Dynamic Risk Analysis of Maritime Autonomous Surface Ships

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Abstract: The objective of this study is to analyse the risk related to power management of maritime autonomous surface ship (MASS) operations. MASS may operate independently of human operators, making technical components such as sensors essential to maintain the situation awareness (SA) and to enable missions. MASS may utilize different types of technologies in operation, including green energy sources for propulsion and to power on-board systems. For MASS, balancing power generation, distribution, and consumption between the different components of the vessel may be critical, because of the total dependence on a stable power supply. Power management may be performed by the control system itself or by human operators and is important to ensure safe operation. MASS will be subjected to dynamic factors, including environmental factors, and changing requirements to the technical system according to the operational specifications. Therefore, a framework for using a Bayesian approach to model the risks related to the generation and use of energy on board MASS is presented, with a focus on energy consumption and SA, and the effect on mission performance. The method is applied to an unmanned surface vessel (USV). The results of the analysis show that risk changes with time, and that the prioritization between maintaining a sufficient SA and preserving energy is important for ensuring safe operations of MASS. The resulting risk model may be used to support human operators during planning and performance of operations, as it indicates when risks are higher, and resources should be allocated to mitigate the consequences.

1. INTRODUCTION

MASS are currently under development. However, no highly autonomous ship has yet been put into commercial operation [1]. MASS may be used for transportation of people or goods, and performance of scientific missions, etc. Before MASS can be put into operation, safety must be ensured, and risk analysis of MASS is therefore required. Ships may in the future use different types of advanced technological solutions, such as supervisory risk control and intelligent power management [2], green energy sources to power propulsion and on-board electrical systems [3], and sensors and cameras for ocean surveillance and navigation [4]. Characteristics of the operational environment for ships include rapidly changing conditions relating to the system, its environment, and planned operations. Advanced technical systems, such as MASS, degrade with time. The requirements for MASS operations are thus dependent on many factors and can change with time and circumstances. The presence of dynamic, time-dependent factors in the operation of MASS, introduces the need for dynamic risk analysis (DRA).

For MASS, sensors, actuators, and computers, gradually take over the tasks previously performed by the crew [5]. One of these tasks is developing an understanding of the surroundings of the system, namely the situation awareness (SA) [6]. The implementation of autonomous functionalities in ships can have many advantages. However, it also makes the realization of necessary functions onboard the vessel, such as maintaining an adequate level of SA, more dependent on technical components and a stable power supply. Maintaining an adequate level of SA is important for reducing risks, because it contributes to better decision-making by the control system. Improved SA may be achieved with more sensors and higher sampling frequency, but this requires more power.

Risks related to MASS have been investigated in recent years. Some works have focused on the impact of MASS on the maritime safety. [7] analysed accident investigation reports for conventional vessel accidents to investigate the effect of introduction of MASS. It was concluded that MASS could contribute to reduce the frequency of accidents, but that the consequences might be more severe. In general, many questions relating to MASS safety remain unanswered.

Risk assessment consists of three steps: identifying, analysing, and evaluating risks [8]. DRA can be defined as "a method that updates estimated risk of a deteriorating process according to the performance of the control system, safety barriers, inspection and maintenance activities, the human factors and procedures" [9]. The risk estimate in DRA is updated frequently in comparison to static risk analysis, where update intervals may be several years [10]. A key difference between conventional risk assessment and DRA is that the latter includes updating the risk estimates with new information.

Static risk analysis methods have been developed to support design of safe maritime autonomous systems, and for planning of autonomous missions [11] [12] [13]. Risk influencing factors (RIFs) for MASS have been investigated [14] [5]. DRA has been applied to several aspects of the maritime industry. [15] presents a dynamic Bayesian belief network (DBN) model for the risk of ship-ice collisions for conventional ships. The model considers primarily environmental factors, such as properties of the ice, and weather states. [16] used DBN to evaluate the risks related to autonomous underwater vehicles operations in the Arctic, with a focus on the effect of changing environmental conditions on the operational risks. [2] presented a framework for developing a risk model for use in MASS control systems. A Bayesian network (BN) was constructed based on results from System-theoretic process analysis (STPA), and the model was meant to be updated with new evidence during operation of the vessel. Building on this methodology, [17] demonstrated how risk information from a BN can be integrated in a MASS control system.

