# Predicting Performance of Unattended Machinery Plant: A Step Toward Trustworthy Autonomous Shipping

Mohammad Mahdi Abaei, Ahmad Bahootoroody and Ehsan Arzaghi



September 19, 2020

# Predicting Future of Unattended Machinery Plants: A Step Toward Reliable Autonomous Shipping

M M Abaei[1]* PhD, Postdoctoral Research Fellow
A BahooToroody[2] PhD, Postdoctoral Research Fellow
E Arzaghi[3] PhD, Postdoctoral Research Fellow

[1] *Technical University of Delft, Netherlands;* Corresponding Author. Email: m.m.abaei@tudelft.nl
[2] *University of Strathclyde, UK;* Corresponding Author. Email: ahmad.bahootoroody@unifi.it
[3] *Queensland University of Technology, Australia;* Email: ehsan.arzaghi@qut.edu.au
* *Corresponding Author: m.m.abaeiA@tudelft.nl*

**Synopsis**

Future waterborne transport operations in short-sea, sea-river, and inland waterways can be performed by autonomous vessels. The automation of maritime shipping directly emphasizes reducing crew numbers, minimizing operational costs, and mitigating human error during the operation. Recent researches have focused on understanding autonomous navigation while the reliability of unattended machinery plant has received very little attention. This paper aims at developing a method for predicting the performance of failure-sensitive components that may be left unattended in autonomous shipping. The presented methodology adopts Bayesian Inference as the basis of the artificial intelligence for predicting maintenance schedules including repair, inspection, and irregular checks of unattended systems. A Multinomial Process Tree (MPT) is used to model the failures within the system, identify faulty components, and to predict their failure times. A real case study from a short sea voyage is adopted to demonstrate the application of the presented methodology. The results of this research will assist decision and policy-makers to prevent costly failures in Maritime Autonomous Surface Ships (MASS) and extend the service life of autonomous systems before any human intervention.

Keywords: Autonomous Shipping, Reliability Engineering, Multinomial Process Tree, Bayesian Inference Unattended Machinery

## *1. Introduction: Maritime Autonomous Surface Ships*

Future Maritime Autonomous Surface Ships (MASS) are expected to have a considerable impact on maritime trade. The European Waterborne Technology Platform (Waterborne TP) states that smart marine transportation is essential for safe, sustainable, and efficient shipping. For the development of effective autonomous operations, it is vital a ship's ability to monitor the health of on-board systems, conduct prognosis to establish what is going wrong, and make informed. For the smart-ship revolution to become a reality and for the societies to confidently benefit from it, autonomous shipping must be trustworthy. Many tasks that are currently done by a ship's crew cannot so easily be replaced by a machine within an unmanned vessel. This challenges the effectiveness of maintenance and repair procedures on broken equipment when the crew is planned to be eliminated by autonomous shipping. In the absence of the on-board crew, the operation will be susceptible to emerging risks and will create an unprecedented demand from system design including propulsion. For example, the machinery used in the main engine consists of many critical components that still are preserving the hard-to-replace skills and expertise of a crew. The most straightforward solution to minimize failures of machinery on unmanned vessels is to make all critical components redundant or eliminating the failure-sensitive moving components for the engine room by replacing the conventional diesel engine with batteries. However, these solutions are impractical (i.e. not very energy-dense) and expensive which leads to very limited demand for these solutions from ship owners. Further to this, the existing market and regulatory arrangements mainly focused on investigating how advanced control systems, navigation software, and online communications could control an unmanned vessel. DNV GL has initiated projects revolving around ship automation and autonomous control. The ReVolt project is one example that has designed as a proof of concept for autonomous ships. Other projects conducted with DNV GL involvement for the Advanced Autonomous Waterborne Applications Initiative (AAWA), led by Rolls-Royce, are investigating a wide array of aspects relevant to commercial unmanned shipping from technical development to safety, legal and economic aspects as well as societal acceptance, Rolls-Royce (2017). The project Maritime Unmanned Navigation through Intelligence in Networks (MUNIN) was a collaborative research project, co-funded by the European Commissions under its 7$^{th}$ Framework Program, with aiming to develop and verify a concept for an autonomous ship. Ships have multiple crew members that are employed to keep the engine room operating, and their absence may change the design of power plants significantly, *Colon (2018)*. To determine the required changes in the machinery of autonomous ships is necessary to understand the reliability of the current engine rooms. The AAWA states that the systems of an autonomous ship "should be resilient to failure and extended maintenance intervals", *Rolls-Royce (2017)*. The findings of MUNIN include that "Current preventative maintenance procedures need to be updated to ensure operability of components during the voyage", *Rødseth and Burmeister (2012)*. What is often neglected is the importance of trustworthy and enabling effective maintenance for the unattended system integrated with autonomous ships. Trustworthy can come from all levels of the system, including reliability, predictive maintenance, mitigating emerging risks that result in extending the operation time of autonomous ships without human intervention and reducing marine accidents by eliminating human interventions. This needs to incorporate the system's reliability to rare and unanticipated disturbances and compromised functioning, as an integrated capability. This paper proposes a dynamic predicting approach for the reliability of the marine machinery systems when they are unmanned. A systematic framework is presented for modeling failures propagated through the machinery that results in operation disruption. The main concern is to understand the failure events that will put the system performance at risk without human intervention. To this end, a "closed-loop" reliability model is constructed to act as a framework for evaluating the degradation of the system under the influence of the disruptive event. A real case study of Maine Engine (ME) is adopted to demonstrate the application of the presented research methodology. The results highlight the importance of predicting appropriate hazard rate functions that is essential for understanding the performance of the system or redesign unattended machinery according to the maintenance activities.

