposed methodology is explained via a practical example of a machinery plant fitted with four-stroke diesel engines used in three typical short sea merchant ships (cargo RoRo (Roll-on/Roll-off) ships with age ranging from 14 to 18 years) operating in the same sea region; the Mediterranean Sea. The interarrival times between events for cylinder cover, gear box, stern tube, piston cylinder, manoeuvring system, clutch, attached pump, driving gears, turning gear and tuning wheel was adopted in time series from the ship alarm system records, the maintenance records, and the engine logbooks (see Fig. 3). To structure the data for this study (including the definition of interruptions), survey analysis and interviews were conducted with the ship machinery crew. Accordingly, check is defined as inspection (visually or with a dedicated tool). While maintenance is pre-scheduled actions according to the prescription given by the manufacturer, replacement is defined as an unplanned operation conducted due to an abnormal performance. Lastly, failure is defined as inability to meet the

requirements.

A General overview of machinery plants representing the linear and nonlinear interaction between different sub-systems and individual subsets is plotted in Fig. 4.

Based on ET in different ADs, the MCMC simulation, with 1000 burn-in iterations, is followed by 3×10^5 iterations through three chains with an over-dispersed initial value of α and β. To validate the calculation in MCMC, the convergence of chains was monitored through trace plot and history of iterations of hyper-parameters. The expected value of α and β are 1.573 and 262.5 for AL1, 1.123 and 50.07 for AL2, 1.025 and 17.46 for AL3 and 1.019 and 3.071 for AL4, respectively. Shape factors of all ADs are more than one, depicting that the number of events increases over time, supporting the NHPP assumption considered in this study. Fig. 5 presents the posterior probability density function of shape parameters α for all ADs as well as their history of iterations to check how the chains reach the convergence. As it can be seen, there are three colors in the history plot representing three initiated chains for carrying out the Monte Carlo estimation of the formulated posterior distribution. The illustrated history plot is confirming the convergence and meanwhile validating the estimated posterior values for α and β.

The expected values of the posterior distribution of α and β can be applied to predict the trusted operational time of the ship system in different ADs (the time in which the system is expected to be safe without experiencing any event and subsequently can be trusted to be left unattended). Different results inferred from the proposed model are discussed in the ensuing section.

4. Discussion

The data scarcity associated with smart shipping specifically the functionality and performance of the ship system in AL4 and AL3, is one of the primary challenges in estimating the reliability function. An event perception model based on the limit state concept was proposed to overcome this lack of knowledge and reduce the integrated epistemic uncertainty. Later, the event rate has been introduced probabilistically with a Weibull distribution using Bayesian inference and MCMC simulation. Establishment of Bayesian inference in this study mainly aimed at accounting the uncertainty associated with variability between the source of data and correlation between data.