The primary focus in current risk analysis of MASS is often navigational risk, while less focus has been directed towards the energy production on board the vessels. [18] investigated the reliability of unmanned engine rooms using multinomial process tree and hierarchical Bayesian inference, focusing on combustion engine power plants. [19] performed an assessment of the probability of power blackout of cruise ships using fault trees in combination with simulation.

From the reviewed literature and the safety challenges of MASS, DRA may be an important tool for reducing risks related to MASS operations. Safe and efficient operation of MASS requires an adequate level of SA, and sufficient energy supply for on-board systems. However, SA for highly autonomous vessels depend on sufficient power available. Reduced energy consumption on the vessel may be a measure for reducing risk, as it can prevent a complete loss of power. From the reviewed literature, it can be said that the relationship between power management and SA, and its effect on risk for MASS, has not been a focus area so far. This paper therefore seeks to investigate this challenge. DBN is identified as a suitable tool for modelling risks related to MASS operations, because it has been used for similar applications [15] [16], and because it incorporates time-dependent factors. The use of the method can enable an investigation of the relationship between power management and SA for MASS, and its effect on mission performance.

The objective of this paper is to develop a method for performing DRA of MASS using DBN, with a focus on the effect of inadequate SA and loss of power on the mission performance. Balancing energy generation and consumption can have a large influence on the risks related to MASS operations. The purpose of analysing this risk is to support safe and efficient operation of MASS. The AutoNaut, a USV, is used as a case study for the proposed methodology.

The paper is structured as follows: Section 2 contains a description of the method used in this study. Section 3 presents a case study, section 4 the results of the study and section 5, the conclusion.

2. METHOD

2.1 BN and DBN for Risk Analysis

A BN can be described as an acyclic direct graph, meant for demonstrating the conditional dependencies of a set of random variables [20]. In this graphical representation, the random variables are represented by nodes, and the causal relations between the variables are shown by drawing arcs between the nodes. Conditional probability tables (CPTs) are made for each node based on the causal relationship between parent and child nodes. DBN is defined as a type of BN that considers the development of the system over a defined number of time steps [20]. A BN is acyclic, but dynamic systems can be represented by unrolling the dynamic model for a number of time steps, and solving the model as a static problem. The model is the same for every time slice, but nodes are connected by temporal links between time slices. In DBNs, nodes may depend on their parent nodes in the current, and previous, time steps. This makes it possible to analyse the effect of new evidence on risk, and the development of variables with time.

2.2 Proposed Methodology

In the proposed methodology for performing DRA of MASS, a BN will first be used for modelling the relevant risk aspects, while the dynamic functionality of the DBN will be used to incorporate time-dependent factors. The proposed methodology is based on the approach presented in [11], because it was developed for risk analysis of autonomous marine systems. However, adaptions have been made to MASS and power management, and the related dynamic factors. The steps of the method are listed below, and a detailed description is given in the remaining part of this section.

1. Describe the aim and context of the DBN
2. Collect and group information
    a. Determine the type of MASS
    b. Determine type of operation
    c. Determine relevant environmental factors for type of MASS and operation
3. Connect nodes and arcs
4. Identify time-dependent nodes and arcs
5. Develop CPTs and quantify
6. Validate the risk model

Step 1 Describe the aim and context of the DBN: The aim of the risk model is important for the identification of relevant risk factors and for the development of the model. The end node of the BN is determined based on the goal of the analysis. As the focus of the analysis is on the influence of SA and a potential loss of power on the performance of the mission, the end node is defined as Mission failure. The exact relation between mission performance and the other nodes in the network will be dependent on the nature of the mission, defined further in the description of step 3 of the framework.

Step 2 Collect and group information: The information collection is closely related to the defined aim and context of the BN. Because the focus is on power management and mission performance, certain factors and sub-systems will not be considered. Factors such as human-autonomy collaboration or structural integrity, are not included because they are not of primary importance for the analysis. The collected information may be categorized as either relating to the system, operation, or environment.

Determining the type of system is important for including the correct information in the BN. Different types of MASS exist, and consequently, it is essential to define some key characteristics of the vessel type. As the focus of the method is the prioritization of energy and SA, factors relating to generation, storage, distribution of power, and maintaining the SA will be of particular importance.

