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Risk-Based Control of Autonomous Surface Ships

Doctoral thesis

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Abstract

The last few decades has seen tremendous technological development in the maritime industry. Improvements in navigation systems such as Global Navigation Satellite System (GNSS) have reduced measurement error and uncertainty for both position and velocity data. In addition, improvements in computational power have contributed to the development of more advanced ship control systems. Increased focus on greenhouse gas emissions have further driven the maritime industry into developing new and more efficient ship transport systems. More and higher levels of autonomy at sea is one way to address this challenge and utilize the technological improvements.

A crucial part of developing autonomous ships is ensuring their ability to operate safely. To address this, the overall objective of this thesis is to develop methods and tools for assessing and controlling risk when operating autonomous ships. To achieve this, risk related to autonomous ships needs to be analyzed and modeled. Since autonomous ships are complex systems that include hardware components, software, interact with humans, and operate in highly unstructured environments, traditional risk analysis methods focusing on single component failures are not considered sufficient. Instead, newer methods such as Systems Theoretic Process Analysis (STPA) focusing on system interactions and Bayesian Belief Network (BBN) for modeling the system, combined with additional methods for analyzing specific parts of the ship are used to get sufficient information.

The data and output from analyzing and modeling risk are further used as input to a high-level controller. The result is a risk-based control system with improved decision-making capabilities compared to existing control systems. At the center of this control system is a Supervisory Risk Controller (SRC) capable of high-level control of an autonomous ship. It can make decisions about what motion controller to use, how the machinery should be operated, and choose what routes to follow. In addition, it is also designed to notify a human supervisor if it starts reaching its operational limits to avoid loosing control of the ship.

Three versions of the controller addressing different challenges, such as switching between transit and docking, sailing on preplanned coastal routes while accounting for changing environments and conditions, and switching between routes, have been studied and tested in simulations. These show promising results where the SRC is able to adjust both the speed, control mode, and machinery mode to balance safety and efficiency based on the environment and conditions. In addition, the performance and decision-making capabilities shown in the simulations are compared to operational measurements from and existing manned ship. This comparison shows that the risk-based control system is capable of both safe and efficient operation of ships. Overall, simulations shows that the autonomous ship operates with a similar or higher level of safety, without compromising efficiency and performance compared to existing manned ships.

The main result of the thesis is the SRC that can combine information from a risk model with operational measurements from a ship control system to handle a wider range of challenges compared to existing ship control systems. Existing ship control systems are great at optimizing efficiency and costs. However, they often lack the ability to assess safety. By introducing a risk model in the control system, both safety and efficiency can be evaluated as part of the decision-making process similar to the way human operators and crew do on traditional ships. This is an important contribution towards operating autonomous ships by improving the decision-making capabilities accounting for both safety and efficiency.

Preface

This thesis is submitted in partial fulfillment of the requirements for the degree of Philosophiae Doctor (PhD) at the Norwegian University of Science and Technology (NTNU). The work has been conducted at the Department of Marine Technology (IMT). The work has been part of the Knowledge-Building Project for Industry (KPN) project Online Risk Management and Risk Control for Autonomous Ships (ORCAS) funded by the Research Council of Norway (RCN), Kongsberg Maritime, and DNV (RCN project number 280655). In addition, the work has been associated with the NTNU Centre of Excellence Autonomous Marine Operations and Systems (NTNU AMOS) project (RCN project number 223254).

My main supervisor was Professor Ingrid B. Utne from IMT, and my co-supervisors were Professor Asgeir J. Sørensen from IMT and Professor Tor Arne Johansen from the Department of Engineering Cybernetics, NTNU. In addition, two PhDs besides my own has been part of the ORCAS project. My colleague Tobias Rye Torben focused on the design and verification of control systems for autonomous ships, and my colleague Simon Blindheim focused on risk-based Model Predictive Control (MPC). Associate Professor Børge Rokseth has also been involved in the ORCAS project as a Postdoc.

Acknowledgments

I would like to give special thanks to my main supervisor Ingrid for being a great mentor. Her structured approach to supervising, detailed feedback, and reviews have been important for both delivering the research results my development as a person. I have learnt a lot during our meetings and discussions, which has developed me as both a researcher and person.

I would also like to thank my two co-supervisors Asgeir and Tor Arne. You have both contributed with valuable guidance and feedback on my research. In addition to my supervisor, I would also like to thank my fellow PhD students, especially my office mate Ruochen Yang has been a great support while working on this thesis. Our discussion have been very valuable for both the research conducted as part of this thesis, but also for broadening my perspectives on other topics. I would further like to thank my fellow PhDs in the ORCAS project, Tobias and Simon. Your input and contributions to the research conducted in this thesis has been of great value.

Lastly, I would like to thank my parents Vibeke and Finn-Arne Johansen for always encouraging me, supporting me in my choices, and showing interest in my work.

Trondheim, May 14th 2024 *Thomas Johansen*

Contents

List of Acronyms

AMMS Autonomous Machinery Management System
ANS Autonomous Navigation System
AUV Autonomous Underwater Vehicle

BBN Bayesian Belief Network

CPT Conditional Probability Table

DP Dynamic Positioning

ENC Electronic Navigational Chart

FMEA Failure Modes and Effects Analysis
FMECA Failure Modes, Effects, and Criticality Analysis

GLONAS Globalnaja navigatsionnaja sputnikovaja sistema
GNSS Global Navigation Satellite System
GPS Global Positioning System

H-STPA Human Systems Theoretic Process Analysis

IMO International Maritime Organization
IMT Department of Marine Technology

KPN Knowledge-Building Project for Industry

LIDAR Light Detection And Ranging
LoA Level of Autonomy

MPC Model Predictive Control
MRC Minimum Risk Condition

NTNU Norwegian University of Science and Technology

NTNU AMOS NTNU Centre of Excellence Autonomous Marine Operations and Systems

ORCAS Online Risk Management and Risk Control for Autonomous Ships

PHA Preliminary Hazard Analysis

PhD Philosophiae Doctor

PID Proportional–integral–derivative

PMS Power Management System

R&D Research and development

RCN Research Council of Norway

RIF Risk Influencing Factor

ROV Remotely Operated Vehicle

SRC Supervisory Risk Controller

STAMP System-Theoretic Accident Model and Process

STPA Systems Theoretic Process Analysis

UAV Unmanned Aerial Vehicle

UCA Unsafe control action

USV Unmanned Surface Vehicle

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Part I

Thesis Overview and Background

Chapter 1

Introduction

1.1 Motivation and Background

The work in this thesis is part of the Online Risk Management and Risk Control for Autonomous Ships (ORCAS)-project (NTNU, 2018), a knowledge-building project for industry funded by the Norwegian Research Council, Kongsberg Maritime, and DNV. The project aims to develop solutions for online risk management and risk-based control of autonomous ships by combining control theory and risk management.

Ships are a crucial part of the global transport network for goods and people. The International Maritime Organization (IMO) state that shipping accounts for more than 80 % of global trade (IMO, 2022). This in turn accounts for around 2.8% of the global greenhouse gas emission (IMO, 2020). Improvements in sensors technology, computation power, and more efficient machinery systems are expected to enable more autonomous ships, along with other maritime systems. Increased autonomy can be one way to address this by enabling new ways to operate ships by reducing crew and opening up for unmanned operation. This can help improve working conditions (Burmeister et al., 2014) and reduce the number of incidents involving ships (de Vos et al., 2021; Porathe et al., 2018; Wróbel et al., 2017), fuel consumption (Kretschmann et al., 2015), and crew and structural costs (Rødseth, 2018). Overall, this can help minimize cost and improve environmental performance.

Autonomous ships can help to reduce the need for land transport by offering smaller electric cargo ships as an alternative to trailers, such as Yara Birkeland (Yara, 2018) and Asko's autonomous electric barges (Kongsberg, 2020b). In addition, increased autonomy can also enable new ways of transportation where traditional ships are not used today. One such example concerns small autonomous ferries suggested for transporting people in cities and over shorter distances. Norwegian University of Science and Technology (NTNU) has built and developed a small passenger ferry prototype, MilliAmpere for testing in Trondheim (Springwise, 2018). Zeabus (2021) has moreover started operating an autonomous ferry together with Torghatten in Stockholm (Zeabus, 2023). Similarly, Hyke have presented an autonomous ferry indented for operations in Fredrikstad during the fall of 2023 (Teknisk Ukeblad, 2023). They have also signed a contract to deliver four autonomous ferries that will operate in Paris during the 2024 Olympics (MASS World, 2022).

The autonomous cargo ship Yara Birkeland is also an example of ships developed to operate at a higher Level of Autonomy (LoA) (Yara, 2018). Yara Birkeland is now operated as a manned ship, but with plans to transition to more autonomy over the coming years. Reach Subsea, together with Kongsberg Maritime and Masterly are working to develop a Unmanned Surface Vehicle (USV) intended for working in the offshore industry capable of doing inspection, survey, and light repair tasks (Offshore Energy, 2021, 2022). DeepOcean, together with Solstad Offshore and Østensjø have ordered a USV intended for work in the offshore industry through their joint venture company USV AS (DeepOcean, 2023). Autonomous cars are under development and being tested for both (BBC, 2020) and human transport (Mashable, 2022). Autonomous Underwater Vehicles (AUVs) that can be stationed at offshore installations are under development and being tested for conducting maintenance and inspection. This is expected to reduce the need for larger supply ships, which reduces cost and increases efficiency (The Maritime Executive, 2021).

As ships are designed to operate at a higher LoA, they need more complicated machinery and control systems. An autonomous ship control system includes automatic systems for controlling and navigating the ship, power, and propulsion systems. In addition, they need systems for improved situational awareness and the capability to plan and make decisions in uncertain can unstructured environments (Brito, 2016; Zhang et al., 2023; Zheng et al., 2023). This means relying on advances in optimization, artificial intelligence, computer vision, and sensor fusion. In addition, the constant improvement in computational power available is an important perquisite for developing autonomous ships. As the systems become more complicated, so do the interactions between them. This means that it is not sufficient to assess individual parts of the ship to ensure that they are safe. Instead, it is necessary to also consider the interaction between different parts to ensure that the whole system is safe. Since humans are still expected to be involved in operating autonomous ships, either directly or as a supervisor, it will also be important to assess how this can affect overall system performance (Ramos et al., 2020a,b).

An important prerequisite for autonomous ships, and other autonomous systems, is ensuring that they are safe and reliable (DNVGL, 2018). The Norwegian Maritime Authority states that risk assessments are a necessary step towards autonomous operation (Norwegian Maritime Authority, 2020), and Utne et al. (2020) state the importance for autonomous ships to assess and control risk while sailing. Existing control systems, such as autopilots and Dynamic Positioning (DP) controllers, are able to control ships in specific situations. Similarly, engine control systems can manage individual engines and power production. However, these systems are designed to control specific parts of the ship, or control the ship in certain situations and operations. Human operators and supervisors are still responsible for managing the ship as a whole and change between operation modes depending on the situation. As mentioned above, including risk of collisions, grounding, and allision in the decision-making process is one possible way to improve autonomous control systems. Compared to existing ship control systems, this is expected to improve the decision-making capabilities and lead to safer operations.

Risk-based decision-making has been addressed in previous works focusing on different aspects of operating autonomous ships and similar systems. Utne et al. (2020) propose a method for using information from a risk model as part of the decision-making process by combining making a Bayesian Belief Network (BBN)-based risk model based on the results from a Systems Theoretic Process Analysis (STPA). The data from the risk model can then be used to assess different decisions and control actions in the ship control system. Blindheim et al. (2023a) use a similar approach where Model Predictive Control (MPC) is combined with risk assessment to enable risk-based control for autonomous ships. Similar methods have also been used for AUVs in Bremnes et al. (2019) and Bremnes et al. (2020). Xiang et al. (2017) use a fault tree and a Mamdani fussy neural network model to evaluate the risk and do critical decision-making in case of emergencies. Chen et al. (2021) conduct a systematic review of risk analysis research in order to improve the safety performance of AUVs. Moreover, Brito and Griffiths (2018) propose a hybrid fuzzy system dynamics risk analysis to assess how the experience of the operators affect the probability of loss of AUVs, whereas Loh et al. (2020) use a Bayesian approach to assess and update the risk profile for AUV operations.

Tengesdal et al. (2020a,b) use a risk informed MPC to handle collision avoidance for autonomous ships. Specific parts of an autonomous ship control system such as collision avoidance (Gil, 2021; Li et al., 2021) and emergency management (Blindheim et al., 2020) have also been presented in previous works linking these to risk management. However, many of these use very loose definitions of risk such as distance to land and time to grounding. They also have a limited focus on how to identify and analyze risk related to operating the ship. Thieme et al. (2021) describe four areas where risk analysis could be implemented in ship control systems aimed at improving decision-making and operational performance. Risk models can be used directly to make decisions; the output from risk models can be used as input to decision-making and optimization algorithms; the output from risk models can be used as constraints for algorithms; and the output from risk models can be represented in maps of the environment. Blindheim et al. (2023b) use a particle swarm optimization to manage the machinery system aboard an autonomous ship, also combining risk assessment with optimum control by using the output from a risk model as input to a decision-making algorithm.

Previous work has also addressed how to analyze and model risk related to autonomous ships. Thieme et al. (2018) assess different methods for modeling risk related to autonomous ships and defined a set of criteria for modeling this. Risk factors and indicators specifically related to autonomous ships have also been identified in Fan et al. (2020) and Guo and Utne (2022). STPA has moreover been used in multiple works related to autonomous ships. Valdez Banda et al. (2019) use it for hazard identification for an autonomous ferry, as well as suggesting safety controls to mitigate the identified hazards when designing the ship. Ventikos et al. (2020) use STPA to determine hazards as a function of the LoA. Further, Wróbel et al. (2018) use STPA to assess the safety of autonomous ships and provide recommendations for the design process while Daya and Lazakis (2023) combine Failure Modes and Effects Analysis (FMEA), dynamic fault tree analysis, and Bayesian Belief Networks (BBNs) to assess the reliability of power production systems for ships. Tsoumpris and Theotokatos (2023) use BBN to assess the system reliability for autonomous ships, focusing on how the machinery system should be configured to optimize the balance between system reliability and energy consumption. In general, previous works on risk analysis and modeling related to autonomous ships have shown that STPA and BBNs are useful for analyzing such complex systems.

Much previous work has also focused on either parts of, or a more complete control system for autonomous ships. Path planning and following have been addressed in multiple papers such as Zhang et al. (2023), Sawada et al. (2023), Peng and Li (2023), Park et al. (2023), and Wu et al. (2023) addressing trajectory tracking and autonomous docking. Zhang et al. (2023) focus on collision avoidance while considering uncertainty in the ship motions and accounting for this when planning an alternative path. Wang et al. (2023) present a more general decision-making system aimed at switching between different navigation tasks for the autonomous ship. However, work focusing on controlling autonomous ships generally focus on limited parts of the control system. Much of the low level controllers and systems that can be used on an autonomous ship is also well developed and in use on many ships already, such as DP-controllers (Sørensen, 2011), autopilots, and power management systems (Ådnanes, 2003).