## *2. Reliability Assessment of Unattended Marine Machinery*

The focus of this study is on the machinery plant used on merchant ships. Generally, most of the ships run on two-stroke diesel engines, connected to the propeller via a gearbox. They are usually equipped with a single main engine and outfitted with at least two diesel generators and auxiliary engines. Both main and auxiliary engines are supported with a fuel oil system which cleans the fluid and prepares it for use. The engine is started with air from the compressor and cooled with a triple layer seawater-based cooling system. Mostly, they are equipped with a single rudder and propeller and one or two bow thrusters. Auxiliary systems need to keep the engines running, which will be in connection with the fuel oil system, lubrication oil system, cooling water system, starting air system, and exhaust gas system. A schematic overview of the power plant machinery is illustrated in Figure 1. The figure is only an overview of the critical components in the engine room, while the case study of this research will only consider the main engine, gearbox, clutch, stern tube and manoeuvring system for implementing the reliability assessment of unattended machinery as the example of the framework. The engine itself consists of many parts, but not all the components will be weak points if left unattended, Colon (2018).

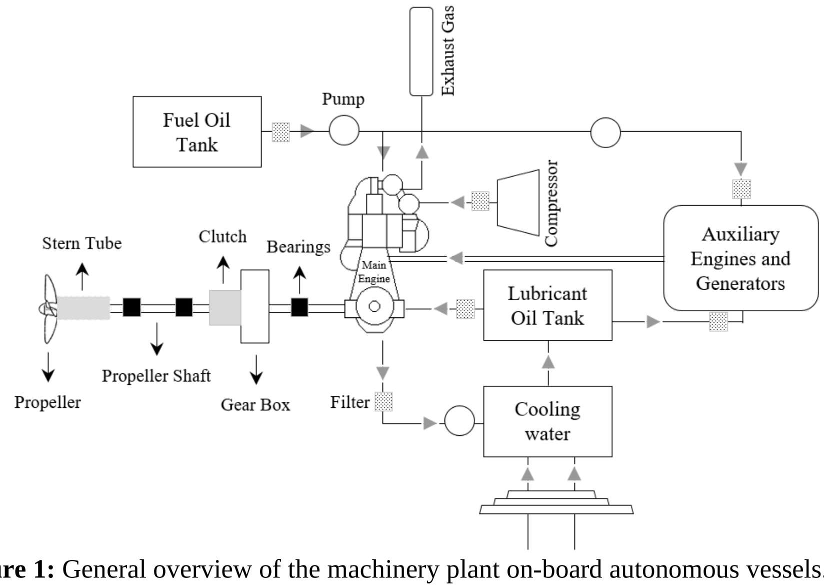


**Figure 1:** General overview of the machinery plant on-board autonomous vessels.

No engine room can operate continuously forever, and it will experience break-down eventually. This means without human inspection an autonomous ship essentially needs to be able to evaluate the performance of the entire system and at least to understand faults, Colon (2018). To remove humans from operations, it is first essential to understand the impact of human intervention on critical components. It is therefore crucial to combine the empirical knowledge of expert engineers about maintenance processes with operational data obtained from previously performed activities. This will assist in the prediction of system health state and provide important information to establish optimal maintenance strategies for mitigating technical and operational failures. Despite