The level of autonomy (LOA) of the system may influence the risk level during operation. The LOA may be defined as "a set of metrics that describe the detailed aspects of an autonomous system and operation, including operator dependency, communication structure, human-machine interface (HMI), a dynamic or online risk management system, intelligence, planning functionalities, and mission complexity" [5]. The LOA says something about the responsibilities of the autonomous system, and therefore also about the importance of sufficient power supply to sensors, actuators, and controllers. Four levels are defined by [5], from LOA 1 meaning automatic operation, to LOA 4, meaning highly autonomous operation. A MASS may operate dependently or independently of human operators, and the operators may be situated on shore or on the vessel [21]. If the SA depends on communication with operators on shore, then the distribution of power must be adapted to this operational mode.

The source of energy used for the MASS is important for the risks related to operation. Several different energy sources may be used for powering propulsion and onboard systems, such as combustion engines, batteries, solar power, wind power, wave power, and fuel cells [3]. The different sources may be used separately, or they can be used in combination, in so-called hybrid formats.

The type of operation will have an impact on the analysis, as different operations have different objectives that must be prioritized. Four complexity characteristics of operations of autonomous marine systems may be defined [5]. The characteristics are related to risk management of the systems, and include sub-tasks (path planning, navigation, manipulating), organization, collaboration, communication, SA, and duration of mission. The first point refers to the requirements to the system with respect to the tasks necessary for performing the operation. For MASS, the operations are commonly related to navigation. However, for some vessels, other tasks are essential for performing the mission, such as gathering data or preserving cargo. This also requires power. Requirements to communication and collaboration can be dependent on the mission specifications, and on the LOA.

The SA is important for safe and efficient operation of MASS. According to [6], several definitions of SA exist in relation to safety. However, they are all related to the level of which a human or system is aware of its surroundings. The realization of the SA depends on different components on the vessel, the crew on the vessel, or communication with an operator on shore, depending on the LOA. For higher LOA, the SA capabilities are transferred from the human operator to the system [5]. This implies that for a highly autonomous vessel, the SA is dependent on the functionality of technical components.

Table 1: Vessel power source and relevant environmental factors influencing generation of power, based on [3] and [22].

	Temper-ature	**Sun exposure**	**Wave height**	**Wind direction**	**Wind speed**	**Currents**	**Distance to refuel**
Combustion							X
Battery	X						X
Solar energy	X	X					
Wave energy			X	X		X	
Wind				X	X		
Fuel cells							X

Depending on the type of power system used on a MASS, certain environmental factors can influence the ability of the MASS to produce power [3]. Consumption of power is related to two main aspects of the MASS operation, namely propulsion and utility systems. The propulsion system is essential for moving the vessel in the desired direction and performing the intended mission. The SA of the vessel is handled by various parts of electric system, such as sensors and controllers. An overview of the environmental factors that must be considered related to generation of power for the different power sources of the vessel is shown in Table 1.

In addition to the environmental factors that influence the probability of running out of power for the vessel, there are several factors relating to the environment that influence the ability to navigate and avoid collision. Relevant factors to consider and include in a BN for analysing the risk related to mission performance for MASS, with a focus on the trade-offs between adequate SA and power consumption, are summarised in Table 2. Depending on the system, environment, and operation, different nodes may be relevant for different analysis.

Step 3 Connect nodes and arcs: The BN can be constructed in accordance with the approach outlined by [23]. It is suggested that the structure must be built so that factors that are dependent, are connected with arcs. This will be influenced by the characteristics of the MASS and the type of operation. Connecting arcs with nodes correctly is important for the accuracy of the results produced by the model.

Table 2: Relevant nodes for DRA for MASS with focus on power management and SA.