Blindheim (2023) focuses on extracting data from electronic navigation charts, risk-based MPC, and particle swarm optimization where risk is one term included in the optimization to enable risk-based control of autonomous ships. Torben (2023) focuses on approaches to design and verify safe control systems for autonomous ships such as safety assurance and formal methods, whereas Rothmund (2023) has developed new methods for giving robotic systems better risk awareness to enable safer and more efficient autonomous systems. The work conducted as part of Yang (2023) has also presented methods and tools for analyzing and controlling safety focusing on autonomous marine systems.

To summarize, existing research that is considered relevant for autonomous ships focusing on risk and control have mostly focused on either control or risk analysis. A few works have started combining them, indicating potential advantages by including risk in the decision-making process, for example, combined with some version of optimum control theory (Blindheim et al., 2023b; Bremnes et al., 2019, 2020; Utne et al., 2020). However, it is still necessary to go more in depth into how to combine risk analysis and modeling to show how the results can be used for optimum control and reduce the need for human control of autonomous ships. Combining this with existing ship control systems is a topic that needs to be addresses in more detail before it can be used on actual ships. To address these gaps, the work conducted in this thesis presents a more detailed approach to combine risk analysis, modeling, and optimum control theory in a high-level controller. It also presents how such a controller can be combined with existing ship control systems to enhance the decision-making capabilities.

1.2 Research Objectives and Scope

Before highly autonomous ships can be used in normal operations, it is important to ensure that they are safe. One step towards doing this is making control systems with improved decision-making capabilities, similar to how humans control conventional ships where they can assess both risk and reward. To achieve this, an autonomous system needs improved perception, situation awareness, and planning capabilities (Utne et al., 2020).

Existing ship control systems are mainly designed to handle specific systems such as Power Management Systems (PMSs), or control the ship in certain situations with autopilots and DP-controllers. High-level control and decision-making, such as switching between different motion controllers and machinery modes, are usually done by human operators. This thesis aims to enable autonomous control systems to operate at a higher LoA by including risk of collision, grounding, and allision in the decision-making and control process. This is expected to lead to safer operations of autonomous ships compared to existing control systems.

Overall Research Objective:
The overall objective of this thesis is to develop methods and tools for assessing and controlling risk when operating autonomous ships.

When comparing existing control systems and the decision-making by human operators, one important difference is that a control system is designed to optimize the reward or minimize the cost of operating. However, without sufficient information about risk, it has no possibility of considering whether this is a safe way to operate. A human on the other hand, can both assess the reward of finishing a task and the related risk. Enabling autonomous ships to both assess and control risk is therefore considered an important step towards safe operations.

To achieve this, the overall objective is divided into three research objectives. An important step in managing risk when operating autonomous ships is identifying how accidents occur. With the increased system complexity in autonomous ships, this is more challenging compared to conventional manned ships. The interaction between physical components, software, human operators, the environment, and other ships make it challenging to analyze with conventional risk assessment methods. Finding suitable methods to identify the different factors, or Risk Influencing Factors (RIFs) contributing to the overall risk picture, is an important part in analyzing and controlling risk for autonomous ships.

Risk models can further be used to structure both qualitative and quantitative data from different risk assessment methods. The risk model should provide information for the control system about how RIFs are connected and contribute to the overall risk picture. Based on this, the first research objective is formulated as follows:

Research objective 1:
Identify methods for assessing risk influencing factors relevant for autonomous ships and modeling these for use in an autonomous ship control system.

The first research objective provides the foundation and an important first step towards risk-based decision-making for autonomous ships.

The next step then builds a control system capable of utilizing the information from the risk model and evaluating risk against other objectives. Such objectives can be energy and fuel consumption, operation costs, and mission specific objectives such as deadlines for reaching different ports and delivering goods. The resulting control system should also be assessed in a systematic manner to ensure that it has the necessary capabilities to control an autonomous ship. To achieve this, research objective two is formulated as follows:

Research objective 2:
Develop a method for enabling risk-based decision-making in ship control systems.

Research objectives one and two focus on identifying and modeling risk, and developing a control system capable of risk-based decision-making. However, humans are still expected to be involved in operating autonomous ships. This could be both active control for ships operating at a lower LoA, and more supervising of the ship with more advanced control systems.

Compared to conventional ships, ships with a high LoA provide different challenges to humans when supervising and operating the ship. Traditional control systems depend on humans having an updated view of the situation and regularly adjusting how the ship is sailing. However, a higher LoA means that humans are less involved in normal operations. On one hand, this might lead to less human errors, but it could also make it more challenging when the control system is unable to handle the situation and humans need to make decisions or take over control of the ship since they do not have the same situational awareness. This research is intended as a first step towards designing a risk-based autonomous control system, where a human supervisor is still involved in the operation.

To address this, research objective three is formulated as follows:

Research objective 3:
Investigate the inclusion of the human supervisor in the design of a risk-based control system.

This is expected to increase the chance that a human supervisor will be able to react in a safe manner when the control system is unable to handle the situation.

1.3 Scope and Delimitations

Autonomous ships consist of multiple complex sub-systems and operate in challenging environments and situations. In addition, humans are still expected to be involved in the operation in different capacities, adding to the complexity of the system. Accounting for all aspects of the physical, cyber-physical, and human element when assessing risk and designing a control system is considered too much for one thesis. The following work has therefore been limited to certain aspects of autonomous ships, with focus on developing a methodology for building a risk-based control system.

When describing and analyzing the physical ship, the machinery system, propulsion system, navigation system, and communication system are considered at a general level. Each system is described with its main components, such as the main engine, main propeller, and the GNSS system. However, going more in detail and assessing specific parts of each main components is considered outside the scope of this thesis. Similarly, the computer-based control system consists of the different motion controllers, where each controller is considered as one component. The human aspects presented are limited to those useful for building the control system, and topics such as human reliability, reaction time, and human-machine interfaces are therefore only briefly addressed.

The testing conducted as part of this thesis is done using simulations of an autonomous cargo ship. The cargo ship is based on an actual conventional manned ship sailing along the Norwegian coast and modeled in a Python based simulator. The simulator uses a simplified kinetic model without considering the wave forces affecting the ship. This makes it easier and more efficient to test the controller, but also affects the accuracy of the simulations, in turn making it more difficult to control the ship movements, especially in tight turns since the ship is drifting more. However, since the thesis focuses on the risk-based decision-making, it is still considered sufficient to show that this works. The control system has not been tested in real life, but the results have been compared to how the conventional manned ship is operated in similar conditions. The ship considered in the case studies conducted as part of this thesis is assumed to be operating LoA-3 - LoA-4 (from Table 2.2). However, it is also intended to switch between different levels, in situations where the controller is unable to continue operating safely. A more thorough description of LoA is given in Section 2.1 and the publications included as part of this thesis.

1.4 List of Publications

Publications included as part of this thesis:

- Johansen, T. and Utne, I.B. (2020). Risk analysis of autonomous ships. *30th European Safety and Reliability Conference, ESREL 2020 and 15th Probabilistic Safety Assessment and Management Conference, PSAM 2020*, 131–138
- Johansen, T. and Utne, I.B. (2022). Supervisory risk control of autonomous surface ships. *Ocean Engineering*, 251, 111045
- Johansen, T., Blindheim, S., Torben, T., Utne, I.B., Johansen, T.A., and Sørensen, A.J. (2023). Development and testing of a risk-based control system for autonomous ships. *Reliability Engineering and System Safety*, 234, 109195
- Johansen, T. and Utne, I.B. (2023). Human-autonomy collaboration in supervisory risk control of autonomous ships. Submitted to Journal of Marine Engineering & Technology

1.5 Thesis Organization and Overview

Part I

Part one of the thesis consists of the following. Chapter 1 is an introduction to autonomous ships and risk-based control of these. It also presents the research objectives, scope, and delimitations for the PhD project. Chapter 2 presents the theoretical background for the PhD project, while Chapter 3 presents the research approach and methodology used. Chapter 4 presents the main results from the research, including they addresses the objectives in the PhD project, and how they can help the development towards safe autonomous ships. Chapter 5 concludes the thesis and makes recommendations for further research regarding risk-based control of autonomous ships.

Part II

Part two of of the thesis contains the scientific papers.

Chapter 2

Theoretical Background

This chapter presents relevant theoretical background relevant to address to the research objectives in Section 1.2. This include a description of relevant terms, definitions, and different systems that make up an autonomous ship. It also describe terms related to risk analysis and modeling use full in risk-based control systems.

2.1 Automatic VS Autonomous

Automatic and autonomous are two important concepts to differentiate between when evaluating the development of smarter and safer ships. An automatic, or automated system, is able to operate independent of human input. Automatic doors are a good example of this, where the doors open and close without the need for human control or automatic lights can turn on for a limited time if they sense motion. Similarly, many existing ships have automatic systems such as autopilots, DP-controllers, and PMSs capable of controlling parts of, or the whole ship, in specific situations. However, automatic systems are designed to do specific tasks or operations.

Autonomy, on the other hand, describes a system's ability to plan, make decisions, and act to achieve different goals. A useful way to describe an autonomous system and its capabilities is LoA. This describes an autonomous system in terms of human dependency, communication structure, risk management capabilities, intelligence, and planning functions (National Institute of Standards and Technology (NIST), 2008; On-Road Automated Driving (ORAD) Committee, 2021; Utne et al., 2017). Multiple scales for describing the LoA have been proposed in previous works (Huang, 2008; Sheridan, 1992; Sheridan and Verplank, 1978; Vagia et al., 2016). Lloyds Register (2017) presents seven different LoAs from L 0-Manual steering, up to L 6 - Fully autonomous. Similarly, both IMO (2018) and Rolls Royce (2016) have their own scales describing the different LoAs.

The different scales start with low LoAs where human operators receive information, make decisions, and provide commands to the hardware. With higher LoAs, computers and controllers take over more of the tasks and humans do more

IMO levels	Lloyds register levels	Rolls Royce levels
L1 - Ship with automated processes and decision support. L 2 – Remotely controlled ship with seafarers on board. L 3 – Remotely controlled ship without seafarers on board. L 4 – Fully autonomous ship.	L 0 – Manual steering. L 1 – On-board decision support. L 2 – On and off-board decision support. L 3 - "Active" human in the loop. L 4 - Human in the loop. L 5 - Autonomous. L 6 - Fully autonomous.	L 1 – The computer provides no assistance, human in charge of all. L 2 - The computer provides a complete set of decision alternatives. L 3 - Computer narrows alternatives down to a few. L 4- Computer suggests single alternative. L 5 - The computer executes the suggested action if human approves. L 6 – The computer provides human beings limited time to veto before automatic execution. L 7 – The computer operates automatically, when necessary, informing human. L 8 – The computer informs human only if asked. L 9 – The computer informs humans only if it decides to. L 10 – The computer does everything autonomously ignoring humans.

Table 2.1: Levels of Autonomy from IMO (2018), Lloyds Register (2017), and Rolls Royce (2016)

supervising. At the highest LoAs, the human can also have a reduced ability to take control of the system. The scales presented in Table 2.1 describe how LoA can be related to both the ship control system and human interaction. To describe the LoA in this thesis, the scale displayed in Table in Table 2.2 (based on Utne et al. (2017)) is used. This includes aspects from all three scales considered most relevant for the ship considered. Compared to the scales shown in Table 2.1, this provides a sufficiently detailed description of each level in terms of both system functions and human interaction and contains enough levels to clearly differentiate between them, but still limits the number to keep it clear which level is used. It also covers sufficient levels to describe the different phases that many projects are using, or planning to use, when introducing more autonomy to ships.

As shown in Table 2.2, autonomy is a more general term describing the system at a higher level, compared to automatic. It is also important to remember that autonomous does not mean unmanned, even though an autonomous system may need less human input (Ramos et al., 2020a,b).

Another important point to assess is how the LoA can vary depending on the type of operation. An autonomous ship can, for example, sail in open water without the need for human input. However, when it reaches harbor or more congested waters, it can be necessary for a human supervisor to be more involved. Similarly,

LoA	Type of operation	System description
1	Automatic operation/ Remote control	The system operates automatically. The human operator controls all high-level mission planning. The human operator has access to system states, environmental conditions, and sensor data.
2	Management by consent	The control system can make recommendations about specific parts of the operation. The human operator still controls the system. The system can perform many tasks independently, if approved by the operator.
3	Management by exception	The system automatically executes the mission plan, and has the ability to make small changes when the available time is too short for human intervention. A human supervisor can take control over the system or change the plan. The human supervisor is notified by the system when it is necessary to take over or update the plan.
4	Highly autonomous operation	The system automatically plans and executes the operation. The system can change and alter the plan during operation. Humans can supervise the operation, but not take direct control of the system.

Table 2.2: System description for different levels of autonomy (based on Utne et al. (2017))

modern cars can control the speed and stay inside their lane while driving on the highway. However, most cars are not able to drive autonomously in cities and more challenging areas.

2.2 Autonomous Ships

Autonomous ships, as described in this thesis, are ships with reduced need for human control and supervision. As previously described, existing ships have many automatic systems capable of controlling the ship in different operations. These often operate at LoA-1 where the ship has automatic systems and controllers, but a human operator does the high-level planning and make decisions on how manage the ship. Offshore ships are a good example of this. They often have autopilots to control the ship when sailing, and DP-controllers for station-keeping when they are servicing offshore installations (Sørensen, 2005). They also often have PMSs for managing power production to ensure sufficient power to the whole ship (Ådnanes, 2003). However, these ship are still dependent on human operators to manage the different systems and switch between different modes and objectives. Some existing ships are operating, at least partially, at LoA-2 such as ferries with auto crossing and auto docking systems (Kongsberg, 2020a). Human operators are still necessary to monitor the ship, and decide when to switch between transit and docking.

However, more ships and concepts are now under development or testing to operate at higher LoA, where humans can take a more supervisory role in operating the ship, either LoA-3 or LoA-4. Multiple examples are mentioned in Section 1.1. Most of these are today operated with crew aboard, but in many cases this is a reduced crew intended as an extra safety and to satisfy rules and regulations that still makes this necessary.

Control systems for ships can generally be divided into three main levels (Ludvigsen and Sørensen, 2016): planning, guidance and optimization, and execution. At the planning level, the mission or voyage is planned together with objectives or tasks for the ship. Guidance and optimization is more specific than the mission planning. This level considers way-points for the ship to follow and optimizes resources. The execution level consider the specific controllers that execute and control the ship according to the objectives and plans from the higher control levels, such as DP-controllers and autopilots (Sørensen, 2005). The execution level can also include the individual actuators, such as thrusters and rudders. These often also include some controllers that map a control command to a physical parameter such as engine speed or rudder angle.