the advent of sensing and monitoring technologies that enable detection of component malfunction, not every failure can be predicted automatedly, and engineers play an imperative role in identifying and diagnosing faults in ship engine rooms. These unbound observed values are an assistive source of data for the reliability analysis of the Unattended Machinery Plant (UMP). The inspections performed by engineers are important to estimate the level of component reliability according to the frequency required actions for maintenance schedules. In general, crew tasks can be divided into four major categories including: (1) irregular checking of equipment; this action leads to an understanding of whether something is wrong with the system or not. It is assumed that if a crew member spends more time on equipment, or deals with it more frequently, then that equipment is deemed less reliable; (2) performing planned maintenance; this action represents performing the repair on equipment according to the schedule. Therefore, the frequency of 'Maintenance' will be used here as a conservative indication of non-critical failure in the system i.e. a part of the system is not in a nominal state, but performing maintenance can be postponed until a more convenient time; (3) repairing equipment that regrading as performing unplanned maintenance**.** This action represents performing major repairs before maintenance is planned. Therefore, the frequency of 'Repair' will be used here as an indication of a critical failure in the system which leads to stoppage in operation; (4) Continue operating safely. These four actions form the basis of the analysis in this article as they can give the best available indication of the reliability of machinery if the main objective is to remove human interruption. The frequency of each action is adopted from Colon (2018) to populate the reliability model.
To understand how disruptive failure events, propagate through an unattended system and cause a drastic change in the operation from its nominal condition to degraded functioning of the critical components; it is essential to understand how the system will change from its nominal condition. For this purpose, the performance of such components will be modelled by introducing the Categorical Failure Functions (CFFs) dependent on operation time. Defining CFF is however not a very straightforward task since the process involves a great deal of uncertainty and unknown probabilities of the problem variables. Moreover, CFF should be defined in the context of multivariate activities that represent required "Repair", "Maintenance" and "Check" actions for a group of components in a system. This will result in a nonlinear CFF with multiple unknown variables. As suggested by *Heck et al. (2013)*, Multinomial Process Tree (MPT) is a good option to describe CFF for multiple failures in the form of categorical probability distributions. MTP models are simple, substantively motivated statistical models that can be applied to categorical data and represent the performance of operation globally. MPT models address categorical data based on the assumption that the sample frequencies observed for the Event-data set follow a multinomial distribution. In the case of categorical data, a multinomial distribution is the most general and theoretically neutral statistical distribution, which is a generalization of the binomial distribution to more than two categories. In a multinomial distribution, observations are independent and identically distributed (iid) over the categories and each category has a parameter representing the probability that a random observation falls into it, *Batchelder and Riefer (1999)*. MPT will, express the probability parameters as a function of the system behavior for different circumstances and re-parametrize the multinomial distribution for an objective situation. Each branch of the tree represents a different hypothesized sequence of the processing stages of operation, resulting in a specific response category regarding the obtained knowledge from the system. Hierarchical Bayesian Model (HBM) is a statistical approach to reasoning under uncertainty using probability distributions of problem parameters and provides a tool for the propagation of uncertainty in risk and reliability analysis applications, *Kelly and Smith (2009)*. Due to the complexity of systems in autonomous ships, any reliability prediction model needs to perform as a function that follows a desired trusted level. Recently conducted researches on reliability assessment of marine operations and predicting the availability of systems highlight the key attributes of HBM, namely the ability to incorporate qualitative information (i.e. evidence) into the parameters, *Bahootoroody et al. (2019a,b)*, *Khalaj et al. (2020)*, *Leoni et al. (2019)*. In this study, HBM is employed to estimate the uncertainty of random variables associated with the MPT model.

## *3. Method: Prediction of Disruptive Events*

In this study, an MPT model is constructed based on engineer tasks to prevent failures in the critical components of an unattended system. A processing tree consists of a single root and a collection of processing branches, each terminating in a particular response category. The necessary activities can be divided into four main categorial actions as Repair, Maintenance, or Check, and Do nothing/Continue operation. The general overview of the MPT model for predicting the functional capacity of the system is shown in **Figure 2**. The unknown parameters $\boldsymbol{\theta} = \{\theta_1, \theta_2, ..., \theta_i, ..., \theta_n\}$ represent the probability of each processing branch $P(B_{ij}; \boldsymbol{\theta})$ that will result in proceeding to the probability of a category $P(\mathbf{C})$. The categories $\mathbf{C} = \{C_1, C_2, ..., C_i, ..., C_n\}$ represent a nonlinear function that stands for the behavior of the system. As illustrated in the MPT model, the right-hand side of the root categories shows the critical failures and the rest describe non-critical or negligible failures (i.e. malfunctions), and the $C_n$ is specifically considered as no failure in the system. In general, an MPT model can have paths (denoted by $B_{ij}$, $i = 1, 2, ..., I_j$) leading to category $C_j$. For each branch, there is a probability distribution over the directed links that proceed from that node, and these distributions are required to satisfy a certain functional form underlying parameters, as suggested by Batchelder et al. (1999), that leads to a particular form for the branch probabilities, given by Eq. (1):

$$P(B_{ij};\boldsymbol{\theta}) = \delta_{ij}\prod_{s=1}^{S}\theta_s^{a_{iks}}(1-\theta_s)^{b_{iks}} \tag{1}$$

Where $B_{ij}$ is the $i^{\text{th}}$ branch that leads to category $C_j$, furthermore, the parameter $\delta_{ij}$ is always a positive number and also $a_{ijs}$, $b_{ijs}$ are non-negative integers. For example for a simple tree consist of two three node as $C_1 \leftarrow A \rightarrow C_2$, there is two Branches as $B_{11}$ $(C_1 \leftarrow A)$ represents for $\theta_1$ and $B_{22}$ $(A \rightarrow C_2)$ represents for $\theta_2$. Therefore, the branch probabilities are defined as $P(B_{11};\theta_1,\theta_2) = 1\times(\theta_1)^1\times(1-\theta_2)^0$ and vice versa. Once the tree structure of the model has been established, the probability of categories is given by

$$P(\mathbf{C}) = \sum_{i=1}^{I_j} P(B_{ij};\boldsymbol{\theta}) \tag{2}$$

Where $I_j$ is the number of branches ending in category j, and $j = 1,2,...,J$ The essential condition for the final probabilistic structure of the model are that it needs to satisfy that $\sum P_j(\boldsymbol{\theta}) = 1$, for all the processing branches $\boldsymbol{\theta}$, which allows each parameter to vary independently between [0,1]. The developed MPT model of the machinery performance is presented in **Figure 2**.