Category	**Node**	**Description**	**References**
Target node	Loss of mission	End node	
System	Available power	State of power level based on the consumption of power balanced against the power production	[13]
	SA	Overview and understanding of the vessel surroundings, either for the vessel itself or for the operator	[5]
	LOA	The LOA of the vessel, defined in four levels	[5]
	Energy consumption	The level of energy consumed by the components on the vessel	
	Energy generation	The level of energy generated on the vessel	[12]
Operation	Sub-tasks	Relevant tasks that have to be performed according to the mission specifications (navigate, collect data, or other specifications)	[5]
	Organization, collaboration, and communication	Requirements to communication for performing the mission (dependent on mission specifications, type of vessel, and LOA)	[5] [14]
	Propulsion and steering	The state of the propulsion and steering system	[12]
	Duration of mission	The time the mission of the vessel lasts	[5]
Environment	Temperature	The temperature in the surroundings of the vessel	[3]
	Wave height	The wave height in the surroundings of the vessel	[24]
	Sun exposure	The sun exposure in the area of operation	[3]
	Wind speed/direction	The wind speed in the area of operation	[3]
	Current strength/direction	The strength and speed of the currents in the area of operation	[3]
	Distance to refuel	The distance to a location where fuel is available	
	Obstacle density	The density of objects that the vessel can collide or allide with, and the closeness of areas where stranding is a possibility	[13] [14]
	Communication coverage	The coverage of communication channels necessary for communication between the vessel and the human operators on shore	[24] [14]

Step 4 Identify time-dependent nodes and dynamic arcs: The risks related to MASS operations are affected by dynamic properties. These properties can be related to the vessel, such as degradation of equipment, it can be related to the environment, with changing weather conditions, and it can be related to the operation, through the different requirements it will place on the system performance. Dynamic nodes in a BN are nodes that change with time [25]. By investigating the effect of time on the nodes, dynamic nodes can be defined. The temporal order must also be defined. This means the time before a node influences another node. In this way, nodes that affect another node multiple time steps from now can be modelled, as well as nodes that give some effect already in the next time step [25]. The time step in the analysis must also be defined and the BN model is transformed into a DBN.

Step 5 Develop CPTs and quantify: The CPTs are determined according to the theory presented in section 2.1 and 2.2. Defining the tables can be a very resource demanding process, depending on the size of the network [23]. Several methods for determining these exist, including data-driven methods and expert opinion reliant methods [20]. Quantification of prior probabilities can be done based on literature, statistics, or expert opinion.

Step 6 Validate the risk model: Validating a model means to check if the developed model represents the real system it was meant to describe [26]. Sensitivity analysis can be used to analyse the validity of the quantitative values used in the network [25]. Sensitivity analysis is used to investigate the influence of changes in parameters or evidence in the network, on the decision. It may be used to evaluate the predictive validity of the model, by comparing results of the sensitivity analysis with other models [26].

3. CASE STUDY

A case study is used to illustrate the application of the proposed methodology. The system and operation under analysis will be described, and the results from each step in the method will be presented. The descriptions given of the system and the mission are based on the information given in [24] and [22].

3.1 System and Operation Description

An USV, namely the AutoNaut, is used as a case study [27]. The vessel is owned and operated by NTNU and has been used for several missions. The vessel is solar-powered and wave-propelled and runs solely on renewable energy. The main system specifications are given in Table 3. Under normal operation, the vessel is operating autonomously, but is supervised by human operators on shore. The vessel control system has three main modules; one for handling advanced navigation and collision avoidance (M1), one for health monitoring of the system and power management and contains the fallback autopilot (M2), and a third module for collecting and storing scientific data (M3).

Table 3: Case study system description.

System aspect	Description	System aspect	Description
Type of vessel	USV	Length	5 m
Source of power for on-board system	Solar power (PV panels)	Source of power for propulsion	Wave power (wave foils)
Weight	360 kg (with payload)	Max speed	2 knots

The power for all onboard electric equipment is generated from solar power, through three photovoltaic (PV) panels on the vessel. The energy is stored in four batteries. A power management system (PMS) is responsible for shutting down the modules that are not safety-critical if there is not enough power. M3 is considered to be the least safety critical, followed by M1. The forward propulsion of the vessel is ensured using wave foils. These do not require any electric power but are dependent on sufficient waves to generate movements of the vessel. For steering, the vessel has a rudder. The vessel is also equipped with a small propeller for use in emergencies, for example, in flat sea.

The USV was used for a 19-day mission in Frohavet in the coast of Norway in March and April 2021. The mission consisted of operating in a defined area and collecting specified data. The exposure to sun was limited, and communication coverage was adequate. Low battery levels, in combination with high waves and hight wind speed caused the vessel to ground after having lost communication connection to the operator. Data could only be collected at a limited rate, as the use of M3 required too much power. Data from the missions show that power generation is limited due to bad weather, and cyclic depending on the time of the day and exposure to solar radiation.