2.3 Ship Control Systems

Typical controllers for more advanced ships, such as supply ships, include DP-controllers (Balchen et al., 1980; Sørensen, 2011), autopilots, thrust allocation (Skjong and Pedersen, 2017; Sørdalen, 1997), and PMS. These are used to control the ship's motions and power production. DP-controllers are used for station keeping and fine maneuvering. These are typically used on offshore supply vessels that need to maintain a stable position when doing intervention, maintenance, and repair jobs both under and above water. In both cases, the DP-controllers are crucial ensuring that the ship maintains its position. Today, DP is also used on other ships such as cruise ships and research vessels.

Autopilots for ships have also improved significantly over the last decades (Fossen et al., 2003). Simple autopilots were typically used to maintain a course set by human operators, but with little ability to change it later. Today, autopilots can follow longer routes between multiple way-points by automatically changing the course at each way-point (Chen et al., 2020; Kinaci, 2023). Collision avoidance is also starting to be included in autopilots, where the autopilot can change the course of the ship to avoid collision before returning to the original route(Lyu and Yin, 2019; Woo and Kim, 2020). Thrust allocation and PMS (Ådnanes, 2003) have also become more advanced to handle more advanced power and propulsion systems.

In addition to different controllers, advanced ships include multiple sensors for monitoring both the ship and the environment. These include Global Navigation Satellite Systems (GNSSs) for getting position and speed measurements, speed sensors measuring the flow of water over the ship hull, radars, and sensors for monitoring the weather. These have also improved significantly over the last decades. Early GNSSs where limited to only using the American Global Positioning System (GPS). This offered limited accuracy which made it less reliable for accurate navigation. Today, modern GNSS units can use both GPS, the Russian Globalnaja navigatsionnaja sputnikovaja sistema (GLONAS), the European Galileo system, and some even the Chinese BeiDou Navigation Satellite System (Shukla et al., 2018). This has improved the accuracy significantly by increasing the number of satellites available. With the introduction of more autonomy on ships, new sensors such as Light Detection And Ranging (LIDAR) sensors are also used more on ships to provide even more accurate information about the environment (Sawada and Hirata, 2023; Yao et al., 2023).

A typical control structure for advanced ships, such as supply ships, is shown in Figure 2.1.

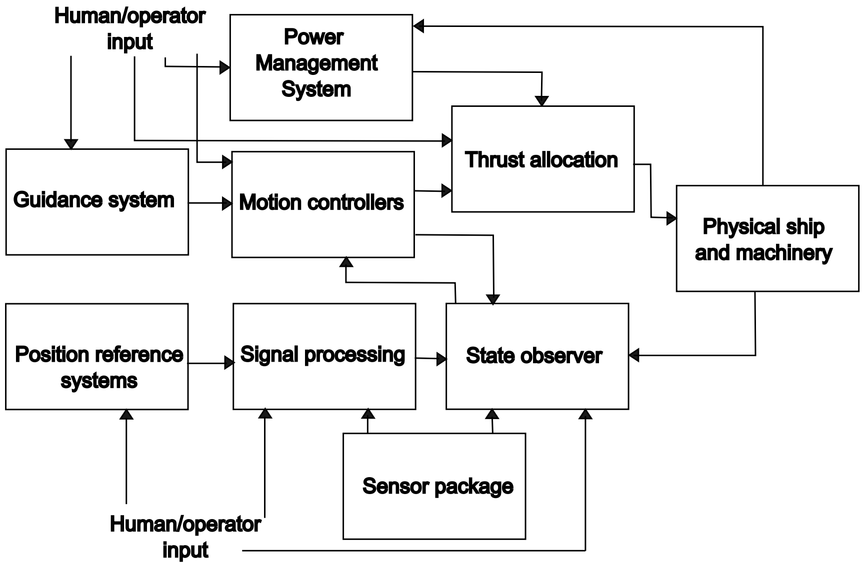

Figure 2.1: Typical control structure for advanced ships (based on Rokseth (2018) and Sørensen (2005))

As ship control systems become more advanced, the methods used in the control systems also become more advanced, but the overall structure is not changing as much. Many early DP-controllers are relatively simple Proportional–integral–derivative (PID)-controllers (Balchen et al., 1980). PID-controllers are still in use on many more advanced ships, although they have become more advanced in the way they are set up and tuned. Since the basic control system used in this thesis has the same overall structure and PID-based motion controllers as shown in Figure 2.1, it is still important to have knowledge about how these work, what type of input they need to function, and what data they can provide to a high-level controller.

In most conventional control systems, data are used in the specific controllers, such as autopilots following a specific route or course (Chen et al., 2020; Kinaci, 2023), or PMSs (Ådnanes, 2003) to optimize the specific functions in terms of energy consumption or time usage. Also, systems using more advanced control methods focus on specific aspects of the operation. An example of this is MPC-based control systems that use a simulation model of the system to simulate how potential control inputs affect a cost function to find the optimum input (Rawlings and Mayne, 2009). However, even control systems using this for specific tasks such as DP (Hu et al., 2023; Luan et al., 2023) or collision avoidance (Park et al., 2023) rely heavily on human control and decision-making to operate in a safe and efficient manner.

For ships intended to operate at higher LoAs, it is therefore necessary to consider additional types of data, and how to use these in new ways. Thieme et al.

(2021), Utne et al. (2017), and Utne et al. (2020) highlight the need for including more risk-based information to ensure safe and efficient control of autonomous ships to address this challenge. Compared to existing control systems, this is expected to improve the decision-making capabilities of the control system and reduce the need for human control. A PMS capable of considering fuel consumption, machinery health, and the potential for increased risk of collision or grounding when selecting how the machinery should be used is an example of this (Blindheim et al., 2023b; Tsoumpris and Theotokatos, 2023). However, this is still a field under development where more work is necessary to both find and use data in new ways.

2.4 Risk Analysis and Modeling

A commonly used definition of risk is the answer to the three questions (Kaplan and Garrick, 1981); What can go wrong? What is the likelihood of it happening? And if so, what are the consequences? IMO (2013) defines risk as a measure of the likelihood of an undesired event event occurring together with a measure of the resulting consequences within a specified time. In ISO (2018), risk assessment is defined as the process of risk identification, analysis, and evaluation. Risk identification is the process of finding and describing how risk can prevent an organization, or system, from achieving its objectives. Risk analysis is defined as a detailed consideration of uncertainties, sources leading to risk, consequences, likelihoods, events, and scenarios. A risk analysis can also consider ways to control risk and to what effect. Next, risk evaluation is the process of comparing results from a risk analysis with criteria for what is acceptable in order to make decisions. This thesis focuses on the risk analysis part as well as risk modeling.

Hazard identification focuses on answering the first question from Kaplan and Garrick (1981): What can go wrong? DEF-STAN 00-56 (2007) defines hazard identification as the process of identifying and describing all the significant hazards, threats, and hazardous events associated with a system. Hazard identifications methods can vary considerably in terms of both objective and methodology. However, the general objectives are as follows (Rausand and Haugen, 2020):

- Identify hazards and hazardous events.
- Describe the characteristics of each hazard.
- Describe when and where the hazard is present.
- Identify possible triggering events.
- Identify conditions where the hazard could lead to a hazardous event.
- Make system stakeholders aware of hazards and potential hazardous events.

Multiple methods for hazard identification exists with different details and purposes. Preliminary Hazard Analysis (PHA) is a simple method commonly used for identifying hazards in the design phase, such that it can be updated and analyzed in more detail later. Failure Modes, Effects, and Criticality Analysis (FMECA) is a method intended to identify all potential failure modes of the system components and the cause of the failures, as well as assess the effects on the entire system. The Hazard and Operability Study method was developed to identify deviations and situations that can be dangerous in a process plant. STPA is another hazard identification method focusing on how interactions in systems can lead to accidents (Leveson, 2011; Leveson and Thomas, 2018).

The next step of a risk analysis is assessing the causes and frequency of the hazardous events. This is done to identify causal effects, establish relationships between causes and hazardous events, and determine how often the hazardous event occurs based on the causes. This can also be considered as answering the second question asked by Kaplan and Garrick (1981), namely what is the likelihood of a hazardous event occurring. As with hazard identification, there are multiple methods for doing this, depending on the purpose. Cause and effect diagrams (Ishikawa, 1986) are an easy way to identify the cause of hazardous events, but will not provide any quantitative results. Fault tree analysis is a widely used method for causal analysis used for both qualitative and quantitative purposes (Bobbio et al., 1999). BBN is another method suitable for causal analysis (Fenton and Neil, 2019). It can be used with the same purpose as fault trees but is much more flexible. Other methods are Markov methods (Althoff and Mergel, 2011) and Petri nets (Taleb-Berrouane et al., 2020), which can be used to analyze the information provided by other tools, such as fault trees, but are not suitable for identifying the causes themselves.

The final part of risk analysis is analyzing the consequences and thus answering the third question asked by Kaplan and Garrick (1981). The purpose of this is to describe accident scenarios that can occur after a hazardous event, identify barriers that can stop or mitigate this, identify external events and conditions that can influence the accident scenarios, describe end events, consequences, and specify the probability and frequency of each accident scenario.

Event tree analysis is the most common method for developing and describing accident scenarios. These can also be combined with fault trees to analyze barrier failures. Event sequence diagrams (Swaminathan and Smidts, 1999) are very similar to event trees, but with a different graphical layout. These can also be used for more specialized purposes such as analyzing failures in human-system interactions (Ramos et al., 2020a,b). Cause-consequence analysis (Nielsen, 1971) are also similar to event trees, but with logic gates such that they can combine event sequences to produce more compact diagrams.

2.5 System-Theoretic Accident Model and Process (STAMP) and System-Theoretic Process Analysis (STPA)

As systems become more complex, with multiple sub-systems, the interaction between different parts become increasingly important. Individual components might function as intended, but the interaction between them can have a negative effect on safety. Processes executed in wrong order are a good example of this and can lead to problems. Identifying these challenges can be difficult with more traditional risk analysis methods. To address this, Leveson (2011) developed System-Theoretic Accident Model and Process (STAMP) as a new tool for modeling causation and STPA for hazard identification (Leveson and Thomas, 2018). STAMP treats safety as a control problem to force safe behavior, rather than just focusing on preventing failures.

STAMP consists of three main concepts: safety constraints, a hierarchical control structure, and process models. Safety constraints are used to describe how unwanted events occur by violating the constraints. The hierarchical control structure models how the system is built up with multiple controllers. Each controller gives control actions to lower-level controllers and feedback signals to those at a higher level in the control hierarchy. Process models are used to describe the individual controllers and actuators with the goal of satisfying the safety constraint, control actions, feedback signals, and a model of the controlled process.

The aim of STPA is to identify how safety constraints can be violated. STPA is based on two main steps: identify how inadequate control of the system can put it in a hazardous state, and identify how this can occur. To do this, STPA starts by identifying losses, system-level hazards, and system-level constraints. Leveson and Thomas (2018) define a loss as loosing something of value to stakeholders. This can include loss of human life, human injury, damage to property, environmental damage, loss of mission, loss of reputation, loss of information, or other losses that are unacceptable to the stakeholders. A hazard is defined as a state or condition that, when combined with a set of particular worst-case conditions, will lead to a loss, whereas a constraint is defined as a condition or behavior that needs to be satisfied to prevent hazards.

The next step in an STPA is to define the hierarchical control structure with the different controllers. The hierarchical structure shows how the system can be divided into levels where each imposes constraints on the levels beneath it. By organizing the controllers this way, the model shows which controllers can affect each other. Each controller has a set of control actions, or commands, it can give to the process it controls. STPA consider four types of inadequate control called an Unsafe control action (UCA), which could lead to a hazardous state (Leveson and Thomas, 2018):

1. A control action necessary to keep the system in a safe state is not provided or not followed.
2. A control action putting the system in a hazardous state is provided.
3. A control action is provided too late, too early, or in the wrong order.
4. A control action is stopped too soon or applied too long (only relevant for continuous or non-discrete signals).

Causal scenarios are used to describe how an UCA can occur. These are identified by analyzing the control loop for the considered control action to identify causal factors that can cause or contribute to a UCA. By identifying potential causes, the system can be designed to mitigate these and control these, or they can be specifically monitored to get an early warning. By treating safety as a control problem, STAMP and STPA are designed to pick up unsafe interactions between the different processes and controllers. In addition, it still accounts for failures in components as these are also potential causal factors identified when analyzing UCAs.

2.6 Bayesian Belief Networks (BBN)

BBNs is a tool that can be used to model risk in a graphical manner (Fenton and Neil, 2019; Pearl, 1988). These are especially well suited for modeling more complex systems since they provide a good representation of causal relationships, their ability to combine empirical data with expert knowledge, and flexibility in setting up and adjusting the model (Fenton and Neil, 2019; Utne et al., 2020).

These are based on Bayes' theorem for computing conditional probabilities and how different events are related. The basis of this theorem is that the probability of an event A is dependent on K, which describes the context and previous knowledge. Bayes' theorem then says that the probability of K, given that we know that A has happened, can be calculated with the following formula:

$$P(K|A) = \frac{P(A|K) \times P(K)}{P(A)} \tag{2.1}$$

When building BBNs, four idioms are used to speed up the process and give better results (Fenton and Neil, 2019). The cause-consequence idiom is used to model the uncertainty in causal processes with the observable consequences. The second idiom is the measurement idiom, used to model the uncertainty in measurements. The definition and synthesis idiom is used when combining multiple nodes into one in order to simplify the BBN-structure. This is used when describing cases with a definitional relationship between nodes, such as velocity depending on both time and distance with a well defined law. The second case involves hierarchical definitions where multiple synthesis and definitional idioms are joined in one structure. The final case using the synthesis and definitional idiom is combining multiple nodes together in order to reduce the number of inputs to certain nodes, also called divorcing, whereas the fourth idiom is the induction idiom, used to model uncertainty related to inductive reasoning when observations about a population are used to learn about population parameters. These are further used to make predictions about the future.

A challenge with using BBNs is defining node probability tables, or Conditional Probability Tables (CPTs). These describe how the probabilities in a node depend on the input from its parent nodes. CPTs often need a large number of probability values, despite trying to structure the network as good as possible. Fenton and Neil (2019) list four different types of functions that can be used. Labeled nodes use labels at the states, where the CPT often need to be manually filled since they labels do not have any underlying meaning regarding how the states compare. An example of this could be a node describing the color of different cars with the states green, yellow, red, and blue. There is, however, no information about how the different colors compare. Another approach is a more iterative process where an initial BBN is made and then sequentially updated as the available data improve (Podofillini et al., 2023).

