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The Overview of Risk Analysis Methods and Discussion on Their Applicability for Power System of Autonomous Ships

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ABSTRACT: The aim of system safety, as a sub-discipline of engineering, is to implement scientific, engineering and management knowledge to provide identification, evaluation, prevention, and control of identified hazards throughout the life cycle and within the defined boundaries of operational effectiveness, time, and cost. By utilizing risk analysis, the system safety function can assign expected values to certain hazards and/or failures to determine the likelihood of their occurrence. Autonomous and unmanned shipping are emerging topics, where technologies needed for their successful implementation in global fleet already exists and it is crucial to demonstrate that they are as safe as conventional ships. Through literature it is suggested that by eliminating human error as a cause of 53% of maritime accidents, autonomous and unmanned shipping will increase maritime safety, but it is important to consider that new types of accidents can appear. Considering that autonomous and unmanned ships need to operate with unattended ship machinery for extended time periods and that empirical data is not available, new framework for reliability assessment is needed. The aim of this paper is to provide overview of risk approaches that can be applied for reliability assessment of autonomous and unmanned ship. Within this paper, literature review is performed where reliability methods and their application to autonomous shipping are outlined. Furthermore, Bayesian network is selected as most promising one and further discussed.

1 INTRODUCTION

As a result of continuous development of novel marine systems, in the last 20 years, autonomous and unmanned ships have become subject of intense research in academia and industry. This resulted in numerus research projects and scientific articles. The motivation for introduction of autonomous and unmanned ships lies behind expected benefits, such as improved safety level, increased energy efficiency, reduced operational and lifecycle costs, and environmental footprint [1,2,3,4], however all these claims need to be justified. Despite intense research, the introduction of autonomous and unmanned ships is associated with several challenges. One of main challenges is related to the design of safe autonomous ships. Taking into account that, at time being, there is no detailed regulatory framework for autonomous and unmanned ship, conventional maritime safety approaches and tools cannot be used. New approaches such as probabilistic risk assessment [5], are required for carrying out the safety assessment of next generation autonomous ships [6]. This is connected to a set of other challenges, such as the lack of standardised assessment methodology, acceptable risk levels, statistical data, hazardous events and scenarios and so on [7,8,9].

In reality, the introduction of autonomous ships in the maritime transport would result in disruptive changes in all layers of maritime industry. The novel systems required for successful operation of autonomous ships are highly complex, software-intensive and are composed of not only hardware components but also numerous sensors and communication devices. Although some studies have claimed that autonomous and unmanned ships can increase maritime transportation safety [10], the safety of autonomous systems has to be verified in detail. Although there are some prototypes thar are tested in controlled environment, autonomous ships are not yet commercially applied. It is important that the minimum requirement for an autonomous vessel is for it to be at least as safe as conventional manned ships [11], presenting an initial high-level demand. Therefor, all potential risks, hazards and disruptive events need to be comprehended and evaluated.

Survey conducted by van Cappelle et al. [12] analysed technology readiness for remote, unmanned, and autonomous operations. Results indicate that technology is mature enough and the next step is to successfully implement it on ships to increase autonomy and reduce crew. Costs savings and changes in the design of the unmanned autonomous bulk carrier are outlined by Kretschmann et al. [13]. Besides crew savings, improved energy efficiency, safety and hull optimization are expected. Jovanović et al. [14] simultaneously investigated the applicability of autonomous shipping and alternative power options for the Croatian ferry fleet. Both economical and environmental benefits are outlined, with the electricity-powered autonomous ship being most attractive from both points of view. Peeters et al. [15] provided a solution for road-based freight transport in Europe by employing unmanned inland cargo vessels. Guidelines are also given for design, control, and interaction with other vessels and the environment [15].

Thieme et al. [16] reviewed 64 risk models published since 2005 to investigate the applicability of modelling approaches for autonomous ships. The analysis results indicated that most models use historical or published data, and a combination of these to obtain the input for risk approaches.