3.3 DRA of AutoNaut

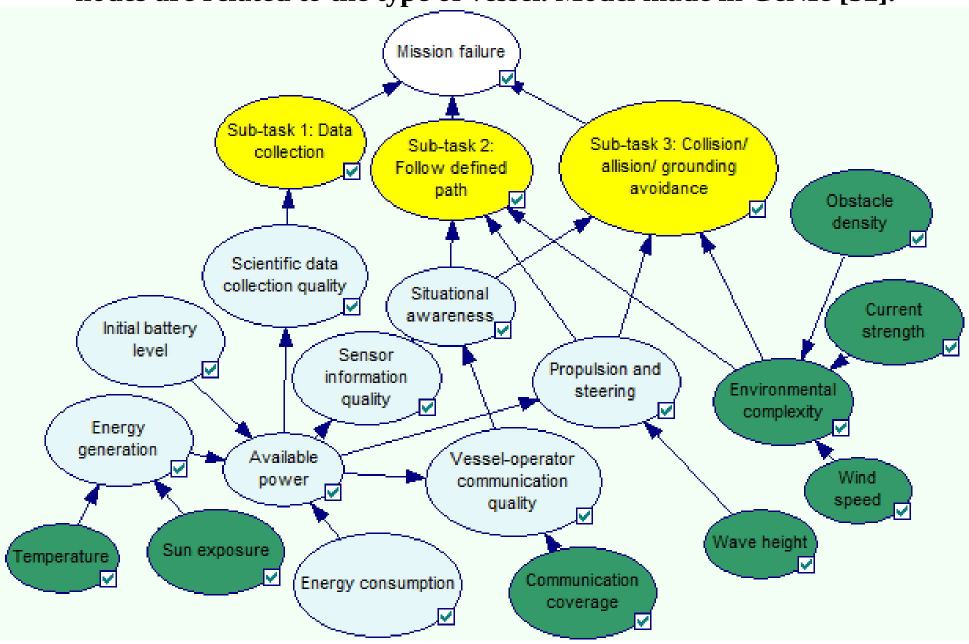
The aim and context for the risk analysis determines the end node and the directly connected parent nodes in the BN. The focus of the analysis is on the performance of the mission of the vessel, and the influence of SA and power management. Based on the information about the vessel, the mission, and the operating environment, the input nodes and related states described in Table 4 were identified. The SA of the vessel is realised by information collecting through sensors, and reasoning performed by the system itself and the operator. The relevant influences from the environment on the power generation were identified to be sun exposure, wave height, and temperature. The mission consists of navigating in a defined area and collecting defined data. Both activities consume power and are necessary for performing the mission, and hence, they are included in the model.

The states of the end node “Mission failure” are defined as either failure or no failure. The first state, mission failure, refers to a situation where it is not possible to perform the defined mission within the defined operational specifications, without manual intervention. The end node is directly related to the performance of the operation, described by the performance of defined sub-tasks. The different sub-tasks can have different influence on the end node.

Table 4: Description of the nodes, states, and probabilities for the case study DBN.

Node	Type	States	Input prob.	References
Wind speed	Input	High, medium, low	0.2/0.7/0.1	[28]
Sun exposure	Input	High, medium, low	0.2/0.6/0.2	[28]
Obstacle density	Input	High, medium, low	0.4/0.3/0.3	[29]
Communication coverage	Input	Sufficient/Insufficient	0.7/0.3	[30]
Temperature	Input	High, medium, low	0.2/0.8/0	[28]
Wave height	Input	High, medium, low	0.1/0.8/0.1	[31]
Current strength	Input	High, medium, low	0.3/0.4/0.1	Assumption
Initial battery level	Input	Fully charged, empty	0.9/0.1	Assumption
Energy consumption	Input	High, medium, low	0/0/1	Assumption
Energy generation	Intermediate	High, medium, low	-	-
Available power	Intermediate	High, medium, low	-	-
Energy consumption	Intermediate	High, medium, low	-	-
Scientific data collection quality	Intermediate	Sufficient, insufficient	-	-
Situation awareness	Intermediate	High, medium, low	-	-
Vessel-operator communication	Intermediate	Sufficient, insufficient	-	-
Environmental complexity	Intermediate	High, medium, low	-	-
Propulsion and steering	Intermediate	Electric, wave propelled, none	-	-
Sub-task 1: Data collection	Intermediate	Sufficient, insufficient	-	-
Sub-task 2: Follow defined path	Intermediate	Sufficient, insufficient	-	-
Sub-task 3: Collision/allision/grounding avoidance	Intermediate	Sufficient, insufficient	-	-
Mission failure	End node	Failure, no failure	-	-

Figure 1: A BN model for the influence of SA and loss of power on mission performance. Green nodes represent environmental factors, yellow nodes represent operational factors, and blue nodes are related to the type of vessel. Model made in GeNIe [32].