Boolean nodes are another typical node. Fenton and Neil (2019) define boolean nodes as any node with exactly two states, true and false. The two simplest boolean nodes are OR and AND nodes. An OR node will have a CPT such that state will be true unless all parent nodes are false. AND nodes, on the other hand, are the exact opposite where all parent nodes have to be true for the state to be true. M from N nodes are true if M of the N different parent nodes are true. The two last boolean nodes are noisy OR and noisy AND nodes. These are similar to the OR and AND nodes, but with a leak factor. The leak factor describes the chance of an OR nodes being true despite all parent nodes being false, and the chance of an AND node being false despite all parents being true. The final boolean node is the weighted average. This uses weights to describe how much each parent node should affect the state of the child node.

Ranked nodes are similar to labeled nodes, but with an ordered set of states. An example of this could be a node describing the amount of water in a glass with the states nothing, half, and full. To fill out such nodes, it is possible to use different functions and probability distributions to describe the different states and fill out the CPTs.

In risk assessment, BBNs are useful when modeling the risk to have a graphical representation. However, they can also be used to identify possible decisions and check how they will affect the risk (Bremnes et al., 2019, 2020). When using BBNs for decision analysis, there are three main components: decisions, chance variables, and utilities. Decisions are what we want to assess to see how they affect the system. This can be assessed in terms of cost, risk, energy consumption, etc. Chance variables are the second main component, used to describe variables that are outside our control. These can be either observable or not observable. An observable variable can be measured or reported on during the analysis. This can be both a result of a decision, or a variable affecting what decision should be made. It is also important to note that an observable variable might be inaccurate and contain a certain degree of uncertainty. Utilities are used to describe the outcome of the decisions and these can be both costs or benefits and can be measured in either economic measures or more subjective utilities. A decision analysis model can then be used to find the decisions that maximizes the rewards or minimizes the cost.

After building a BBN, either to model and analyze risk or analyze decisions, the model can be assessed using a sensitivity analysis (Hänninen and Kujala, 2012). A sensitivity analysis can either be used to check the validity of a model by assessing which nodes have the greatest impact on a target node, or how sensitive the results of a decision analysis are related to observable variables. This makes it very useful after building a BBN and can give additional information and value to a decision analysis.

As presented in Section 2.4, BBNs can also be used as alternative ways to represent other risk models, such as fault trees and event trees. A fault tree can easily be modeled using Boolean nodes. Using BBNs instead has several benefits (Fenton and Neil, 2019). A discrete BBN gives exact values for the probabilities, instead of the approximations given in fault trees, reducing the inaccuracy in the model. BBNs can also be extended much easier to include additional states, resulting in a more realistic model. Traditional fault trees also assume that the primary events are independent, which is often wrong. In a BBN, it is easy to model common cause failures. BBNs can also easily be extended to dynamic BBNs to account for time when analyzing risk.

Similar to fault trees, event trees can also be represented by BBNs. Traditional event trees model assume that accidents are a sequence of conditional events. This makes it intuitive to model, but such a scenario is seldom the case. Both the state of the system and the environment will influence the causal sequence. Some accidents can also depend on other factors that just the hazard, which makes the event tree invalid. To address these limitations, Fenton and Neil (2019) argue that a BBN can be used instead. BBNs are also easier to use in more dynamic applications due to their flexible structure (Khakzad et al., 2013).

2.7 Risk-based Decision-making and Control of Autonomous Ships

Thieme et al. (2021) present four potential areas to merge control of autonomous systems and risk analysis in order to improve the decision-making capabilities: (i) Risk models, such as fault trees or BBNs can be used directly to make decisions, (ii) the output from risk models can be used as input to decision-making algorithms, (iii) the output from risk models can be used to constrain decision-making algorithms, or (iv) the output from risk models can be represented on maps and be used in path planning.

Bremnes et al. (2019) present an example of how risk and control can be merged in practice where a BBN is extended to a decision network and used directly in the control to set the altitude set-point for an AUV when operating under ice. By doing this, the AUV can find the optimum balance between mission reward in terms of data quality and the risk of colliding with the ice. Bremnes et al. (2020) present and alternative approach for a similar problem where the mission reward is maximized and risk is only used as a constraint in the optimization.

One approach to combining risk and control is using MPC-based applications such as Blindheim et al. (2020). Here, a metric describing the risk of grounding or colliding with an obstacle is used as input in the optimization and for emergency management of an autonomous ship. Blindheim et al. (2023a) present an alternative approach where a risk-based MPC is used for autonomous navigation in a way more similar to the path planning approach proposed in Thieme et al. (2021). Blindheim et al. (2023a) show an example of how the output from a risk model can be used in a decision-making algorithm for machinery management and combining this with a form of optimum control in particle swarm optimization. However, neither of these uses a risk model for solving these problems. Instead, they take either a risk metric based purely on the time to grounding, collision, or allision if the ship were to lose power, or assess whether the ship violates the minimum separation distance to land or an obstacle.

As indicated in Thieme et al. (2021) and shown in these works, risk information can be used to improve the decision-making capabilities of autonomous ships compared to conventional control systems. However, the data included in the risk metrics and the inclusion of risk models is still something that should be addressed in more detail as existing work is still limited in this area. This thesis therefore focuses more on the risk analysis and risk modeling task following a similar approach as presented in Utne et al. (2020). For this purpose, MPC and similar control approaches are deemed unnecessarily complicated. Instead, more conventional PID-based controllers are used for autopilot and DP controllers. Hence, this thesis aims to show how a ship control system as described in Figure 2.1 can be combined with risk analysis methods such as STPA and models such as BBNs.

Chapter 3

Research Approach

3.1 Research Methodology

Research and development (R&D) can generally be divided into three different types: basic research, applied research, and experimental development (OECD, 2015). Basic research is the work done to acquire new knowledge without any specific application or use in mind. Applied research acquires new knowledge directed towards a specific use or objective. Experimental development is systematic research and testing aimed at developing new, or improving existing, products and processes.

The research conducted in this thesis is mostly in the applied research category with the objective of acquiring new knowledge and developing methods for risk-based control of autonomous ships. This starts by evaluating existing methods and tools that can be used to improve decision-making in control systems for autonomous ships and provides a good foundation for developing new tools and methods suitable for operating autonomous ships.

Compared to traditional research in natural and social sciences, the research performed here has not used experiments to validate the proposed methods. Instead, simulations have been used to measure the performance of the proposed control systems. This is used because autonomous ships are still in development, meaning there are limited physical systems available. In addition, risk and safety are more conceptual and difficult to measure in real-world experiments. The models used in this research are one way to measure these, without offering an absolute value. Instead, the same model can evaluate different solutions such that the values can be compared. The results have also been presented to industry partners and academic peers to evaluate if the results are reasonable. Experience from simulations and feedback from experts have then been used to further improve the methods.

The simulations used have been based on an 80 m long cargo ship transporting fish goods along the Norwegian coast. The simulator is based on previous work conducted at the Department of Marine Technology (IMT) at NTNU, and extended with additional components and controllers. This includes a guidance module for following preplanned routes and a DP-controller for low speed maneuvering and station keeping. For more details about the simulator, the reader is refereed to Johansen and Utne (2022) and Johansen et al. (2023). The models used in the simulator are based on simplified kinetic models of the ship. This is deemed sufficient to show how a risk-based control system works. However, it introduces some inaccuracy in the ship motions. The lack of wave forces especially means that they can behave differently than an actual ship, but it will only affect the motion controllers and not the Supervisory Risk Controller (SRC).

The research conducted in this thesis is focused around three tasks: (i) reviewing existing methods and tools suitable for risk-based control of autonomous ships; (ii) developing new methods and tools for this purpose; and (iii) testing the developed methods and tools.

Reviewing existing methods is necessary to identify the state of art. Scientific literature databases, review articles, and books have been used to identify relevant methods. This is used to find both tools and solutions that can be used further, as well as identifying areas which need further work. Examples of such areas includes finding ways to measure risk such that a computer-based control system can use the information in the decision-making process. This must then be combined with other performance parameters to find a balance between efficiency and safety when operating the ship. Existing control systems usually focus on optimizing efficiency, while satisfying specific rules related to safety. This can work, to a certain extent, if the rules cover all potential situations. However, autonomous ships are complex systems operating in a constantly changing environment such that it is impossible to cover all potential combinations. Instead, this research considers it an optimization problem where efficiency and safety are combined. In this way, the control system can be adjusted to acquire the desired balance between risk and reward.

The second task combines methods identified in the first task and develops new methods to improve decision-making capabilities in autonomous ship control systems. To achieve this, the research conducted in this thesis combines methods from risk and decision sciences, such as STPA and BBN, with control theory and optimization. Another important part of this work is the use of experts to identify data necessary to develop models, especially since autonomous ships are still in development and there are close to no historical data available. This means that the equations used in the SRC describing risk and operational costs have been based on a mix of expert judgment and historical data from similar systems.

The last task consists of testing the proposed control system. Simulations are an important tool for this since autonomous ships are still in development and therefore difficult to test in real-world experiments. This includes both testing the proposed control system itself, and comparing it against historical data from conventional manned ships. Comparing it to existing solutions is important to show that autonomous ships can operate in a safe and efficient manner.

The data necessary to build the models used in the simulations and compare the results have been gathered through collaboration with specialists from both industry and academia, as well as literature on similar applications. The risk analysis and risk models are based on the results from internal STPA workshops with with 12 experts conducted as part of the ORCAS-project. The participants have 5–30 years of experience from industry and academia working with marine technology and maritime operation, ship control system design, risk assessment, testing, verification and validation. The workshops were conducted over multiple sessions and provided valuable information for building the risk models. The results from the simulations have also been assessed with experts on ship control systems and crew working on conventional ships to assess the validity.

3.2 Work Process

The work and research conducted as part of this PhD project included the following main steps: Firstly, writing a research plan, then writing the papers included in this thesis, and finally writing this thesis. Other activities such as courses in relevant topics have been important to get a good foundation for working on the papers and thesis.

The research plan included developing the research objectives and identifying the state of art relevant to the research objectives. This includes answering questions such as:

- What methods can be used to analyze risk related to operation of autonomous ships?
- How is risk controlled and managed when operating conventional manned ships?
- How can risk and safety be included when designing control systems for autonomous ships?

When developing the research plan and research objectives, it was also necessary to gather information about how existing ships are operated, and how this could differ from autonomous ships. This included both talking with experts from academia and industry, and visiting ships and talking with the crew. This provides very useful data and input when describing and analyzing the autonomous ship concepts assessed in this research.

The research objectives are developed based on the current state of art, and gaps identified related to the control and management of risk related to autonomous ships. The gaps identified mainly relate to analyzing risk in complex systems, building quantitative risk models describing autonomous ships, and how can this quantitative information be used when operating an autonomous ship.

The first paper identifies and evaluates state of the art risk analysis methods for use in the further research work. The following papers papers describe different versions of a risk-based control system for autonomous ships addressing different challenges and problems. Through this process, experience from testing the different versions of the SRC and feedback from industry partners and academic peers have provided possible improvements to address in the later versions. The same process have also been used to improve the equations used in the control system to make decisions. The risk cost is described using the same equations in all iterations, but the risk model has been modified based on reviews and assessing the results.

The equations used to describe the operational costs have changed significantly more. The first version of the SRC calculated the assumed cost of fuel used in cruise or transit and docking and compared this to the risk cost. When assessing the results from this, the ship behavior was good, but the costs were highly inaccurate, which made it difficult to further improve the system. The second version of the SRC therefore divided the operational costs in fuel, other operational costs, and a term called potential future loss used to penalize the controller if it used longer time than necessary. Using this process, the equations could be improved as more data became available from talking to industry experts and testing the previous versions.

The thesis aims to summarize the contributions, results, and conclusions for the papers and describe and discuss how these address the research objectives holistically. In addition, it describes the theoretical and practical implications of the work and outlines further work that should be conducted in order to continue developing autonomous ships.

3.3 Quality Assurance

The quality of the research conducted as part of this thesis has first and foremost been tested through reviews from the supervisors, co-authors, colleagues, and industry partners. The research has been presented and evaluated at project meetings with both the ORCAS- and related projects. There have also been multiple meetings with industry partners to provide a status update on the work and get feedback on both the conducted and planned work. Further, the quality has been tested through peer review in scientific journals. Parts of the research have also been presented at workshops and conferences where the content is also reviewed by peers. Feedback from reviewers has been valuable to improve the quality of the research.

The proposed control system has been tested extensively in simulations to evaluate its performance. In addition, the results from simulations have been compared against operational measurements from actual ships to evaluate the validity and realism of the results.

Chapter 4

Main Results and Contributions

This chapter describes and assesses the main contributions from the research in this thesis in terms of the research objectives. A synthesis of the work and contributions from the research is also presented together with an assessment of the theoretical and practical implications of the research. The last section addresses limitations that have affected the research.

The connections between the overall research objective, individual research objectives and research papers are illustrated in Figure 4.1. Research objective 1 is addressed in papers 1-2, objective 2 in Paper 3, and objective 3 in Paper 4.

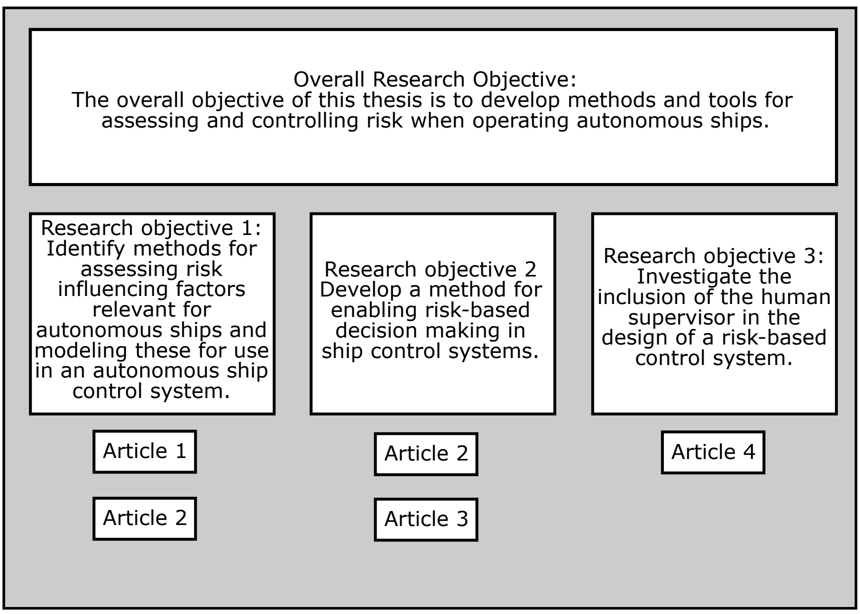

Figure 4.1: Overview of main objective, research objectives and papers.