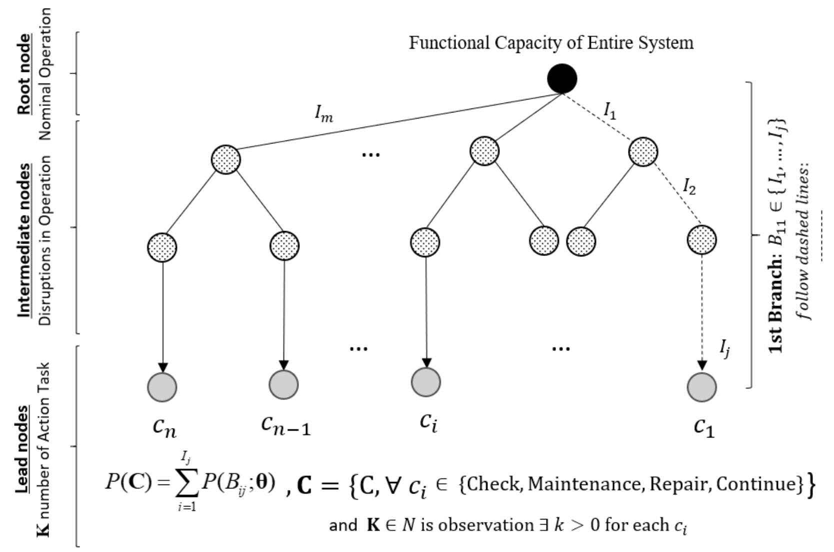


**Figure 2:** Conceptual method for performance analysis of unattended machinery subject to random disruptions.

The circles show the uncertain condition of the system due to experiencing random disruptions such as abnormality or breakdown in an operating component. The probability model consists of two main parts, firstly modelling the failure by running the MCMC package for predicting unknown parameters from available observation event data, and secondly running Monte Carlo simulation for predicting the frequency of required actions (e.g. maintenance or repair) based on the posterior distribution derived from Bayesian Inference. The parameter $k$ is represented for the observation of event data. Generally, a system may need a $k$ number of actions to maintain its components in a reliable condition. Therefore, the observation parameter will be a set of frequencies $\mathbf{K}_{n,k}$ for each action in connection with the related critical component. Parameter $n$ is defined as the total number of critical components. Each set of frequencies will describe the outcome of the required action as $C_{jk}$ for a particular component $j=1,\dots,n,$ and $k^{\text{th}}$ observation. Node **C** is the nonlinear function for predicting the probability of categorial actions $P(\mathbf{C},\boldsymbol{\theta})$, while $\boldsymbol{\Theta}$ is the unknown and unobservable parameters in the MPT. Then Monte Carlo Simulation will set for **N** trials to populate the posterior distribution obtained from MCMC for estimating failure events in each consecutive trial. Subsequently, the set of variables $k$ is the observation that is connected to the categories C for monitoring performance of critical system components, for instance, the frequency of repair planned maintenance, or unregular check for the gearbox in the main engine. The lead node C is defined as the nonlinear categorical failure function that forms system behaviour in connection with the branches variables $\boldsymbol{\theta} \in \mathbf{I}$. To set up the hierarchical Bayesian inference for the proposed model **Figure 2**, first, it is needed to identify the prior distributions of unknown parameters of process branches $\boldsymbol{\theta}$. Due to the shortage of engineering data and physical information regarding the details of the entire process, non-informative prior distributions must be adopted for inference, as recommended by previous researches Batchelder et al. (1999) and Heck, et al. (2018). Based on the recommendations made by Kelly, et al. (2009), in this study the $Beta(\alpha,\beta)$ prior distribution is used with

$\alpha = 1$ and $\beta = 1$, that simply represent uniform distributions to remove any bias in addressing the unknown parameters as well as making the inference easy to implement and to utilize new evidence through multinomial distribution. Assuming independent branches, the probability for a category $C_i$ is given by summation of branch probabilities followed by Eq. (1). This will allow constructing of the categorical likelihood function as a platform to feed the observation in the model. Sine the categorial functions are assumed to be indirectly depended distributed, then the likelihood can represent by the multinomial distribution. As the concern is to understand the behaviour of the whole system then the final likelihood should be based on the augmentation of all possible observations, that will result in a product of k number of multinomial distributions for n failure sensitive components with the conditions in categorial actions C and unknown parameters of disruptions $\boldsymbol{\theta}$. The open source Monte Carlo Markov Chain (MCMC) WinBUGs software package, developed by Spiegelhalter et al. (2003), is used to predict the marginal posterior distributions of parameters and to estimate the system hazard rate needed for evaluation of system reliability and the possibility of extending maintenance intervals of UMP. The next section presents a case study to demonstrate the application of the presented methodology. This includes the recommended procedure to implement the model for estimating unattended system reliability, as presented in Table 1.