The proposed model can estimate the probability of event occurrence for the ship system in any desired time interval. To this end, a conditional probability (see Equation (7)) for the obtained Weibull distribution was offered to estimate the posterior predictive probability of events (PPPE). Accordingly, the PPPE in $t = n + 1$ was estimated, given that an event was observed in $t = n$. The calculations were then followed by calculating the PPPE in $t = n + 1$, assuming that the event also occurred in $t = \{n-1, n-2, ...\}$. For this purpose, a cumulative function must be developed. Fig. 6 depicts the cumulative posterior predictive number of the event over the voyage time for different ADs with its
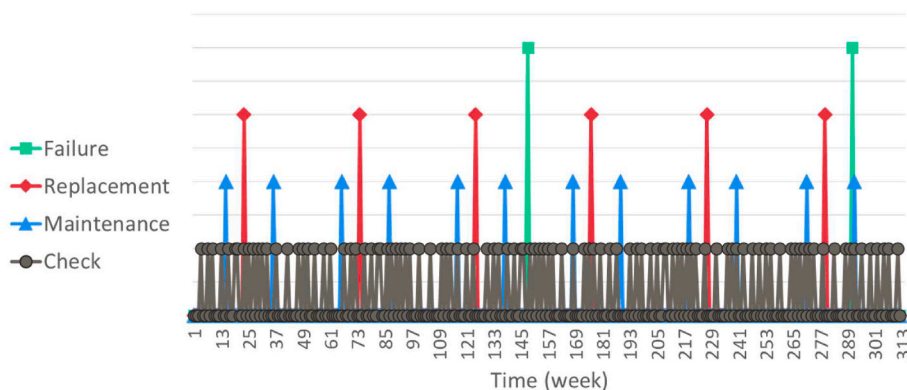
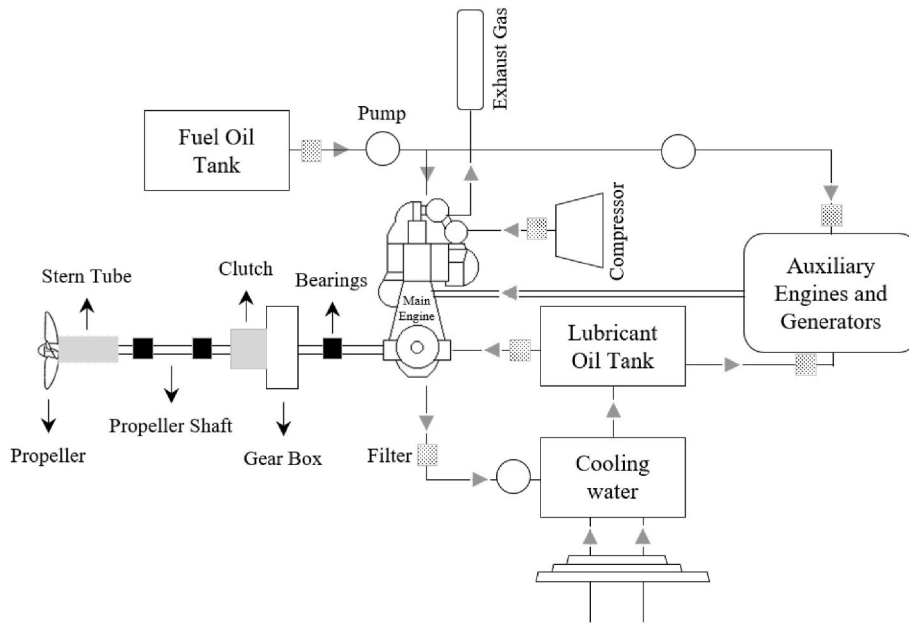**Fig. 3.** Operational data including event times (ET).

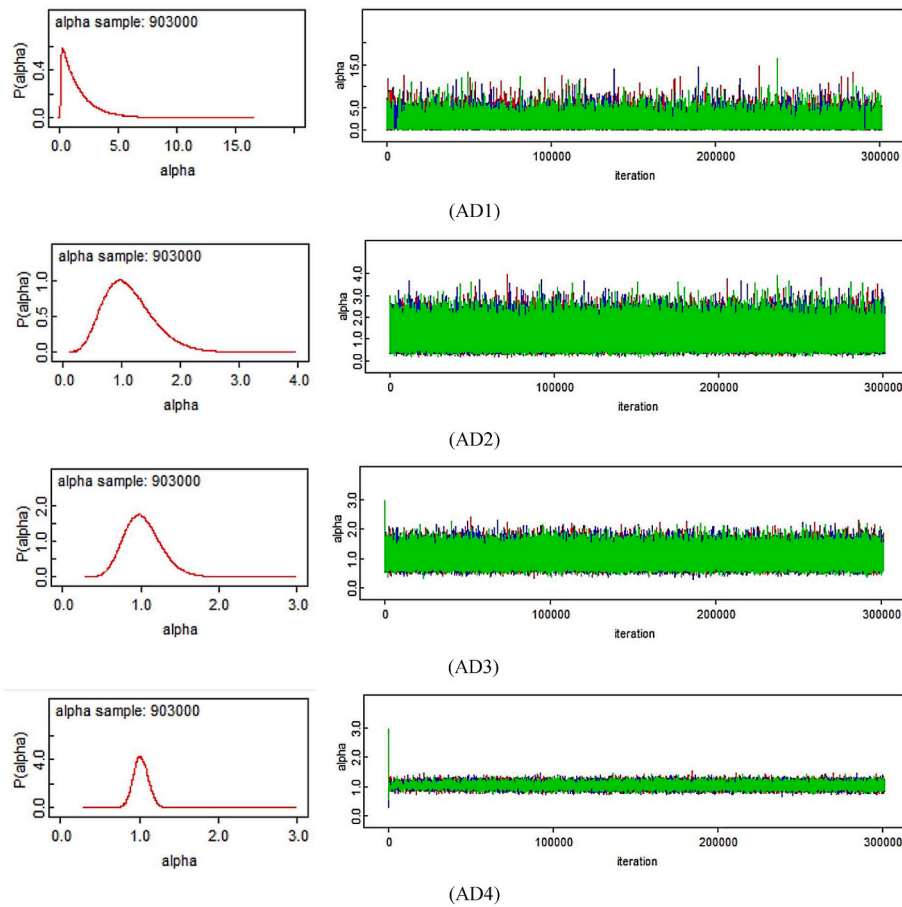**Fig. 4.** A schematic arrangement of the machinery plant.