A summary of the papers with their objectives, methods, results, and contributions can be found in Table 4. This shows how the three research objectives are addressed in the papers and what methods have been used. The table also shows the main results and conclusions from each paper as well as a more general conclusion. Lastly, the table presents further work identified from each of the research objectives.

<table>
<tr><td colspan="5">The overall objective of this thesis is to develop methods and tools for assessing and control ling risk when operating autonomous ships.</td></tr>
<tr><td>Objectives</td><td>Identify methods for assessing risk influencing factors relevant for autonomous ships and modeling these for use in an autonomous ship control system.</td><td colspan="2">Develop a method for enabling risk-based decision-making in ship control systems.</td><td>Investigate the inclusion of the human supervisor in the design of a risk-based control system.</td></tr>
<tr><td>Addressed in</td><td>Paper 1 - Risk analysis of autonomous ships</td><td>Paper 2 - Supervisory risk control of autonomous ships</td><td>Paper 3 - Development and testing of a risk-based control system for autonomous ships</td><td>Paper 4 - Human-autonomy collaboration in supervisory risk control of autonomous ships</td></tr>
<tr><td>Objectives in papers</td><td>Assess the feasibility of using STPA for risk analysis and quantitative risk modeling of autonomous ships.</td><td>Develop an online risk model that can be updated as conditions change, using risk as one metric to control an autonomous ship in operation.</td><td>Present a methodology to develop an SRC for high level control of autonomous ships that bridges risk modeling, optimization, electronic navigational charts, and formalized verification to achieve safer and more intelligent performance of autonomous ships.</td><td>Present a methodology for designing and testing a risk-based control system, focusing on both the autonomous control system and the human supervisor.</td></tr>
<tr><td>Background</td><td>Few methods exists for building risk models for autonomous ships that include both hardware software, and human factors.</td><td>No previous work uses risk as a metric for high-level control of autonomous ships</td><td>No previous work showing a full methodology for designing and verifying a control system for autonomous ships.</td><td>A first step towards including a human supervisor in the design of a control system for autonomous ships.</td></tr>
<tr><td>Literature</td><td>Risk assessment
Risk modeling
Software
Human factors
Autonomous ships
BBN</td><td colspan="2">Autonomous ships
Online risk modeling
Supervisory control
Optimization
Ship control systems</td><td>Human factors
Risk assessment
Optimization
Ship control systems
Route selection</td></tr>
<tr><td>Research methods</td><td>Literature review</td><td colspan="3">Hazard identification
STPA
Risk modeling
BBN
Simulation-based testing
Control optimization
PID controllers
Use-case
Expert judgments</td></tr>
</table>

	Paper 1 - Risk analysis of autonomous ships	Paper 2 - Supervisory risk control of autonomous ships	Paper 3 - Development and testing of a risk-based control system for autonomous ships	Paper 4 - Human-autonomy collaboration in supervisory risk control of autonomous ships
Results	A set of potential methods for complementing STPA to enable quantitative risk modeling of autonomous ships.	A method for using online risk models to include risk as a metric when operating autonomous ships.	A method for designing and verifying as SRC for risk-based control of autonomous ships.	A control system designed to notify a human supervisor with sufficient time to react and make alternative plans to ensure safe operation of an autonomous ship.
Conclusions from the papers	STPA is a suitable method for assessing risk related to autonomous ships. However, it needs to be complimented with other methods for quantitative risk modeling of autonomous ships.	STPA can be used as the foundation for building a BBN-based online risk model that can provide a risk metric to control systems for autonomous ships.	As SRC can be combined with existing ship control systems to enable safe operation of autonomous ships.	A risk-based control system for autonomous ships should still be designed with a human supervisor as part of the system.
Conclusion	This thesis identifies potential ways and methods for assessing risk related to the operation of autonomous ships. A method for modeling risk-based on BBN is used to provide a risk metric that can be combined with operational measurements from the ship control system to improve the decision-making capabilities.			
Further work	Use additional risk analysis methods to improve the online risk model and enable safer operation of autonomous ships.	Add more functionality to the SRC to reduce the need for human control of autonomous ships. Conduct model and real world testing of a risk-based control system for autonomous ships. Test with more advanced motion controllers and ship control systems.		Investigate further how a risk-based control system for autonomous ship can be designed to include a human supervisor.

Table 4: Summary of the contributions from the different papers together with the main methods and results

4.1 Contributions Towards Research Objective 1

Johansen, T. and Utne, I.B. (2020). Risk analysis of autonomous ships. *30th European Safety and Reliability Conference, ESREL 2020 and 15th Probabilistic Safety Assessment and Management Conference, PSAM 2020*, 131–138 - Paper 1

Johansen, T. and Utne, I.B. (2022). Supervisory risk control of autonomous surface ships. *Ocean Engineering*, 251, 111045 - Paper 2

Paper 1 assesses the feasibility of using STPA as a basis for risk analysis of autonomous ships and quantitative risk modeling of autonomous ships. The paper also identifies methods for addressing limitations in STPA with the aim of building a quantitative risk model for autonomous ships. Paper 2 presents an online risk model based on STPA and BBN, an approach based on Utne et al. (2020). This was also one of the papers identified in Paper 1.

Due to the increased system complexity in autonomous ships, traditional risk assessment methods focusing on single component failures are not sufficient. Instead, there is a need for methods designed to analyze interactions between different systems, as well as the individual systems. To address risk analysis of autonomous ships, Paper 1 defines seven requirements for risk analysis of autonomous ships:

Number	Assessment questions
R1	Including software.
R2	Including humans in the loop.
R3	Including security aspects, especially cyber security.
R4	Including hardware.
R5	Including risk from unsafe interaction between different parts of the system.
R6	Including the environment around the autonomous ship, both nature forces and other vessels.
R7	Addressing emerging risks.

Table 4.2: Requirements for risk analysis of autonomous ships

STPA, as described in Leveson (2011), is chosen as the start point since it addresses multiple requirements; the focus on unsafe interactions in the system especially provides a good foundation. The other requirements are also addressed to a lesser degree. However, since STPA is only a qualitative hazard identification method, the results cannot be used directly in a ship control system to make decisions. To do this, more quantitative data are necessary, especially about consequences from hazardous events.

Methods that complement STPA by addressing the other requirements can also provide useful information. Paper 1 therefore defines eight assessment questions/criteria and uses these to evaluate 35 additional methods identified by assessing relevant literature.

Number	Assessment questions
Q1	Is the method already based on STPA?
Q2	Can the results from an STPA analysis be used in the further analysis using this method?
Q3	Does the method complement the results from an STPA analysis with additional important information?
Q4	Can the results be used to build a quantitative risk model for autonomous ships, including software, hardware, and humanware?
Q5	Is it easy to find good literature that describes the method?
Q6	Is the method designed to be easily updated with new information?
Q7	Is the method applicable for analyzing risk for autonomous ships?
Q8	Can the method be modified so it can be used on autonomous ships? (Only relevant when the answer is no on question seven)

Table 4.3: Assessment questions/criteria for risk analysis of autonomous ships

In addition to evaluating against the different questions, each method is classified based on the main topic addressed or tool used. Seven methods are assessed to be more relevant based on the assessment. The first method presented in Wróbel et al. (2018) addresses emerging risk and uncertainty related to these, which are important for new technologies such as autonomous ships. The second method from Omitola et al. (2019) is developed based on STPA with a special focus on security risks. Thieme et al. (2020a,b) presents a method for analyzing software. The results from an STPA can be used as input to this to identify what software should be assessed further. Ramos et al. (2020b) and Martins and Maturana (2010) can be used to analyze how human interaction and control of autonomous ships affect the ship safety. Utne et al. (2020) and Thieme and Utne (2017) are both more general methods for assessing and modeling risk related to autonomous ships.

The method proposed in Utne et al. (2020) is developed further in Paper 2 to convert STPA results into a qualitative measurement by mapping it into a BBN. The STPA identifies the hazardous events, system-level hazards, unsafe control actions, and loss scenarios with different risk influencing factors. The results from an STPA is assessed further to also identify potential consequences. The consequences are then classified based on the expected cost. The results from the STPA, together with the consequences, are modeled in a BBN to get an expected risk cost based on the consequences and the assumed likelihood of each category. The BBN is made into an online risk model by assigning input probabilities to the risk influencing factors and defining conditional probability tables. The input probabilities are then updated based on operational measurements from the ship control system to acquire an updated risk cost based on the current conditions and situation.

Working towards the first research objective has provided a good foundation for developing a risk-based control system. The first paper identified a set of useful methods and tools relevant to use further. Paper 2 continued this work and combined STPA and BBN, both identified in the first paper, to acquire a risk model that can provide risk information for use in a cost function. The result is an important step towards risk-based control systems where both risk and operational costs can be used to make decisions.

4.2 Contributions Towards Research Objective 2

Johansen, T. and Utne, I.B. (2022). Supervisory risk control of autonomous surface ships. *Ocean Engineering*, 251, 111045 - Paper 2
Johansen, T., Blindheim, S., Torben, T., Utne, I.B., Johansen, T.A., and Sørensen, A.J. (2023). Development and testing of a risk-based control system for autonomous ships. *Reliability Engineering and System Safety*, 234, 109195 - Paper 3

Paper 2 presents a method for using risk information from a BBN-based online risk model in as SRC. The controller combines the risk information with operational measurements from the ship control system to enable risk-based decision-making. Paper 3 develops the SRC further based on the experiences from Paper 2 and incorporates this in a control system for an autonomous ship. The decision-making capabilities of the resulting control system is compared to how existing manned ships are operated.

To enable risk-based decision-making, the online risk model calculates a risk cost using the output from the risk model. This is calculated by multiplying the probability of different consequences with the corresponding cost as shown in Equation 4.1.

$$\begin{aligned} R(d) = & Pr_{severe}(d)C_{severe} + Pr_{significant}(d)C_{significant} \\ & + Pr_{minor}(d)C_{minor} + Pr_{none}(d)C_{none} \end{aligned} \tag{4.1}$$

R is the risk cost, d is the set of decisions, Pr is the probability of different consequences, and C is the corresponding cost. By including potential decisions, such as setting a reference speed for the ship to follow, the risk cost will change depending on the decisions made by the SRC. In Paper 2, this is compared to a simple estimation of the cost of operating the ship given the current state, conditions, and decisions calculated with Equation 4.2.

$$C(d) = c_{fuel} \times (t_{cruise} \times P \times \eta_{cruise} + t_{dock} \times P \times \eta_{dock}) \tag{4.2}$$

C is the total operation cost, d is the set of decisions, c_{fuel} is the price of fuel per kWh, t is the time spent either cruising or docking, P is the max power from the machinery, and η is the assumed load percentage in cruise and docking mode respectively. This equation was a simple way to describe the fuel cost depending on the power consumption and the sailing distance. The SRC can then assess potential decisions to find the lowest total cost.

The SRC was developed in multiple stages based on experiences and results from the previous papers. Paper 2 showed that an SRC could be used in a risk-based control system. However, the results also showed that the cost functions were inaccurate and could be improved significantly later. The operational cost especially needed to be developed further in order to improve the control system. Paper 1 considered a case study where the ship was supposed to stop at the final way-point. This was achieved by having an operational cost that decreased as the remaining sailing distance became smaller. The risk cost therefore became higher, the closer it drew to the final way-point, resulting in the ship slowing down. The SRC was also improved with additional functionalities to address specific areas identified as further work, such as notifying a human supervisor when the controller is unable to operate safely.

The second version of the SRC uses the same approach to calculate the risk cost, but divides the cost of operation into fuel, other operation costs, and potential future loss due to scheduling challenges. The fuel cost is then calculated as the fuel consumption per distance as a function of the wind, current, ship speed, and machinery mode. This is found by simulating the ship for a wide range of conditions, noting down the specific fuel consumption and making a look up table that can be used to calculate the fuel consumption. The fuel cost is based on the prices found at Ship & Bunker (2022). Other operation costs and potential future loss is calculated using a constant cost per time multiplied with the sailing time. These costs are based on operational costs from existing ships described in Stopford (2009). The cost of potential future loss is a term used to penalize the ship if it uses too much time. This term is estimated to balance the fuel, operational cost, and risk cost, assuming that the ship need a sufficient income to be commercially viable.

$$F(d) = SFC(wind, speed, current, machinery) * distance \tag{4.3}$$

$$O(d) = Cost_{operating} * distance/speed \tag{4.4}$$

$$L(d) = Cost_{futureloss} * distance/speed \tag{4.5}$$

By describing both performance and risk in terms of cost, the SRC can use both to find the best set of decisions. The proposed SRC is combined with an Autonomous Navigation System (ANS) containing motion controllers such as DP controller and autopilots, an Autonomous Machinery Management System (AMMS) that controls the machinery and manages power production, navigation sensors and electronic chart modules to build a risk-based control system. To further address the second research objective, Paper 3 also proposes a specific verification step when designing the control system. This is used to verify that it is designed according to the requirements such that it can operate both safely and efficiently.

Testing shows that the control system proposed in Paper 3 is capable of operating an autonomous cargo ship in a manner similar to how humans operate conventional ships. Data collected from a conventional manned ship, and conversations with crew, shows how human operators adjust the speed of the ship and start additional power sources when operating in more challenging areas such as narrow straights or harbors. An example of this is starting a second generator set when docking a ship to have more power available, and having a redundant system in case one set stops. Similarly, the case studies in both Paper 1 and 2 show that the SRC decides to start additional power sources when reaching more challenging areas or the weather conditions worsen. The proposed control system also reduces the speed to have more control of the ship when there is less space to maneuver. The controller also chooses to reduce the available power in order to save fuel and increase the speed to use less time when the weather conditions are good and the ship has much space to maneuver in. In this way, it can both value safety when the situation demands it, but without sacrificing efficiency when the risk is low. Overall, comparing to how existing manned ships are operated shows that the proposed SRC operates similarly by making decisions to balance safety and efficiency.

The result from the work towards research objective 2 is a risk-based control system capable of operating an autonomous ship in a wider range of conditions compared to existing systems. Where most existing control systems focus on performance and optimizing this, the proposed control system can assess the balance between risk and reward resulting in smarter and safer ship operations. An example of this is found in Paper 3, where the SRC balances the operational risk and the reward from reaching the final way-point faster. Further, the control system presented can easily be developed further by improving the individual parts and using the same interface. Overall, the work done as part of this thesis is expected to be a good step towards safe and efficient operations of autonomous ships.

4.3 Contributions Towards Research Objective 3

Johansen, T. and Utne, I.B. (2023). Human-autonomy collaboration in supervisory risk control of autonomous ships. Submitted to Journal of Marine Engineering & Technology - Paper 4

Paper 4 develops the SRC and control system proposed in Papers 2 and 3 further by adding more functionalities such as a Minimum Risk Condition (MRC) mode and enabling it to make simple route changes. The paper also starts investigating how a risk-based control system can be designed around a human supervisor. To do this, the SRC is designed to notify the human supervisor before it is unable to control the ship.