**Table 1:** Implemented procedure for running MCMC simulations.

| Step | Task |
|---|---|
| 1 | Construct the *categorial process tree* (Figure 2) |
| 2 | Identify *branches*, **I** and unknown parameters, $\boldsymbol{\theta}$ for intermediate nodes |
| 3 | Identify each root ending to the leaf nodes, $\boldsymbol{B_{ij}}$ <br> *i* is the associate categorial action and *j*, the relative branch to reach lead node |
| 4 | Determine *branch probabilities* using **Eq. 1** |
| 5 | Identify all *i* number of category actions $\boldsymbol{C_i}$ in the lead node <br> for repair, planned maintenance, and unregular check items |
| 6 | Derive *categorial failure function* P(**C**) for all root probabilities using **Eq. 2** |
| 7 | Derive *categorial Likelihood function*; $\boldsymbol{L}(k, n \vert \mathbf{C}, \boldsymbol{\theta}) \sim \prod_1^k \text{multinomial}(k, n, \mathbf{C}, \boldsymbol{\theta})$ |
| 8 | Derive *priors* for each random unknown parameter; **Beta** $(\alpha, \beta)$ |
| 9 | Run MCMC for estimating the *posterior distribution* $P'(\mathbf{C}, \boldsymbol{\theta} \vert k, n, \alpha, \beta) \sim \boldsymbol{L}(k, n \vert \mathbf{C}, \boldsymbol{\theta})$ . **Beta** $(\alpha, \beta)$ |
| 10 | Predict the *hazard rate function* for the performance of the system **H(**trials**)** $\sim P'(\mathbf{C}, \mathbf{n}) / \int P'(\mathbf{C}, \mathbf{n})$ <br> , where the trials are performed per each consecutive operation day |

## *4. Case Study: Unattended Main Engine*

To demonstrate the application of the method, a case study is used involving a reliability assessment of the critical components of the Main Engine (ME). This study considers a MAN B&W K98MC-C7-TII which is a two-stroke diesel engine with an output power of 36 to 84 MW; suitable for most large-size vessels. The structure of event data and prior observations is obtained from the survey analysis conducted by *Colon (2018)*. The system breakdown is designed to ensure retaining the most critical components that impact operations directly. This criterion is suggested by *Colon (2018)* to exclude any parts that can only be repaired or replaced during a major overhaul. Accordingly, by creating a list of the critical machinery and equipment breakdowns, the analysis starts with identifying the frequency indices of crew activities on each item. This is done by processing the data acquired from several expert engineers and presented by *Colon (2018)*. A summary of the observed frequencies is presented in Table 2**.** Three main actions are considered for perceiving the frequency index of expert engineer feedbacks about monitoring the machinery namely irregular *Check*, planned *Maintenance*, and unplanned *Repair*. To be more conservative about the performance of unattended machinery under unexpected disruptions, the frequency observations of both planned maintenance and unplanned repair are considered as the critical failure event. In Table 2, $C_i$, i=1,…,9 are categorized for *doing maintenance or repair actions* while $c_{10}$ is defined as an irregular check of critical items. In general, failure of each component may affect the operation of all other sensitive components in ME; however, from the observations, no event-data were reported. Then the off-diagonal arrays categorial actions matrix are left zero.

Recently, *BV (2019)* and *Colon (2018)* have introduced the Frequency Index (FI) to be used in the risk and reliability assessment of autonomous ships. The index is defined as the occurrence frequency of an event per year per ship. The highest values of FI = 5, 4, and 3 represent events occurring '*multiple times per day*', '*once a day to once a week*' and '*once a week to once a month*', respectively. While the lowest values of FI = 2 and 1 represent '*once every 3 months to once a year*' and '*once every 5 to 10 years*', respectively. The highest value of FI $\geq$ 6 indicates the frequency of required actions (i.e planned or unplanned maintenance and checks) that the component may need to be inspected or repaired more than once per day. More details about the adopted FI ranges and their descriptions are provided in *BV (2019)* and *Colon (2018). BV (2019* uses a 0 to 7 FI scale to interpret the index while *Colon (2018) uses* 0 to 5 scale.