Fig. 5. Estimated posterior probability density function (left-hand side) as well as the history of iterations (right-hand side) for shape parameters, α, for all ADs.

associated probability (with what probability, how many events will happen per week).

As an example, if the ship system approaches the second degree of autonomy, it is predicted that the main engine will have four events within the first 170 weeks, while this number of the event is expected to happen in 680 weeks through AL1, 67 weeks in AL3 and within 13 weeks in AL4. The type of event depends on the degree of autonomy, i.e., an event in AL2 referred to failure and replacement, while in AL1 it is only
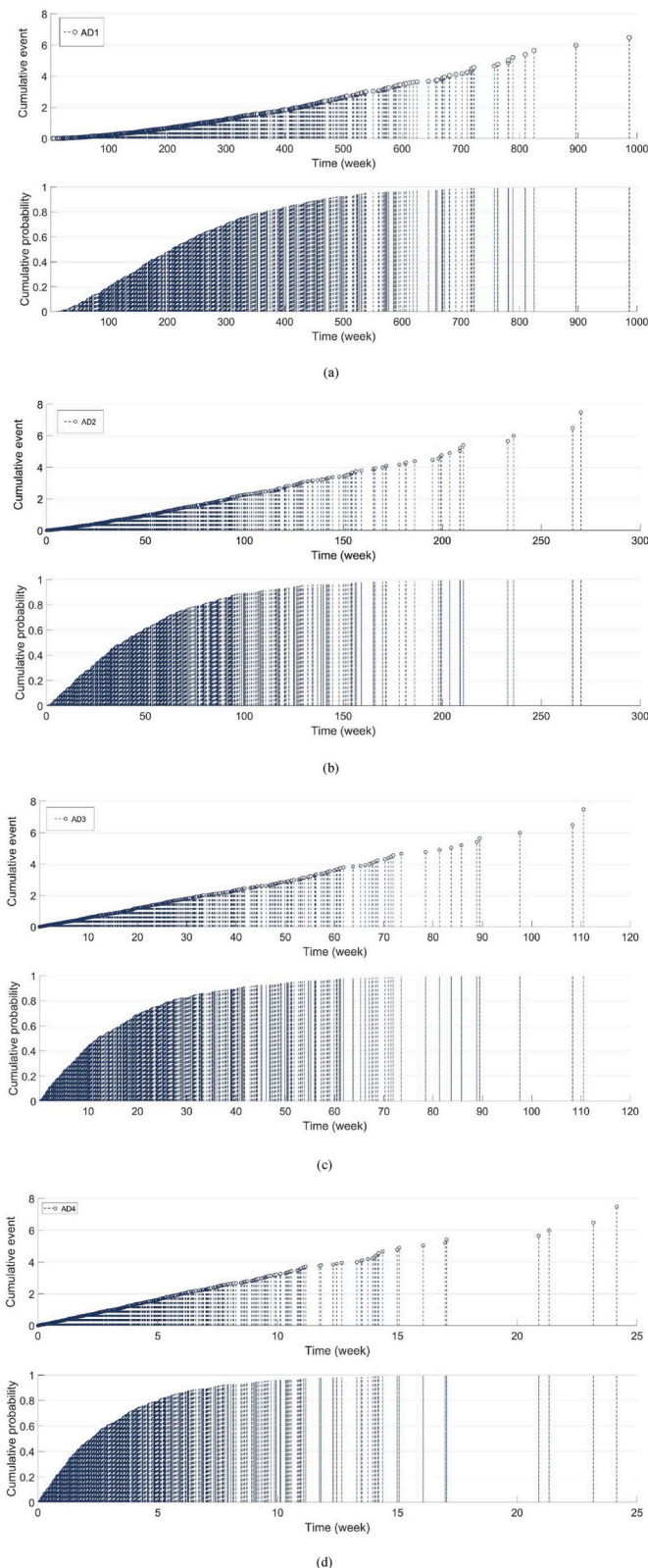
Fig. 6. Cumulative posterior predictive number of events upon time for all ADs (AL1 (a), AL2 (b), AL3 (c), AL4 (d)) with its associated probability.