One of the driving forces behind the development of autonomous and unmanned ships is that they are expected to decrease maritime accidents related to human error. However, it should be noted that autonomy will bring out new types of accidents related to the implementation of advanced technologies, transitions between automatic and manual control, situation awareness, etc [10]. Rødseth and Tjora [17] presented system architecture for an unmanned merchant ship, developed within Maritime Unmanned Navigation through Intelligence in Networks (MUNIN) project. For MUNIN autonomy is constrained and Shore Control Center (SCC) is crucial for successful operation. Unmanned ship systems are classified into 10 functional groups and Hazard Identification (HazId) method is suggested to assess the risks [17]. Rødseth and Burmeister [3] performed HazId for an unmanned merchant ship and identified 65 main hazards of which several were classified as unacceptable (interaction with other ships; error in detection of small objects; propulsion system breakdown; heavy weather manoeuvring; collision in low visibility). Fault Tree Analysis (FTA) and Event Tree Analysis (ETA) are employed to assess hazards for unmanned underwater vehicles, with a focus on human and organisation factors [18]. The results indicate that the risk in autonomous underwater vehicle operation can be reduced by applying the risk management framework. A risk model for autonomous marine systems utilizing the Bayesian belief network to assess the human–autonomy collaboration performance, was developed by Thieme and Utne [19], outlining that the reliability of autonomous functions and situational awareness have the highest probability of malfunction. Starting with the cause root of a potential accident, Wróbel et al. [20], established a three-level safety model. Beginning with an accident event, to which unmanned vessels are susceptible, accidents are divided into navigation, engineering, stability and other related. Both manned and unmanned systems with different autonomy levels are considered by [21]. Emphasis is on safety assessment that includes the whole lifecycle of an unmanned ship, suggesting that uncertainties and knowledge gaps should be taken into account rather than probability. Also, online risk model, developed as part of the unmanned ship, should provide improved performance during the testing and verification phase. Five categories (unsafe acts, preconditions, unsafe supervision, organisational influences, and external factors) of the accident causes are applied in research conducted by [4] to assess the potential impact of unmanned vessels on maritime transportation safety, outlining the benefits and drawbacks that unmanned vessels have regarding maritime transportation safety. The System-Theoretic Process Analysis (STPA) framework is used to create a preliminary risk assessment of remotely-controlled merchant vessels to provide design recommendations [22]. 55 risk influencing factors, categorised into four categories (human, technology, environment, ship), that can affect navigational safety of autonomy level 3 MASS are defined by [23]. Taking into account the lack of knowledge and experience, complexity and limited ability for verification of autonomous systems, [24] presented an online risk model. The online risk model is developed by combining STPA and BBN. By integrating an online risk model and ship control systems, Johansen and Utne [25] demonstrated that improvements can be achieved for both safety and costs. Yang and Utne [26] showed that a combination of different risk analysis methods can contribute to the improvement of an online risk model. Table 1 provides an overview of risk analysis methods used for the safety assessment of autonomous and unmanned ships.

2 BAYESIAN NETWORK

Belief networks (also called Bayes' networks or Bayesian belief networks) are a way to depict the independence assumptions made in a distribution. Their application domain is widespread, ranging from troubleshooting and expert reasoning under uncertainty to machine learning. Bayesian Network (BN) is a graphical structure for representing probabilistic relationships among a large number of variables and making probabilistic inferences using those variables. A BN is a DAG with the nodes representing the variables and arcs representing their conditional dependencies [27]. One of the main advantages of BN is that they allow interface based on observed evidence. For the random variable X_1 and X_2 Bayes rule states [27]:

Table 1. Overview of risk analysis methods and their applications.

Risk method	Literature	Type of problem
Bayesian Network (BN)	Wróbel et al. (2016) [20]	General overview of relationships between safety features of unmanned vessels.
	Thieme and Utne (2017) [19]	Human-autonomy collaboration assessment.
	Utne et al. (2020) [24]	Online risk modelling for autonomous ships.
	Johansen and Utne (2022) [25]	Supervisory risk control of autonomous surface ships.
Event Tree Analysis (ETA)	Thieme et al. (2015) [18]	Risk management framework (RMF) for unmanned underwater vehicles (UUV).
	Wróbel et al. (2016) [20]	General overview of relationships between safety features of unmanned vessels.
Fault Tree Analysis (FTA)	Thieme et al. (2015) [18]	Risk management framework (RMF) for unmanned underwater vehicles (UUV).
Hazard Identification (HazId)	Rødseth and Tjora (2014) [17]	Information and Communication Technologies (ICT) architecture for an unmanned ship.
	Rødseth and Burmeister (2015) [3]	Risk Assessment for an Unmanned Merchant Ship.
	Johansen and Utne (2022) [25]	Supervisory risk control of autonomous surface ships.
Preliminary Hazard Analysis (PHA)	Yang and Utne (2022) [26]	An online risk model for autonomous marine systems.
Procedural Hazard and Operability Analysis (HAZOP)	Yang and Utne (2022) [26]	An online risk model for autonomous marine systems.
Risk management	Thieme et al. (2015) [18]	Risk management framework (RMF) for unmanned underwater vehicles (UUV).
System-Theoretic Process Analysis (STPA)	Wróbel et al. (2018) [22]	Safety of remotely-controlled merchant vessel.
	Utne et al. (2020) [24]	Online risk modelling for autonomous ships.
	Johansen and Utne (2022) [25]	Supervisory risk control of autonomous surface ships.
	Yang and Utne (2022) [26]	An online risk model for autonomous marine systems.
What if	Wróbel et al. (2017) [4]	Potential impact of unmanned vessels on maritime transportation safety.

$$P(X_1|X_2) = \frac{P(X_2|X_1)P(X_1)}{\sum_{all\ i} P(X_2|\ X_1 = x_i)\ P(X_1 = x_i)} \quad (1)$$

The BN qualitative analysis determines the relationships among the nodes, while the quantitative analysis might be performed in two ways: a predictive analysis or a diagnostic analysis. The predictive analysis calculates the probability of any node based on parent nodes and conditional dependencies, while the diagnostic analysis calculates the probability of any set of variables given some evidence. The nodes and arcs are the qualitative components of the networks and provide a set of conditional independence assumptions that can be represented through a graph notion called d-separation, where each arc built from variable X to Y is directly dependent, that is, a cause-effect relationship [28].