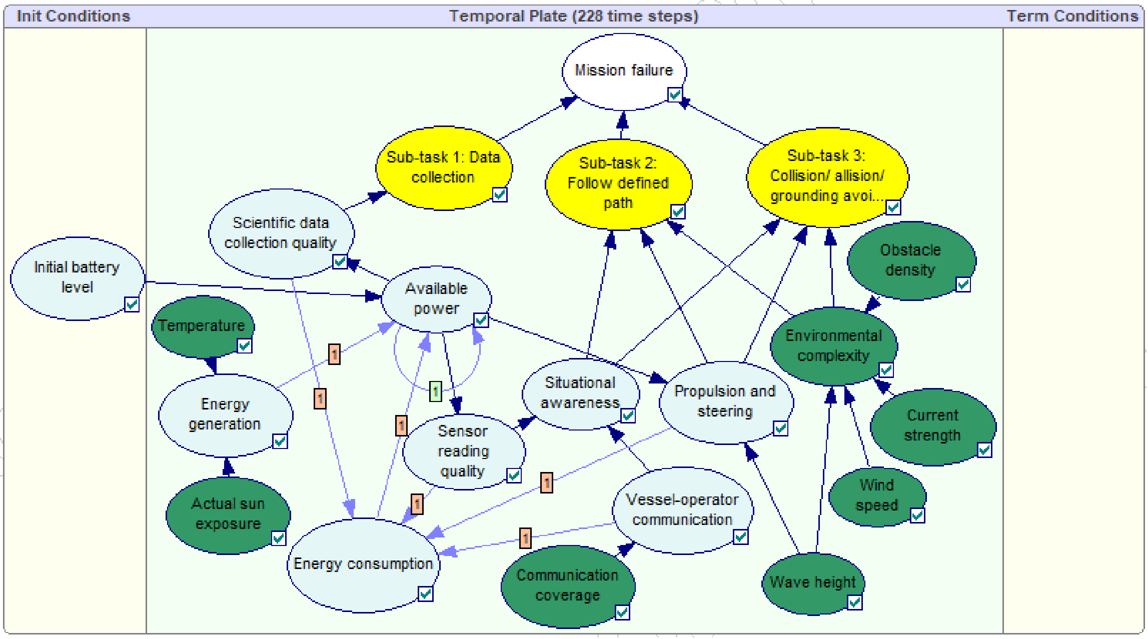


After evaluating dependencies between variables, a BN was constructed, see Figure 1. This is a static network, describing how the different variables influence the end node. The probability of mission failure for the AutoNaut, depends on several time-dependent factors. These functionalities need to be incorporated to model the risks in the system, see Figure 2.

The time step in this model is 2 hours, because the missions of this vessel are typically supervised by an onshore operator every 2 hours [22]. The mission used for reference in the case study lasted 19 days. However, the vessel was retrieved from the ocean and re-charged several times during the mission. Thus, only the final days of the mission were included, corresponding to 120 time steps.

The generation of power is a factor that depends on the sun exposure during operation. The available power is therefore a node connected with temporal arcs between energy generation and consumption. The initial power level for the batteries is added as an initial condition, affecting the system in the first time step only. It was assumed that if the battery was fully charged before the vessel was deployed, it would be less dependent on generating power from the PV panels in the first time steps.

Figure 2: A DBN model for the influence of SA and loss of power on mission performance, including dynamic nodes. Model made in GeNIe [32].