failure. This result can deliver a road map to achieve a higher level of trustworthiness while the ship moves through the phased functional maturation approach to higher ADs as it can figure out the time in which the human intervention might be needed.

The mean time to the first event can also be inferred through the presented cumulative function; that is where the cumulative probability function reaches the level of 0.5, and the cumulative event number hit the level of; 235.7 for AD1, 47.9 for AD2, 17.2 for AD3 and 3 for AD4 (numbers are in week). In the upper figures (cumulative event), the model depicts the time that system will experience the second event, the third event, the fourth event, and so on if the ship's autonomy moves through higher degrees. A predictive policy can be adopted accordingly to avoid the events.

As a foreseen future work, it is suggested to utilize the event perception phase of the proposed model by the application of Machine Learning. This will lead to empowering the dataset for modeling the reliability function probabilistically.

5. Conclusion

This paper presents a probabilistic reliability assessment methodology to predict the trusted operational time of the ship system in which the ship can be left unattended. While the maritime industry is still away from producing autonomous ships, this study can be used to understand how much present ships with the current design, capacity, and performance are ready for semi or fully autonomous operations. To this end, a two-parameter Weibull distribution (t, β, α) is generated to model the trusted time. MCMC simulation through Bayesian inference was later adopted to formulate an appropriate likelihood function for obtaining the joint posterior distribution of hyper-parameters (alpha and beta). Three chains were run to check the convergence through the calculations. The predicted shape parameters of all ADs were higher than 1, supporting the NHPP assumption given for the probabilistic modeling in this study. The results suggest a remarkable reduction of mean time to event as the AD of the ship moves from one to two; 235 to 48, from two to three; 48 to 17 and from three to four; 17 to 3. The developed framework can be exploited to predict ship performance through different autonomy degrees considering the uncertainties integrated with data scarcity. A limit state concept has been proposed to treat the lack of data for estimating the reliability function; however, as a future study, it is recommended to generate a more powerful dataset using different machine learning applications. Moreover, the main challenge of the present study is overlooking autonomous feature of MASS. Therefore, as a direction for future study, the developed model can be improved by estimating the impact of self-governance of autonomous ship on its reliability status.

CRediT authorship contribution statement

Ahmad BahooToroody: Conceptualization, and design of study, Data curation, Formal analysis, Writing – original draft, Writing – review & editing, critically for important intellectual content. **Mohammad Mahdi Abaei:** Conceptualization, design of study, Acquisition of data, Formal analysis, Writing – original draft, Writing – review & editing, critically for important intellectual content. **Osiris Valdez Banda:** Conceptualization, design of study, Acquisition of data, Formal analysis, Writing – original draft, Writing – review & editing, critically for important intellectual content. **Jakub Montewka:** Conceptualization, design of study, Acquisition of data, Formal analysis, Writing – original draft, Writing – review & editing, critically for important intellectual content. **Pentti Kujala:** Conceptualization, design of study, Data curation, Formal analysis, Writing – original draft, Writing – review & editing, critically for important intellectual content.

Declaration of competing interest

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

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