To address research objective 3, Paper 4 starts analyzing the control system by assigning specific tasks to the autonomous control system and the human supervisor. The autonomous system is analyzed, similar to the previous papers, using STPA. To analyze the responsibility of the human supervisor, Paper 4 uses a method called Human Systems Theoretic Process Analysis (H-STPA) to analyze how the human supervisor can fail to act in a safe manner. The purpose of this is to find ways that the control system can be designed to reduce the chance of unsafe reactions by the human supervisor.

The analysis shows that the control system can fail to provide notifications to the human supervisor, significantly increasing the chance of an unsafe reaction. The SRC is therefore designed with extra focus on when the human supervisor should be notified, mainly when it is unable to continue operating the autonomous ship with sufficient safety margins.

The autonomous control system proposed in Paper 4 needs the human supervisor to intervene or take control of the ship if the weather exceeds the operational limits of the autopilot and DP-controller, if the risk cost exceeds the limit where the autonomous system enters MRC mode, if there is a loss of redundancy in critical sub-systems, or if there is a failure resulting in loss of power production, propulsion, or situational awareness.

By allowing for more shared control between an autonomous control system and a human supervisor, the ship can operate safely and efficiently in a wide range of conditions and situations including machinery failure, sudden changes in the conditions, and winds ranging from calm to strong breezes. The work to address research objective 3 in this thesis is considered as a first step towards designing a risk-based control system that includes a human supervisor in the loop.

4.4 Synthesis

4.4.1 Theoretical Implications of the Research

Paper 1 starts by assessing the feasibility of using STPA to analyze risk related to autonomous ships. This gives a good overview of the benefits with using STPA, but it also provides valuable information about the limitations. STPA provides information about how accidents can happen with autonomous ships, especially information about how unsafe interactions and control actions are valuable when designing the ship and the control system. The limitations identified are mainly the lack of quantitative data since STPA is a qualitative hazard identification method. The methods and tools identified in Paper 1 to address these limitations provide valuable information to enable risk-based control of autonomous ships.

The main theoretical implication and contribution from the work is the method for combining a BBN-based online risk model with ship control systems. Some previous works have suggested similar approaches, but the papers included in this thesis are the first to show how this combination can be used for high-level decision-making. This is then extended to gain a measurable output from the BBN that can be used to control the ship. Paper 2 presents a simple cost function for the controller to optimize, and papers 3 and 4 extend this further to acquire a more detailed cost function describing the ship's operation.

Both the online risk model and cost function can be developed further to improve the control system. The risk model can be extended with more accurate models for the ship and the conditions, such as reliability models of the machinery and sensors, and weather models, to provide an even better representation of the risk picture. This can further improve the decision-making capabilities in future control systems. Similarly, the cost function can be improved with more detailed models of the costs of operating the ship.

The method for designing a risk-based control system presented in papers 2 and 3 shows how such a control system can be designed and tested against the design requirements. By using this, the control system can be checked both in terms of safety and efficiency in the design phase. This can either help prove a minimum performance before building the full system, or reveal the need for adjusting or redesigning of the control system. In both cases, this improves the process of designing autonomous control systems by increasing the confidence in the systems ability to operate safely.

4.4.2 Practical Implications of the Research

The main practical implication of the research presented is the risk-based control system proposed in papers 2, 3, and 4. The case studies show how this can be combined with existing ship control systems to improve the decision-making capabilities. The papers demonstrates this through simulations where the ship must handle realistic conditions on routes along the Norwegian coast. To operate safely and efficiently, the proposed control system has to make decisions reacting to changing conditions and environments. To achieve this, the SRC has to adjust the decisions to reduce the risk level when the weather worsens or the space to maneuver is reduced. When the weather conditions improve and the ship has more space to maneuver, the SRC must take slightly greater risk in order to still operate efficiently.

To further show the capability of the proposed control system, both the ship model and routes assessed in the case studies in Paper 3 and 4 are based on a real ship sailing the same route in comparable conditions. By doing this, the decisions made by the control system can also be compared against how conventional ships operate. This comparison also shows that the proposed control system can operate with the same efficiency, while maintaining a lower risk level.

This type of control system allows for an autonomous ship to operate in a wider range of conditions and situations without the need for a human operator or supervisor. In turn, this is an important step towards operating autonomous ships since the SRC is already tested with control systems in use on existing ships. This research shows it in simulations, but it can also be implemented on actual ships to perform real world testing. Such testing can both use the proposed control system to operate the ship with the crew as backup, or run it for decision support and see how often the crew follows the recommendations.

A big difference between existing control systems and human operators is the ability to assess and manage risk. Computer-based control systems are great at optimizing efficiency and costs leading to very efficient systems. However, they often lack the ability to assess whether it is safe to operate or if some efficiency should be sacrificed. An example of this would be a system shutting down an engine to reduce the energy consumption or avoid damage to the components, but exposing the ship to much more risk by not having the same power available to safely navigate in challenging conditions. By introducing a risk model in the control system, it can evaluate both safety and efficiency in the decision-making process to find good balance.

The control system would need some minor adjustments to integrate with an actual ship but can otherwise be tested as is. In this way, the research included here already now have practical implications for how ships can be operated. The solutions proposed in this research focuses on operating autonomous ships, but could also be applicable for other systems.

Chapter 5

Conclusions and Further Work

This chapter concludes the thesis and provides suggestions for future work.

5.1 Conclusions

The overall research objective of this thesis was to develop methods and tools for assessing and controlling risk when operating autonomous ships. The first objective focused on identifying methods for assessing risk related to autonomous ships and how to model these such that an autonomous control system can utilize this information. The second objective focused on how risk could be included in the decision-making process in an autonomous ship control system. The last objective investigated how a control system could be designed to include a human supervisor.

To address the research objectives, this thesis includes four research papers. The key contributions from these are:

- A study of relevant risk assessment methods suitable for analyzing and modeling risk related to autonomous ships.
- A method for building a BBN-based online risk model that can provide information to a control system for autonomous ships.
- A method for designing and verifying a risk-based control system for autonomous ships to enhance its decision-making capabilities.
- A study of how notifications to a human supervisor could be included in a risk-based control system for autonomous ships.

The impact of the thesis and related work is a proof of concept that a risk-based control system can be used to enable safe and efficient control of autonomous ships. The SRC is capable of combining operational measurements from the ship control system with data from a risk model improving the decision-making capabilities compared to existing conventional ships. Without this information, a control system has little to no ability to evaluate whether a decision is safe or not. The proposed controller can also be used as a decision support system for existing ships. A similar methodology could also be used for other systems such as Remotely Operated Vehicles (ROVs), AUVs, and Unmanned Aerial Vehicles (UAVs).

The main result of the thesis and research papers is the risk-based control system for high-level control of autonomous ships. Paper 2 presents an SRC and shows how this can be used to enable risk-based control of autonomous ships. Paper 3 shows how an SRC can be included with a full control system for autonomous ships and utilize information from this, such as data from an Electronic Navigational Chart (ENC)-module. Paper 4 shows how an SRC can select different routes, and notify potential problems before it loses control of the ship to a human supervisor. Extensive testing in simulations, and comparisons with operational data from physical conventional ships, shows how an SRC can reduce the need for human control significantly, without sacrificing safety or efficiency for autonomous ships.

In conclusion, the thesis and research papers have satisfied the objective of developing methods and tools for assessing and controlling risk when operating autonomous ships. The resulting control system demonstrates that autonomous control systems can asses and manage risk, and also provides a starting point for developing these systems further.

5.2 Further Work

In addition to the risk-based control system, the research has also identified topics and challenges that should be addressed further. The research shows how to include information from an online risk model in a ship control system. However, both the risk model and control system can be improved further. Paper 1 identified a set of promising methods for analyzing and modeling risk related to autonomous ships. Some of these have been used further in the research, such as the procedure for mapping STPA results to a BBN. However, Paper 1 also identified methods that could be used to specifically analyze software in the control system and risk related to human factors. Investigating how to use more of these methods to improve the online risk model and provide more information to the control system is therefore one topic for further research.

The proposed controller and control system can also be developed further. The current version has the ability to select what motion controller and machinery mode to use, as well as choosing what route to follow from a set of preplanned routes. A reasonable extension of this would be to enable the control system to plan routes itself. Enabling autonomous ships to plan routes without the need for human intervention, as well as risk-based decision-making, would be a big step towards operating autonomous ships. Paper 3 also briefly addresses the topic of online verification of the control system to check how potential decisions can affect the future safety of the ship. Assessing this in more detail is also an interesting topic for future work.

The current way of calculating the different cost elements and selecting the decisions that give the lowest is and easy and efficient method. However, alternative methods such as MPC can also be used for this type of control. Testing and comparing the current version with an MPC-based approach should be part of further work. Another part is also optimizing based on predictions of the future. The current version of the control system optimizes based on the current conditions and states while assuming that these will stay constant. If the conditions change, the SRC reacts to the changes. However, methods exist that predict the future such as discrete event simulation (Robinson, 2005) and Monte Carlo methods (Fishman, 1996; Hammersley and Handscomb, 1964; Rubinstein, 1981), which can be useful for this. By simulating and predicting the future, the decision-making process can be more proactive compared to the current version of the SRC.

Human interaction with autonomous ships, as briefly addressed as part of research objective three is also a topic that should be investigated in more detail. Investigating what information a human supervisor needs and how much time is necessary in order to handle situations where the SRC is unable to control the ship are especially important topics for further research. The control system proposed in this thesis starts addressing this briefly by focusing on how the control system can maintain a minimum level of control while the supervisor acquires sufficient situational awareness to make decisions. By focusing more on the human side of this process, the full system should improve further. Considering different human machine interfaces is also considered relevant when developing autonomous ships, although this is considered outside the scope of this thesis.

In addition to further developing the proposed control system, model and real life testing should also be part of future work. Simulations are very useful for proving that the concept works. However, it is still beneficial to conduct physical tests with both models and full size ships. These tests can help identify challenges and situations where the controller needs more development. Ways to do this testing can be using the proposed control system as a decision support system for conventional manned ships and seeing how often the crew uses the input from the SRC. Implementing the system on a scale model where the consequences of failure are smaller, or on a full-scale ship with crew and operators on stand-by, are other alternatives for testing a risk-based control system as part of future research.

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Part II

Selected Publications

Article 1:

Risk Analysis of Autonomous Ships

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Risk Analysis of Autonomous Ships

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The main purpose of this paper is to address the feasibility of using the System Theoretic Process Analysis (STPA) for risk analysis and quantitative risk modeling of autonomous ships. The paper defines a set of requirements and questions, which are used to assess 35 potential risk analysis methods related to software, security, humans in the loop, and emerging risks. The assessment identifies seven main methods that can be used to expand the STPA analysis to enhance it for analyzing risk of autonomous ships, i.e., one method for software, security, and emerging risks, two for human factors, and two more general methods based on Bayesian Belief Networks (BBNs). The results show that almost all the applicable methods provide additional information compared to STPA only, but the results vary much from method to method. It is also a challenge to find a way of combining the results in a quantitative risk model that can be used to describe and evaluate the risk level for autonomous ships. The seven most relevant methods can be used as a starting point for further development of a general framework for risk analysis for autonomous ships.

Keywords: Autonomous Systems, Risk Analysis, Ship Control Systems, STPA, Software reliability, Human Reliability Analysis, Cyber Security, BBN, Emerging Risks

1. Introduction

The objective in this paper is to assess the feasibility for extending the System Theoretic Process Analysis (STPA) for use in risk analysis and quantitative risk modeling of autonomous ships. Autonomy is a trend in the marine industry with projects on both autonomous passenger ferries (Springwise (2018); Marine Link (2019)) and cargo ships (Springwise (2017); Yara (2018)) under development. Yara Birkeland is planned to start with manned operations in 2020 and transition towards fully autonomous operations over the next years with remote operation (Yara (2018)). Other projects, such as the Advanced Autonomous Waterborne Applications (AAWA) (Jokioinen et al. (2016)) initiative and the Maritime Unmanned Ships through Intelligence in Network (MUNIN) (Porathe et al. (2013); Burmeister et al. (2014)) focus on autonomous ships with a varying degree of autonomy where the ship could be manned, remotely operated, or fully autonomous with only human supervision. It is expected that the safe operation of autonomous systems requires quantification of risk and risk models to an increasing extent (*IWASS* (2019)).

The STPA analysis (Leveson (2011); Leveson and Thomas (2018)) was developed as a tool for analyzing hazards in complex, software-intensive, sociotechnical systems. Risk analysis is constituted by three questions (Kaplan and Garrick (1981)): what can go wrong, how likely is it, and what are the consequences. STPA focuses mainly on the first question. Hence, to cover risk analysis and development of quantitative risk models, it is necessary to extend STPA to make it better for analyzing risk of autonomous ships. STPA is rooted in the accident model Systems-Theoretic Accident Model and Processes (STAMP), which treats safety as a control objective where accidents are a result of inadequate control or enforcement of constraints (Leveson (2011)). The main purpose of STPA is to analyze the system to identify unsafe situations, and to find safety constraints to keep the system in a safe state.

Previous works on risk analysis of autonomous ships that have focused on STPA analysis have generally found it feasible for qualitative analysis (Rokseth et al. (2017); Wróbel, Montewka, et al. (2018b); Valdez-Banda, O.A. and Kannos, S. and Goerlandt, F. and van Gelder, P.H.A.J.M. and Bergström, M. and Kujala, P. (2019); Rokseth et al. (2019); Wróbel, Montewka, et al. (2018a); Gil et al. (2019); Wróbel et al. (2019); Wróbel, Gil, et al. (2018); Montewka et al. (2018)). Utne et al. (2020) have proposed using the results from

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an STPA analysis into development of quantitative risk models with a Bayesian Belief Network (BBN). Other specific risk elements related to autonomous systems, such as software has been addressed by Thieme et al. (2020a, 2020b), related to cyber security by Tam and Jones (2018), Bolbot et al. (2019) and Omitola et al. (2019) and human failures by Ramos et al. (2018). A challenge with existing methods is to enable analysis of the different elements in a combined and systematic way for risk analysis.

Reliability models, for example, is one way to model different parts of the system, but reliability does not necessarily mean safety (Leveson (2011)). Reliability describes the ability of an item, or system, to perform a required function under given conditions for a given period of time (ISO (1986)). Safety is however related to freedom from conditions that can cause death, injury, or illness to humans, or damage or loss of equipment or property (*MIL-STD-882D* (2000)). Based on these definitions, a system will be reliable if it functions as intended, but it can still cause harm to humans and damage the environment, and therefore be unsafe. Especially in complex systems, each component can have a high reliability and operate without failure, but the system can be unsafe due to unknown interactions between the different components.