**Table 2:** Frequency index for selected critical components and multiple maintenance actions (based on expert crew).

| | Repair or Maintenance | Check |
|---|---|---|

| | | | $C_{10}$ |
|---|---|---|---|
| Cylinder cover | $C_1$ | 3 | 4 |
| Gear box | $C_2$ | 3 | 3 |
| Stern tube seal cover | $C_3$ | 6 | 5 |
| Piston cylinder | $C_4$ | 3 | 1 |
| Manoeuvring system | $C_5$ | 3 | 4 |
| Clutch | $C_6$ | 4 | 2 |
| Attached pump | $C_7$ | 4 | 3 |
| Driving gears | $C_8$ | 3 | 2 |
| Turning gear and tuning wheel | $C_9$ | 2 | 1 |

**Interpreting the definition of FI**

| **FI ranges** | **Frequency (Per ship per year)** | **Definition** |
|---|---|---|
| FI≥6 | <1000 | Multiple times per day |
| 4-5 | 100 | Once a day to once a week |
| 3-4 | 10 | Once a week to once a month |
| 2-3 | 1 | Once every 3 months to once a year |
| 1-2 | 0.1 | Once every 5 to 10 years |
| 1 | 0.01 | Once in a ship's lifetime |
| 1 | > 0.001 | Once in a fleet's lifetime |

To model the performance of unattended ME, an MPT model is constructed based on all failure-sensitive components that understood by engineer tasks aiming to prevent failures in the system. The necessary activities are divided into two main categories as *repair* or *planned maintenance* (represented by $C_i$) for $i=1,\ldots,9$, or *check* (represented by $C_{10}$). The likelihood of a performance deviating from the normal (safe) condition is calculated using Eq. 1 and Eq. 2. The unknown parameters $\theta$ represents the occurrence probability of each processing branch which will ultimately lead to the occurrence of the event category $C$. As illustrated in the MPT model in Figure 3, the right-hand side of each branch represents critical disruptions while the left side describes non-critical conditions in the operation. According to the descriptions, the category $C_i$ needs major actions due to its critical impact on the operation, while $C_{10}$ category requires urgent inspections of the involved components.

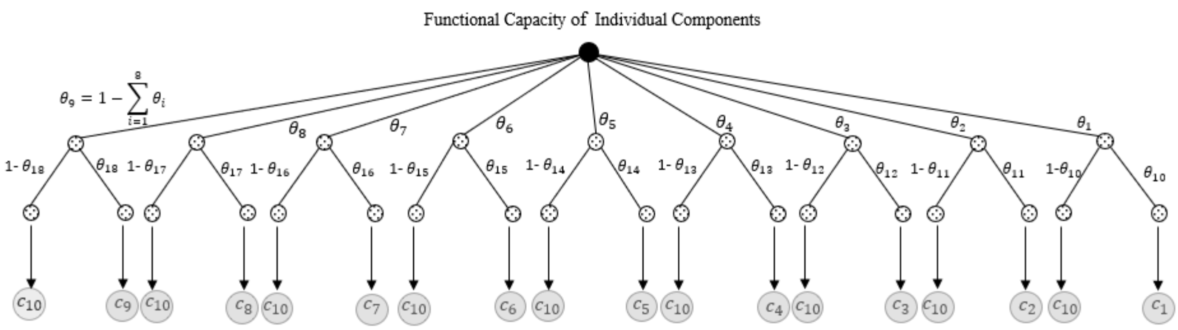


**Figure 3:** Designed MPT model for performance analysis of unattended components listed in Table 2.

The simulations performed for 200 operation days with the assumption that all critical components are in their perfect condition at time zero, and the forthcoming days the performance simulated to evaluate how long the components are enough resilient to survive the critical disruptions in the operation. The MPT model is populated by the frequency data of *repair*, *maintenance*, and *check* that is obtained from expert actions for the manned vessel (colon, 2018). This survey analysis was performed by colon, (2018) to observe the faulty components for the application of unmanned vessels. In the present paper, these event data are adopted to evaluate the extended duration that unattended machinery can continue to operate without any actions by human force is needed. It must be noted that disruption is known to be any condition that the system operation deviates from non-nominal and may need either repair or planned maintenance for recovery, while in the faulty condition the system may need urgent check and the operation will remain in the nominal state. **Figure 4** presents the degradation probability of each failure-sensitive component in the unattended ME due to observing random disruption. It is known that system reliability will be reduced drastically as the major disturbance is spread in any of that critical equipment. It should not that the expected probability of failures predicted over 1000 days of operation. Moreover, the probability of occurrence for the lower line (i.e. normal operation) represents the chance of failure for the critical components without any given conditions, While the upper line (i.e. non-nominal operation) shows the probabilities given that the operation observe major disruption in the system, such as leaking in the stern tube. Therefore, in general the expected probability of failure for the components like stern tube is almost 10 percent while as the major disruption occurs then the probability drastically will increase up to 70 percent, though it is rare. These values are the categorial failure probability that allows assessing of the maintainability of operation for the likelihood to experience entire system failure without human involvement in the operation. For this purpose, the survival function of the main engine is predicted according to the perceived posterior distribution of $P'(\mathbf{C}, \mathbf{n})$. **Figure 5** highlights that the main engine is not reliable enough to be left unattended at least after 100 days of operation as the system will lose 20 percent of its maximum reliability. The upper and lower bound of the survivability of the main engine is also presented with dots to show the extent of uncertainty associated with the estimated reliability of unattended machinery.