The CPTs for the dynamic nodes were constructed according to the following equations. The available power (AP) is a dynamic node, depending both on the use of power and on the generation of power.

$$P(AP_{t=0}|IBL_{t=0}) \tag{1}$$

The available power in the initial time step is dependent only on the initial battery level (IBL).

$$P(AP_{t=1}|EC_{t=0}, EG_{t=0}, AP_{t=0}) \tag{2}$$

The available power in the consequent time step depends on the energy generation (EG) and energy consumption (EC) in the previous time step, in addition to the available power in the previous time step.

$$P(EC_{t=1}|SRQ_{t=0}, PS_{t=0}, SDCQ_{t=0}, VOC_{t=0}) \tag{3}$$

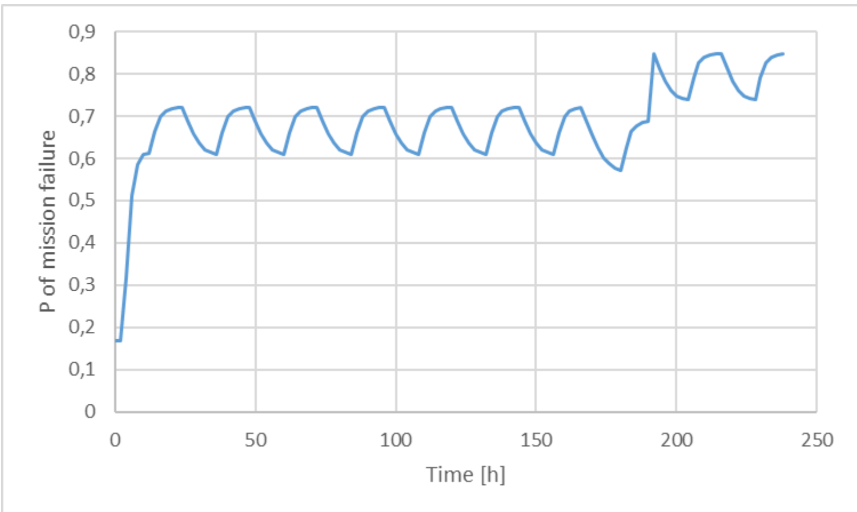
The energy consumption is dependent on the use of electrical equipment in the previous time step, which includes the scientific data collection quality (SDCQ), the propulsion and steering system (PS) and SA sensor reading quality (SRQ), and the vessel-operator communication (VOC). Higher quality of the data collection can require higher sampling frequency, or use of more sensors. This consumes more power.

System data and mission descriptions for the USV were used to develop the CPTs. In the case study, evidence was based on the mission description. There was not much exposure to sun during the operation. Evidence was placed so that the sun exposure was “low” half of the time, to simulate the night, and medium during the day. The battery level was defined to be fully charged in the initial time step. Given the time of year of the operation, the temperature was defined to not affect power generation for all time steps. A storm was forecasted for the days of the mission, so evidence was placed for medium and high wind speed and wave heights, and low solar exposure in the last 72 hours of operation.

4. RESULTS AND DISCUSSION

The developed framework can be used in the analysis of risks related to the balancing of power on board MASS. When the aim is to reduce risks and perform efficient operations, there is a dilemma between preserving power to avoid system blackouts and using power to maintain a sufficient level of SA. The methodology points to relevant nodes to include in a DBN risk model. The risk picture can look different for the variety of MASS that are under development, and hence, the risk model will not look similar for all. However, the methodology might be viewed as a starting point for identifying variables and conducting an analysis. By applying the method to other case studies, with different types of MASS, exposed to other environmental factors, and performing other missions, improvements can be made to the methodology, and more factors can be included.

Figure 3: The case study results.



The resulting risk model used in the case study was made using the developed methodology. The DBN risk model of the USV attempts to capture the complexities relating to the power management. Several dynamic factors influence the use and generation of power, and for this reason the available power is modelled as a dynamic node in the DBN. In the model, several environmental factors are assumed to be independent of its previous states. This is a simplification that is preferable because it reduces the size of the CPTs and the need for subjective judgement to quantify these. The results for the case study show that the probability of mission failure changes with time, as demonstrated in the graph in Figure 3, and is strongly dependent on the opportunity for generating power.