It is therefore necessary to develop methods that can be used to build risk models of autonomous ships that can give an accurate representation of the risk level, combining hardware, software and human factors. This paper is intended as a first step towards this. The next section describes the risk analysis methods, and evaluation criteria, sections three and four present the results and discusses these, and the last section states the conclusions and further work.

2. Method

The paper focuses on risk analysis methods with special focus on humans in the loop, software, security, uncertainty related to emerging risks, and methods intended for risk analysis and risk modeling for autonomous ships based on event trees, fault trees, and BBNs. Alternative methods to STPA for hazard identification are not considered here, with the exception of direct extensions to STPA analysis concerning software, security, humans in the loop, or uncertainty and emerging risks.

For finding potential methods, the Scopus database, and previous review papers and books (Thieme et al. (2018); HSE (2009); Kirwan (1998); Rausand (2011)) as well as the list at PSASS (2020) of previous work on STPA have been used.

2.1. *Developing assessment criteria*

To define a set of suitable criteria for assessing potential risk analysis methods and tools, the systems engineering approach (Blanchard and Blyler (2016)) is used. The first step in this approach is to identify the need, which in this case is risk analysis of autonomous ships, as described in the introduction. The next step is to define the requirements for the system, or in this case, a risk analysis method. For analyzing risk related to autonomous ships, Thieme et al. (2018) present a list of nine evaluation criteria for risk models based on the functional requirements to maritime autonomous surface ship (MASS). In addition to these requirements, a risk analysis for autonomous ships should also consider emerging risks (Wróbel, Montewka, et al. (2018b), Florin and Mazri (2015)). Based on this, the following requirements for a risk analysis method for autonomous ships can be derived, as shown in Table 1.

Table 1. Requirements to risk analysis of autonomous ships, adapted from Thieme et al. (2018)

R1	Including software
R2	Including humans in the loop
R3	Including security aspects, especially cyber security
R4	Including hardware
R5	Including risk from unsafe interaction between different parts of the system
R6	Including the environment around the autonomous ship, both nature forces and other vessels
R7	Addressing emerging risks

2.2. *Evaluation criteria*

From the list of requirements to risk analysis of autonomous ships (Table 1) and the objective of the paper, Table 2 is derived:

The first question is directly related to expanding the STPA analysis for risk analysis of autonomous ships. The second question is relevant since STPA is focused on hazard identification. Therefore, methods are preferred that can use these results in the further analysis. The third is related to assessing how the different methods can be used to get more and important information compared to the STPA analysis. The fourth question is relevant since part of the background for the paper is how to combine risk analysis for both software, hardware, and humanware in one method or framework and use the results for building a risk model that combines the different elements. Question five addresses how easy information about the method can be found and the quality of this. Question six relates to dynamic

Table 2. Assessment questions/criteria to risk analysis of autonomous ships

Q1	Is the method already based on STPA?
Q2	Can the results from an STPA analysis be used in the further analysis using this method?
Q3	Does the method complement the results from an STPA analysis with additional important information?
Q4	Can the results be used to build a quantitative risk model for autonomous ships, including software, hardware, and humanware?
Q5	Is it easy to find good literature that describes the method?
Q6	Is the method designed to be easily updated with new information?
Q7	Is the method applicable for analyzing risk for autonomous ships?
Q8	Can the method be modified so it can be used on autonomous ships? (Only relevant when the answer is no on question seven)

risk analysis (Khan et al. (2016)) and emerging risks (Florin and Mazri (2015)). Question seven is used to assess if the method is developed for or well suited for analyzing autonomous ships, and the last question relates to if the method can be modified to suite autonomous ships.

2.3. *Assessment procedure*

The identified potential methods are assessed by the authors using the questions in Table 2. The scale used is yes, no, or partially. Yes and no means that the method clearly fulfils that for that particular question or not, and a partial answer is somewhere in between. Partially can also mean that the method can be used, but it is necessary with modifications to get good results. The assessment of the different methods are based on the literature describing the methods and review papers.

3. Results

Table 3 shows the list of methods and the results from the assessment. The 35 methods are assessed against the set of questions in Table 2. Where it is possible, the methods are also classified based on the main topic and tool used.

Nine of the methods in Table 3 are focusing on software, five on emerging risks and uncertainty, seven on humans in the loop, and four on security. The other methods are risk analysis methods focusing generally on autonomous systems. Five of the methods are based on STPA and uses this as a part of the method, but almost all the methods can use the results from an STPA as a part of the analysis. All the assessed methods offer additional information, compared to the STPA analysis only, but the type and amount of information varies. Wood (1997), Kang, Lim, et al. (2009), Kang, Eom, et al. (2009), Embrey (1986), Williams (1986, 1988, 2015), Allal et al. (2018), and Hollnagel (1998) are based on reliability theory and provide reliability data for software and humans that can be combined with reliability data for hardware components. BBN is another method that can be used to model the system and combine data for both hardware, software, and humanware in one model. The methods based on BBNs are also easier to update with new information than the methods based on reliability theory. All, but one method can be used to analyze autonomous ships, but many of the methods are designed for other systems, which means that adaptation is necessary.

4. Discussion

4.1. *General discussion of the results*

The results show that it is possible to find methods that contribute with risk data that is not covered in an STPA analysis, since the STPA analysis is mainly focusing on hazard identification part of the risk analysis. In general, a challenge with a lot of the methods is the type of results they produce. Reliability data can be available for different parts of the system, but i can be a challenge to combine this in a meaningful way. Having high reliability for the individual components, for example, does not mean that the system will be safe.

A risk model for autonomous ships may be developed in a BBN combining data for different parts of the system. These can be updated with new probability tables and nodes for changing conditions to represent how the risk level is changing. The challenge using these is how to find the probability tables and combine different types of nodes. A node representing human failure can for example be very different compared to hardware or software in terms of the conditional probability tables.

4.2. *Discussion of the most promising methods*

Wróbel, Montewka, et al. (2018b) is the only method addressing emerging risks without ”no” (cf. Table 3) in any of the categories, with the exception of dynamic risk analysis and updating with new information. The method uses STPA to build a model for analyzing safety for autonomous ships and also addressing uncertainty in the analysis. Wróbel, Montewka, et al. (2018b) has the advantage that it covers both software, hardware, and humanware as a part of the analysis and considers how these interact.

Table 3. Assessment of potential risk analysis methods for autonomous ships

Source	Main topic/tool	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8
Abdulkhaleq et al. (2015)	So/STPA	Y	Y	P	N	Y	N	N	P
Wróbel, Montewka, et al. (2018b)	ER/STPA	Y	Y	Y	P	Y	N	Y	N.R
Wood (1997)	So/RT	N	P	Y	Y	Y	N	N	P
Kang, Lim, et al. (2009)	So/RT	N	Y	Y	Y	Y	N	N	P
Kang, Eom, et al. (2009)	So/RT	N	Y	Y	Y	Y	N	N	P
Thieme et al. (2020a, 2020b)	So	N	Y	Y	Y	Y	P	Y	N.R
Ramos et al. (2018)	H	N	P	Y	P	Y	P	Y	N.R
Ramos et al. (2020)	H/ESD	N	Y	P	Y	Y	P	Y	N.R
Omitola et al. (2019)	Sec/STPA	Y	Y	Y	P	Y	P	P	N.R
Embrey (1986)	H/RT	N	P	Y	Y	P	N	N	P
Williams (1986, 1988, 2015)	H/RT	N	P	Y	Y	Y	N	N	P
Hollnagel (1998)	H/RT	N	Y	Y	Y	Y	N	N	Y
Bjerga et al. (2016)	ER/STPA	Y	Y	P	N	Y	N	N	N
Baybutt (2004)	Sec	N	P	Y	Y	Y	N	N	P
Kavallieratos et al. (2019)	Sec	N	N	Y	Y	Y	N	Y	N.R
Dahll and Gran (2000)	So/BBN	N	P	Y	Y	Y	N	N	Y
OWASP (2015)	Sec	N	P	Y	Y	Y	N	N	Y
Zeng and Zio (2018)	So	N	N	Y	Y	Y	Y	N	Y
Guarro et al. (2012)	So	N	P	Y	Y	Y	N	N	P
Flage and Aven (2009)	ER	N	P	Y	Y	Y	N	N	P
Aven (2008)	ER	N	P	Y	P	Y	P	N	P
Gran (2002)	So	N	P	Y	Y	Y	P	N	Y
Martins and Maturana (2010)	H/BBN	N	Y	Y	Y	Y	P	N	Y
Trucco et al. (2008)	BBN, FTA	N	Y	P	Y	Y	P	P	N.R
Wróbel et al. (2016)	BBN	N	Y	P	Y	N	N	Y	N.R
He et al. (2018)	ER/BBN, BT	N	Y	P	Y	Y	Y	P	N.R
Utne et al. (2020)	BBN,STPA	Y	Y	Y	Y	Y	Y	Y	N.R
Thieme and Utne (2017)	BBN	N	Y	Y	Y	Y	Y	Y	N.R
Allal et al. (2018)	H/RT	N	P	Y	P	Y	N	Y	N.R
Codetta-Raiteri and Portinale (2015)	BBN	N	P	Y	Y	Y	Y	P	N.R
Hurdle et al. (2009)	FTA	N	P	Y	Y	Y	Y	Y	N.R
Biteus et al. (2007)	FTA	N	P	Y	Y	Y	N	N	P
Portinale and Codetta-Raiteri (2011)	BBN,FTA	N	P	Y	P	P	Y	N	P
Jensen (2015)	ETA,FTA	N	Y	Y	Y	N	N	Y	N.R
Tvedt (2014)	BBN,ETA,FTA	N	Y	Y	Y	Y	N	Y	N.R

Abbreviations:
Y = Yes, N = No, P = Partially, N.R = Not Relevant, So = Software, Sec = Security, ER = Emerging Risks, H = Humanware, BBN = Bayesian Belief Networks, FTA = Fault Tree Analysis, ETA = Event Tree Analysis, RT = Reliability Theory, ESD = Event Sequence Diagram, BT = Bow-tie

Omitola et al. (2019) is the only method addressing security that is based on the STPA analysis. The method is structured so it starts with an STPA analysis for identifying system losses. The method includes the security aspect in the analysis by listing eleven possible system threats and links these to the system losses, potential unsafe control actions, and maleficent actions to harm the system. As the method is developed for use with maritime systems, it should also be relevant for autonomous ships.

Based on the assessment, Thieme et al. (2020a, 2020b) is the most relevant method for analyzing risk related to software. The method is not based on STPA, and does not focus specifically on autonomous ships, but the results from an STPA analysis can be used as a basis for selecting what software should be analyzed further. The challenge with this method is how to use the results further in a risk model as the method does not address quantification of failures more than outlining potential ways to do this.

Both Ramos et al. (2020) and Martins and Maturana (2010) are good alternatives for analyzing humans in relation to autonomous ships. Ramos et al. (2020) combines Event Sequence Diagrams (ESDs) and a novel method called Concurrent Task Analysis (CoTA) for analyzing risk in complex systems. Human and other types of failure events are addressed at a system in this method which means that it is easier to combine the results. Martins and Maturana (2010) combine BBNs with human reliability analysis to build a model for estimating how human errors can lead to failures in the system.

Utne et al. (2020) uses STPA analysis to develop a risk model represented by a BBN from STPA results, exemplifying for collision risk of autonomous ships. The BBN can then be used to monitor how the risk level changes over time in an online risk model that can be used further for decision support. The main challenge with this method is determining the conditional probability tables in the BBN.

Thieme and Utne (2017) uses a BBN to assess the performance of human-autonomy collaboration for autonomous underwater vehicles (AUV). The BBN is used as a tool in the design phase, and for decision support in operation of the AUV. The method is developed for AUVs, but the method is also applicable for autonomous ships.

5. Conclusion

This paper evaluates how STPA, which is a qualitative hazard identification method, can be expanded for use in quantitative risk modeling of autonomous ships. A set of 35 potential methods are assessed based on eight questions that are defined for different relevant aspects of the methods. The assessment questions are identified based on a set of requirements deemed necessary for a risk analysis of autonomous ships. The assessment found that seven main methods are in particular relevant for further use in risk analysis quantitative risk modeling of autonomous ships. Wróbel, Montewka, et al. (2018b) is the most relevant for addressing emerging risks and uncertainty, Omitola et al. (2019) for security, Thieme et al. (2020a, 2020b) for software, and Ramos et al. (2020) and Martins and Maturana (2010) for humans in the loop. Utne et al. (2020) and Thieme and Utne (2017) are more general methods for analyzing and modeling risk for autonomous ships that can be used to combine results from the other methods.

Further work in this field is to adapt the above mentioned methods as a basis for developing a framework that can be used to analyze and model hardware, software, humanware and security risks related to autonomous ships in a systemic and integrated manner. This means further reviewing the identified methods more thoroughly and test them in a case study to analyze risk of autonomous ships. How the risk related to the autonomous ship can be combined into one risk model is a major challenge that must be addressed further.

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Article 2:

Supervisory Risk Control of Autonomous Surface Ships

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Supervisory risk control of autonomous surface ships

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ABSTRACT

The objective of this paper is to develop online risk models that can be updated as conditions change, using risk as one metric to control an autonomous ship in operation. This paper extends and integrates the System Theoretic Process Analysis (STPA) and Bayesian Belief Networks (BBN) with control systems for autonomous ships to enable supervisory risk control. The risk metric is used in a Supervisory Risk Controller (SRC) that considers both risk and operational costs when making decisions. This enables the control system to make better and more informed decisions than existing ship control systems. The novel control system is tested in a case study where the SRC can change: (i) which machinery system is active; (ii) which control mode to run the ship in; and (iii) which speed reference to follow. The SRC is able to choose the optimum machinery, control mode, and speed reference to maintain safe control of the ship over a route in changing conditions.

1. Introduction

This paper will demonstrate how risk models can be utilized by ship control systems (i.e., supervisory risk control) to enable better situational awareness and decision support for autonomous ships (Utne et al., 2020b). The development of Maritime Autonomous Surface Ships (MASS) is an important trend in the maritime industry (Kretschmann et al., 2015; Wróbel et al., 2017), which requires the development of more advanced control systems that can function with less human control. Although many ships in operation today already have systems for autonomous control, none of them are designed for fully unmanned operations. Even the most advanced systems, such as the bastøferry crossing the Oslofjord (Kongsberg, 2020) and the Milliampere small passenger ferry that is intended to cross a part of Nidelven in Trondheim (Springwise, 2018), still have human operators who make decisions and supervise the operation.