If the variables are discrete, then the probabilistic relationship of each node X with its respective parents pa(X) is defined using a conditional probability table (CPT). For continuous variables, the conditional probability distribution (CPD), which represents conditional probability density functions, defines this probabilistic relationship, and the quantitative analysis is based on a conditional independence assumption. Considering three random variables X, Y, and Z, X is conditionally independent of Y given Z if P(X,Y|Z) = P(X|Z)P(Y|Z) [28]. The joint probability distribution of a set of variables, based on their conditional independence, can be factorized as shown in Equation (1):

$$P(x_1, x_2, \ldots, x_n) = \prod_{i=1}^{n} P(x_i | Parent(x_i)) \quad (2)$$

The graphical representation is the bridging of the gap between (high-level) conditional independence statements encoded in the model and (low-level) constraints, which enforce the CPD. Given some evidence, the beliefs are recalculated to indicate their impact on the network. The possibility of using evidence from the system to reassess the probabilities of network events is another important feature of BNs, which is useful to determine critical points in the system. Classical methods of inference of a BN for this purpose involve the computation of the posterior marginal probability distribution of each component, the posterior joint probability distribution of subsets of components, and the posterior joint probability distribution of the set of all nodes.

3 DISCUSSION

In this subsection three relevant articles, [1], [29], [30], are selected for further discussion of applicability of BN for reliability assessment of autonomous ships. In all three articles focus is on ship machinery system, Figure 1.

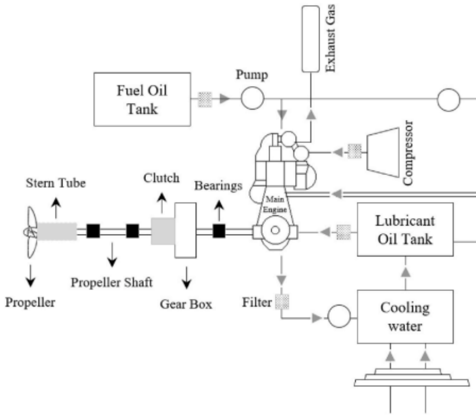

Figure 1. A schematic arrangement of the machinery plant [1], [30].

Abaei et al. [1] proposed and verified methodology to predict failure probabilities in the system that will lead to breakdown of unattended machinery plant. The framework consists of four steps:

1. Identifying failure sensitive components (selecting sensitive components according to severity and risk index, determining type of human activities, and observing data for critical and non-critical failures),
2. Multinominal process tree (constructing branch trees, defining probability function, and developing categorical failure function)
3. Hierarchical Bayesian interface (constructing Bayesian network, setting non-informative prior function for unknown parameters, deriving likelihood function, running MCMC for predicting marginalized posteriori function),
4. Monte Carlo simulations (estimating number of critical and non-critical failures in consecutive intervals).

Abaei et al. [29] updated previous framework and also considered redundancy of autonomous machinery to gain resilience. This study results show that with adding redundancy significant advantages can be achieved regarding costly unplanned interruptions and repairs. BahooToroody et al. [30] employed BN to estimate the trusted operational time of the ship machinery system through four different autonomy degrees (conventional ship, remotely controlled ship with crew onboard, remotely controlled ship, and fully autonomous ship). A two-parameter Weibull distribution is generated to model the trusted time. MCMC simulation through Bayesian inference was adopted to formulate an appropriate likelihood function for obtaining the joint posterior distribution of hyper-parameters.

4 CONCLUSIONS

The modelling power of traditional risk analysis such as fault tree and event tree analysis are clearly surpassed by BN. Both fault trees and event trees can easily be converted to a Bayesian network.

The main advantages of BN, with respect to risk analysis, are summarized as follows:

– They can represent uncertain knowledge which is necessary for novel systems whit no documented failure history,
– They enable modelling of continuous variables,
– They offer possibility of insertion of evidence for system reassessment and updating,
– They provide combination of qualitative and quantitative variables,
– They offer identification of relevant and irrelevant information.

Taking into account that with higher degree of autonomy, complexity of marine systems will increase, employment of BN in risk analysis has immense potential. BN enable quicker and more intuitive modelling. BN has been successfully applied for risk assessment of autonomous ships, providing useful tool to model uncertainty and overcome data scarcity.

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