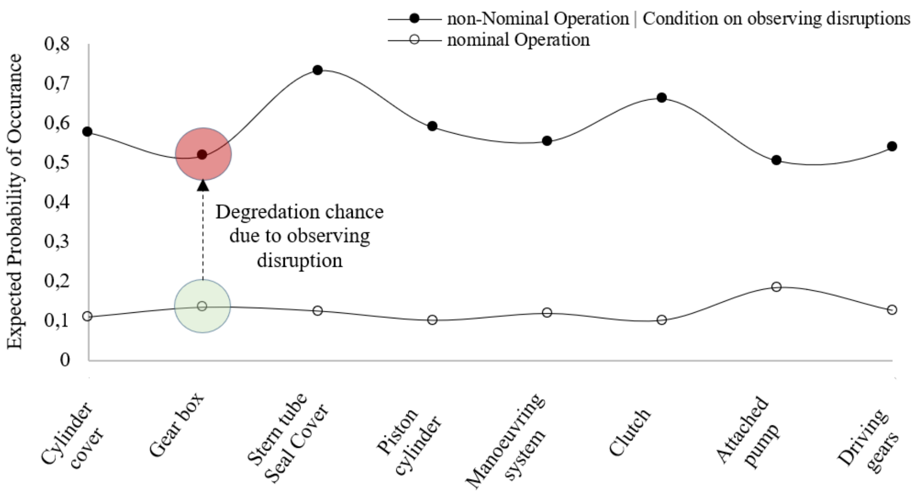


**Figure 4:** Probability of deviation from nominal operation to non-nominal condition due to major disruptions.

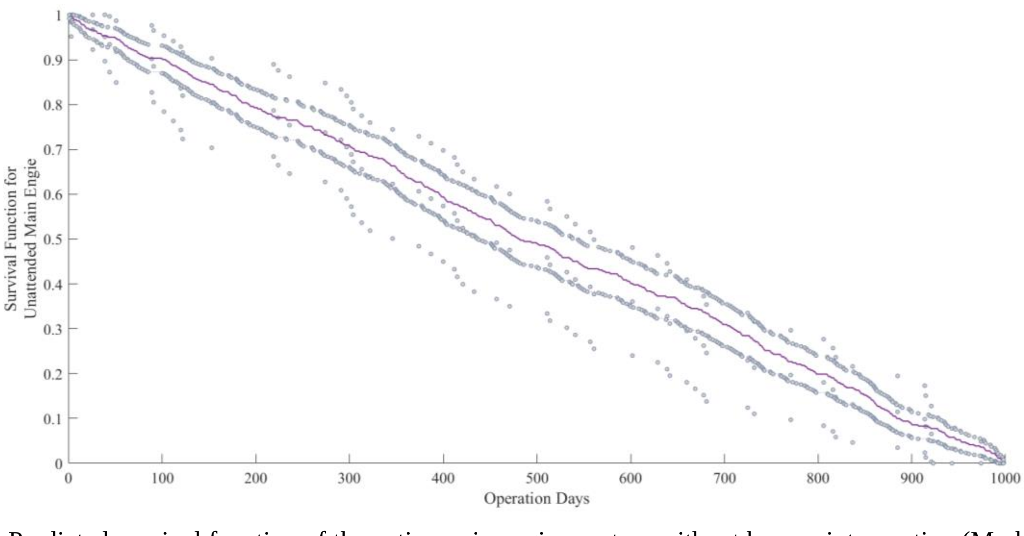


**Figure 5:** Predicted survival function of the entire main engine system without human intervention (Markers in the plots represents for the uncertainty of predicted failure rates in time for different confidence intervals).

It is also necessary to determine the trusted period that the system can be confidently left unattended to operate in with an acceptable level of reliability. For this reason, the hazard rate function of the system obtained for the first

200 days of operation is calculated. The data presented in Figure 6 suggests that system degradation starts to become critical after 216 hours of continuous operation. It is also worth to mention that the system is highly expected to observe at least two major disruptions by approaching its 500 hours of the operation. It can be concluded that the current main engine is reliable enough to be left unattended for 9 days. Figure 6 shows that the system is expected to remain in this state until the 500$^{th}$ operation hour; however, it may be faced with failure or unexpected stops any time after the 10$^{th}$ operation day. The colored circles represent the uncertainty associated with observing the failure rate in the operation.