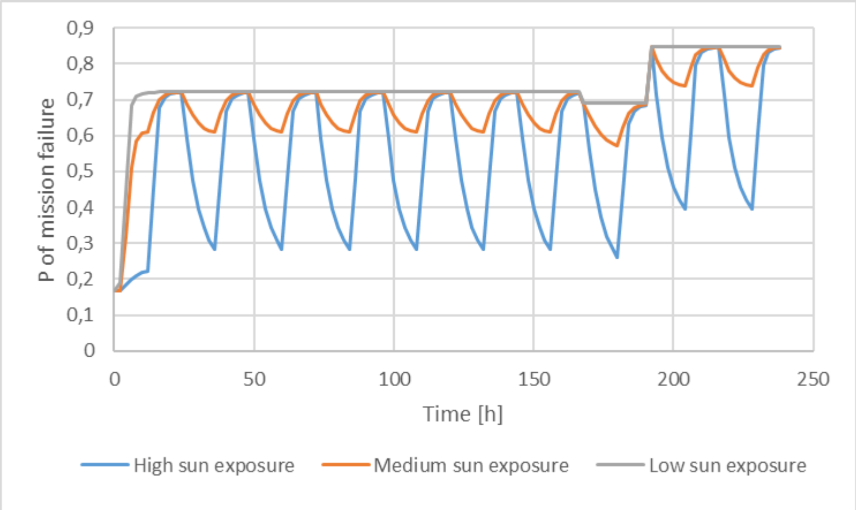
This results from the case study aligns with the observations from the operational experience, as described in section 3.1. The vessel is completely dependent on environmental conditions, such as sun, wind, and waves, to perform its mission. Results from the analysis show a relatively high risk level during the mission, because of the low solar exposure, which results in a limited ability to collect data.

Further, the analysis show that the risk of loss of mission is higher following periods with low solar exposure, see Figure 3. Because the vessel is operating also at night, when the sun exposure is low, the risk level is fluctuating over the mission period. The risk increases at approximately 180 h and remains high during the last days of the mission, due to the forecasted storm. This was also the case in the actual operation, where the vessel stranded due to low battery level and severe environmental conditions at the end of the mission.

The vessel used in the case study has been used for a mission, and by inserting evidence of the conditions observed during the mission, the outcome of the analysis can be compared to the outcome of the real operation. By changing different parameters in the model and investigating the effect of the changes on the analysis results, the sensitivity of the results to changes in the evidence can be mapped. If the model is sensitive to changes in parameters that are believed to be influential for the result, it can contribute to building confidence in the model.

Therefore, the sensitivity of the model to the evidence used was investigated. This was done for the evidence used in the node Sun exposure, see Figure 4. The difference between the model output for the variations of evidence used, is significant. This can indicate that exposure to sun is important in this risk model. The probability of mission performance being affected is higher for lower levels of sun exposure compared to if the weather is sunny (high exposure), which is a reasonable result, according to the operational experience.

Figure 4: Variations in the evidence used in node "Sun exposure".



The developed model can be a tool for operators used in mission planning. Based on the available weather forecast and knowledge about the area of operation, the probability of mission failure can be analysed. The results can be used to allocate resources for mitigating the consequences. It can also give indications for when the human operator on shore should pay more attention to the operation of the vessel, such as in situations where the power level is expected to be critical. In such cases, the human operator can intervene and override the priorities of system. In this way, the developed model can be a tool for risk analysis and provide decision support for operators.

5. CONCLUSION

This study presents a framework for performing DRA of the risks related to MASS mission performance, and the effects from power shortage and the SA of the vessel, using DBN. The methodology provides an overview of relevant factors to include in the analysis, related to the system, environmental, and operational factors. The method was applied to a USV (AutoNaut) which uses wave foils for forward propulsion and PV panels for generating electric power. Information from a previously performed mission is used to test the methodology and estimate the risk of mission failure for the USV.

The results show that the probability of mission failure varies with time, and that there is a large influence on mission failure related to the sun exposure, which is expected. The results were compared and validated to the operational experience for the USV.

Risk analysis related to mission planning of the USV and for decision-making during the mission is currently performed by human operators, using their experience and system knowledge. The DBN model proposed in the paper can be a supporting tool for the operators during this process. The method can also be a step towards incorporating the use of risk models in decision-making during MASS operation, either for the human operators, or for the control systems onboard the vessel. Further work includes applying the method to more missions, other case studies, with different types of MASS, and exposed to other environmental factors. In this way, improvements can be made to the methodology, and more RIFs can be included to provide a more complete risk picture. Further work should include further verification of the nodes and numeric values used in the case study.

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