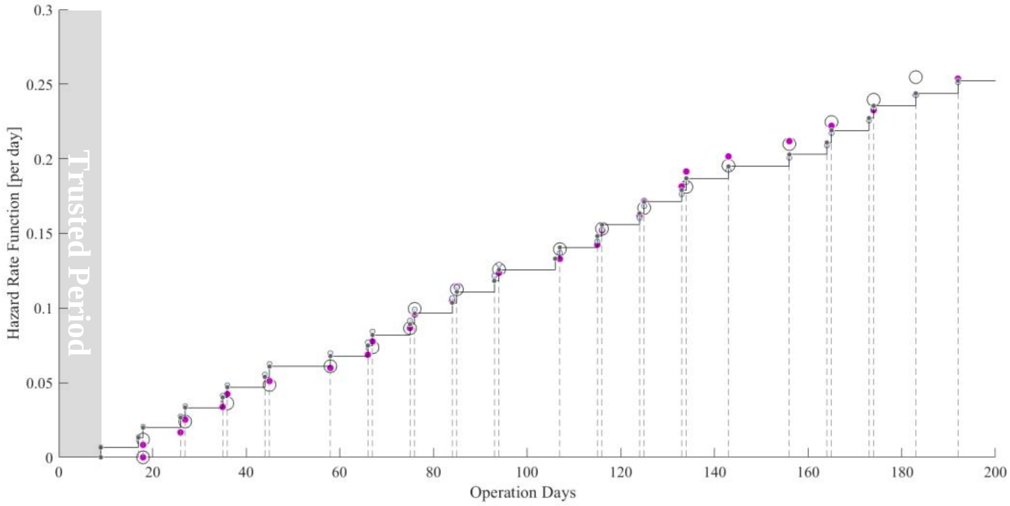


**Figure 6:** Hazard rate of the unattended main engine and the trusted period before human intervention (Markers in the plots represents for the uncertainty of predicted failure rates in time for different confidence intervals).

### *5. Conclusions*

In this paper, a new method is presented for the reliability assessment of unattended machinery in autonomous shipping. A systematic framework is developed for understanding failure events and estimating a trusted period of operation in which the operators and maintenance crew can be removed from vessels. A multinomial process tree is adopted for modelling categorical failures in the system, and Bayesian inference is employed to predict the uncertain parameters involved within the process tree. The event data obtained from the expert engineer actions (Repair, *Maintenance,* and *Check* of the critical components) due to the advantages of providing useful information to the performance evaluation of the system, as well as feedback for identifying and amending the flaws in the design or operation of components. It is realized that for the particular ME examined in the case study, the operation can reliably be continued without human intervention for nine days of continuous operation, while it is prone to have critical disruption within 40 days. The results of this study demonstrate that the proposed method can be significantly helpful for mitigating the risk of failure in autonomous shipping and applying extensions of interval time for maintaining unattended machinery on-board unmanned vessels.

### *Acknowledgments*

The authors would like to appreciate Dr.ir. Robert Hekkenberg from TU Delft for his absolute advising and mentoring on this study from concept, idea, and methodology.

### *References*

Bahootoroody, A.; Abaei, M.M.; Bahootoroody, F.; De Carlo, F.; Abbassi, R.; Khalaj, S. (2019a), *A Condition Monitoring Based Signal Filtering Approach For Dynamic Time Dependent Safety Assessment Of Natural Gas Distribution Process,* Process Safety And Environmental Protection 123, Pp.335-343

Bahootoroody, A.; Abaei, M.M.; Arzaghi, E.; Bahootoroody, F.; De Carlo, F.; Abbassi, R. (2019b), *Multi-Level Optimization Of Maintenance Plan For Natural Gas System Exposed To Deterioration Process,* J. Hazardous Materials 362, Pp.412-423

Batchelder, W.H.; Riefer, D.M. (1999), *Theoretical And Empirical Review Of Multinomial Process Tree Modeling*, Psychonomic Bulletin & Review 6/1, Pp.57-86

Bv (2019), *Guidelines For Autonomous Shipping*, Guidance Note Ni, Vol. 64, Bureau Veritas

Colon. J, (2018), *Identifying And Eliminating Weak Points In Ship's Machinery Plants: A Step Towards Continuously Unmanned Engine Rooms*, Master Thesis, Tu Delft

Heck, D.W.; Arnold, N. R.; Arnold, D. (2018), *Treebugs: An R Package For Hierarchical Multinomial-Processing-Tree Modeling*, Behavior Research Methods 50/1, Pp.264-284

Kelly, D.L.; Smith, C.L. (2009), *Bayesian Inference In Probabilistic Risk Assessment - The Current State Of The Art*, Reliability Engineering & System Safety 94/2, Pp.628-643

Khalaj, S.; Bahootoroody, F.; Abaei, M.M.; Bahootoroody, A.; De Carlo, F.; Abbassi, R. (2020), *A Methodology For Uncertainty Analysis Of Landslides Triggered By An Earthquake*, Computers And Geotechnics 117, P.103262

Knutsen, K.E.; Manno, G.; Vartdal, B.J. (2014), *Beyond Condition Monitoring In The Maritime Industry*, Position Paper, Dnv Gl, Https://Www.Dnvgl.Com/Publications/Beyond-Condition-Monitoring-In-The-Maritime-Industry-12403

Leoni, L.; Bahootoroody, A.; De Carlo, F.; Paltrinieri, N. (2019), *Developing A Risk-Based Maintenance Model For A Natural Gas Regulating And Metering Station Using Bayesian Network,* J. Loss Prevention In The Process Industries 57, Pp.17-24

Rolls-Royce (2017), *Autonomous Ships: The Next Step*, Marine Ship Intelligence

Rødseth. O.J.; Burmeister, H.C. (2012), *Developments Toward The Unmanned Ship*, Int. Symp. Information On Ships (Isis), Vol. 201, Pp.30-31

Spiegelhalter, D.; Thomas, A.; Best, N.; Lunn, D. (2003) "*Winbugs User Manual*," Ed: Version