The control of ships can be divided into three main levels (Ludvigsen and Sørensen, 2016): mission planner level, guidance and optimization level, and control execution level. The mission objective is defined and planned in the mission level. The guidance and optimization level handles way-points for the navigation system and optimization of resources. Control execution controls the actuators (e.g., engines and rudders) and plant, such as Dynamic Positioning (DP) and auto-pilot (Sørensen, 2005). Supervisory risk control focuses on the two highest levels of a control system.

Guidance and optimization have two main challenges: planning an efficient and safe route to follow, and managing resources such that the ship has sufficient power and control but at the same time not use too much energy and lead to higher costs. Many existing ships have systems for planning the route, but this is still a task where human operators are involved by either supervising and controlling, or planning the whole route. The same is the case with optimization, where many ships have power management systems but where humans still supervise and manage these systems. The challenge is similar for mission planning, namely to plan the mission such that safety and efficiency are sufficiently accounted for in the decision process. Risk models can enable the control systems to make better decisions in these cases by showing how decisions affect the risk level.

Control systems for autonomous ships need many of the same functionalities as existing ships but they also require some additional functions to handle higher level decisions. For the ship to maneuver at both high and low speeds, the ship needs two controllers. This can be a DP controller for low speed maneuvering and station-keeping, and a heading and speed controller for higher speeds. Each of these controllers also needs a thrust allocation system to convert the control output to thrust set-points for the different thrusters. An example control system is shown in Fig. 1.

The way-points for the controller to follow are planned by a guidance module. This module must handle both permanent obstacles in the route, and other ships and moving obstacles. For highly autonomous ships, the guidance module also needs a way to prioritize, or handle, multiple obstacles at the same time. For both the controller and guidance module to function, autonomous ships need a system for handling

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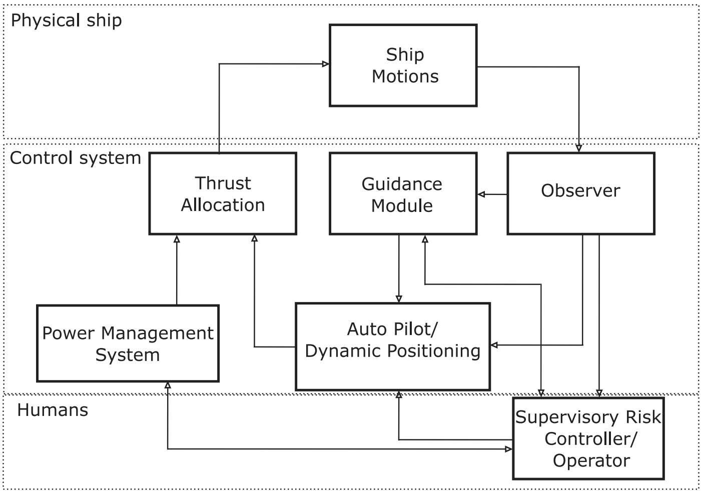


Fig. 1. Ship control system.

sensor-input and sorting this information. Many ships with DP have an observer where position measurements are filtered and processed such that the ship has an accurate position and can handle faulty measurements without losing the position (Sørensen, 2005). Fully autonomous ships need at least this capability, as well as systems for handling cameras and weather sensors. The last main part of the control system is the power management system (PMS). This system must ensure that the ship has enough power available for both propulsion and other loads. Autonomous ships must also have systems for deciding what type of motion controller to use (e.g., DP or auto-pilot). These systems must consider both the type of operation (e.g., cargo or passenger transport) and the specific conditions (e.g., wind, current, and waves) that affect the ship.

Combining and utilizing risk analysis and modeling with existing control systems is one possible way to enable better decisions for autonomous ships and make control systems that can function without human input. In their paper, Utne et al. (2020b) present a framework where the System Theoretic Process Analysis (STPA) is used as a basis for making a Bayesian Belief Network (BBN) risk model. The risk model can then be used to provide information about the current risk level while the ship is sailing by updating the model. The model can then provide information about how different decision options may change the overall risk. This can be especially useful in the two highest control levels: mission planning, and guidance and optimization. The mission, or voyage, can be planned to account for weather information, traffic, maintenance status, and ship conditions such that the voyage can be both safe and efficient. While the ship is sailing, the route can be re-planned and optimized to account for changes in weather, traffic, and the condition of the ship such that the risk can be kept at an acceptable level during the whole voyage. The risk model can also be used to optimize the machinery and control of the ship by including risk when optimizing power production and selecting control modes.

Previous work related to risk analysis and control of autonomous ships has focused on these topics separately, and limited emphasis has been put on not how to use risk models as an integrated part of the control system. An exception is the framework proposed in Utne et al. (2020b), which outlines at an overall level how such integration may occur. One of the challenges faced by the current STPA is that consequences are not considered, which is important information for a risk model. The current paper extends the STPA, advances the framework of Utne et al. (2020b), and tests it in a case study.

Johansen and Utne (2020) discuss how STPA can be used for hazard identification for autonomous ships, and focuses on methods for finding additional data for building a risk model. Fan et al. (2020) present a framework for identifying factors that influence navigational risk for autonomous ships. Chaal et al. (2020) present a framework for how the control structure of autonomous ships can be modeled for use in STPA. Valdez Banda et al. (2019b) use STPA for a systemic hazard analysis of two autonomous ferry concepts and suggest safety controllers to manage these hazards. Valdez Banda and Goerlandt (2018) use a similar approach to the design of a safety management system for Vessel Traffic Services in Finland that may be relevant for autonomous ships. Valdez Banda et al. (2019a) present an evaluation framework for a Systems-Theoretic Accident Model and Processes (STAMP) based safety management system. However, even though these studies are useful, none of them use the results further in either risk models or control systems.

Brito and Griffiths (2016) present a Bayesian approach for predicting the risk of losing AUVs during missions. Brito (2016) proposes a method for handling uncertainty in AUV missions. Loh et al. (2020) present a hybrid fuzzy system dynamic risk analysis that can provide recommendations for risk management in AUV operations. These show different tools that can be useful for risk control and management, but they are not combined with a thorough hazard analysis, such as STPA, nor are they implemented in control systems. A few works have used a BBN risk model for control of AUVs (Bremnes et al., 2019, 2020), where the BBN is based on a checklist based Preliminary Hazard Analysis (PHA), and not STPA. These also consider a different type control where the objective is to follow and measure the ice surface above the AUV.

Rødseth and Tjora (2015) discuss how to include risk when designing the control system, but without showing how it can be used in the control system. Risk analysis of autonomous ships have been addressed in Wróbel et al. (2016) and Shuai et al. (2020), and supervisory risk control in Utne et al. (2020a), but not explicitly implemented in the control system as in this paper. Other works have used BBNs for assessing both autonomous ship operations (Chang et al., 2021) and traditional manned ships (Yu et al., 2021; Ung, 2021; Vojkovic et al., 2021) Risk is addressed as a part of collision avoidance for autonomous ships (Hu et al., 2017; Naeem et al., 2016; Campbell et al., 2012; Campbell and Naeem, 2012; Wang et al., 2019; Woo and Kim, 2020; Lyu and Yin, 2019), but without a direct link to risk analysis and modeling.

The rest of this paper is structured as follows: Section 2 presents the method used for supervisory risk control. Section 3 shows how the method can be used in a case study. Section 4 presents and discusses the results. Finally, Section 5 concludes the paper.

2. Method

The proposed method for implementing supervisory risk control is based on three overall stages (Utne et al., 2020b):

(a) Conduct an extended STPA of the ship and its operation, also including consequences;
(b) Build a BBN risk model based on the extended STPA;
(c) Implement the risk model in a Supervisory Risk Controller (SRC).

2.1. An extended system theoretic process analysis

The first stage is to perform a STPA of the MASS in the operational context that it is designed for. The general STPA consists of four main steps (Leveson, 2011):

(a) Define the system
(b) Identify system-level accidents, and system-level hazards
(c) Identify unsafe control actions (UCA)
(d) Develop loss scenarios

An accident can be defined as "a sudden, unwanted, and unplanned event or event sequence that has led to harm to people, the environment, or other tangible assets" (Rausand and Haugen, 2020). Even though the term "accident" is used in the general STPA, the consequences of the system level hazards and accidents are usually not explicitly considered or described with this method. For supervisory risk, control consequences need to be included to support the decision making of the autonomous control system because potential consequences of hazardous events (and hence risk) may change during operation, which may influence the decisions to be made. Therefore, this paper uses the term "system level hazardous event", instead of accident. This adds the analysis of consequence as a fifth step, meaning that the hazardous event and the potential consequences together may encompass an accident.

The first step of the STPA is to define and describe the system. This includes modeling the control structure and describing control responsibilities, feed-back signals, and process variables for the different controllers. The second step is to define the system-level hazardous events and system-level hazards. Each system-level hazard has a safety constraint. The third step is to identify the UCAs that violate the safety constraints and can lead to hazardous events. The fourth step in the STPA is to develop loss scenarios. These scenarios describe how the hazardous events can occur and what can cause these events. The STPA gives a basis for assessing risk in the supervisory risk controller. Step five is to develop the risk model, it is also necessary to specify the worst-case conditions that, in combination with system-level hazards, lead to the accidents.

2.2. Online risk model

The next phase is to develop the online risk model to be used in the control system. In this paper, this means providing an output that can be used directly in a cost function for finding best set of decisions. The BBN consists of five main type of nodes:

- Consequences
- Hazardous events
- System level hazards
- Unsafe control actions
- Risk influencing factors

The results of the STPA (phase 1) are used to define the nodes and structure of the BBN. The STPA identifies how risk influencing factors (RIF) can lead to unsafe control actions (UCA). These can further lead to system level hazards, hazardous events, and consequences from these events. The same structure is used to build the BBN. The consequences are caused by the hazardous events, and a set of environmental conditions or RIFs. Each hazardous event is caused by system level hazards with certain RIFs, The system level hazards are caused by one or more UCAs. The UCAs are similarly caused by one or more RIFs. For a more detailed explanation of mapping STPA results into a BBN, the reader is referred to Utne et al. (2020b).

The top level nodes and output from the risk model are the consequences. Hazardous events are events that may result in losses (negative consequences). System level hazards are the system states, or conditions, that result from UCAs and which can lead to accidents. The unsafe control actions are control actions that lead to system level hazards. The last type is RIFs, which are either high-level RIFs or input RIFs. High-level RIFs are identified directly from the loss scenarios in the STPA. Input RIFs are causal factors used to characterize high-level RIFs and how hazards can lead to accidents. The risk model is used to assess the risk of accidents at each time step, given the current conditions for the ship in operation.

2.3. Supervisory risk controller

The SRC is the controller that makes the high level decisions based on the risk level and operational costs. The controller has a set of possible decisions that can be made about how the ship is configured, and control objectives and parameters for lower level controllers. The goal is to find the optimum combination of decisions, d, that minimizes a cost function M with both risk, R, and operational costs, C. The risk cost is the cost expected from the accidents and consequences from the BBN risk model. The operational cost is based on the expected fuel consumption for the remaining sailing time. This gives an estimation of the energy cost for the planned sailing route that can be compared to the risk cost from the BBN(1).

$$M(d) = R(d) + C(d) \tag{1}$$

The risk cost is taken directly from the BBN and will vary between zero cost and the cost of the worst consequences considered in the BBN. The operation cost is calculated based on the specific fuel consumption for the ship and the remaining sailing time. A specific example of the cost function is shown in Sections 3.2.1 and 3.3, but these can vary depending on the ship and how it is operated. This make it possible to adjust the cost function based on the specific ship, operation, and available information as long as the cost can be represented as a function of the decisions made by the ship.

The decisions, d, can include which control mode to operate in, the machinery configuration in which the ship should operate, references for lower level controllers, or other decisions that affect the ship. The controller is implemented as a switch that configures the ship based on the optimum set of decisions. The switch checks all possible combinations of decisions to find the best combination. The switching mechanism is implemented with a lower switching frequency to avoid chattering in the controller and to increase the efficiency.

Chattering occurs when the controller switches back and forth between different modes because the system is on the limit between different modes. A switching frequency that is too low means that the controller will not react to changes, such as increased traffic, because the ship passes the traffic before the controller has checked. A switching frequency that is too high will lead the controller to always change, such as constantly switching between DP and auto-pilot, because the conditions are right on the limit between these modes. The frequency can therefore be changed to make sure that the controller reacts fast enough without chattering.

By including consequences and conditions affecting these, the SRC is not only able to prevent hazardous events, but also reduce the severity if such events occur. In a situation, for example, when the weather and area around the ship become so challenging that the ship will most likely collide/allide, the SRC will reduce the speed of the ship to limit the consequences.

3. Case study: Autonomous cargo ship

The case study in this paper uses the presented methodology for an autonomous cargo ship on a voyage between two locations along the Norwegian coast. The purpose of the ship is to deliver fish food to a fish farm. The ship follows a preplanned route, and dock next to a floating fish-farm so that it can unload the cargo. The route consists of both open and congested waters with islands, ship traffic, and other obstacles (e.g., fish farms, oil and gas installations, containers, navigation markers, etc.) that the ship must account for. The case study assumes good weather conditions, i.e., little wind, current, and good visibility, but the SRC is designed to also include different weather conditions. The ship is unmanned with a supervisor on shore that can monitor and, if necessary, take remote control of the ship. The ship is 80 m long and 16 m wide at its widest point.

The ship has a hybrid power system with a gas powered main engine, a set of diesel generators, and a hybrid shaft generator (HSG). The HSG can be used as a generator that is powered by the main engine to produce electricity or as an engine powered by the diesel generators for propulsion. The machinery system can be configured in three different modes:

- Power Take Out (PTO)
- Power Take In (PTI)
- Mechanical (Mech)

In PTO, the main engine is on and the HSG is configured as a generator such that the main engine provides both propulsion and electrical power. In PTI, the diesel generators are used with the HSG configured as an electric engine for propulsion. In Mech, the main engine provides propulsion power and the diesel generators provide electrical power. Of these modes, PTO is the most used mode because the main engine is most economical in normal use. PTI is the least used mode because the diesel generators provide much less power than the main engine and the ship is not able to maintain speeds above 5 m/s. Mech has the most power available because all of the main engine capacity can be used for propulsion, but it is also the most costly because it uses both the main engine and diesel generators.

The ship has two operating modes:

- Heading and Speed Auto Pilot (AP)
- Dynamic Positioning (DP)

Heading and speed auto pilot is used for higher speeds and longer distances. The main propeller provides propulsion and the rudder is used for steering. DP is used at lower speeds when necessary to better control the ship. In DP, the main propeller and tunnel thrusters are used for both propulsion and steering. The SRC is responsible for selecting the best combination of MSO-mode, SO-mode, and reference speed based on both internal and external factors. An example of this is changing MSO-mode when components fail, or lowering the speed and choosing DP when it is necessary with better motion control.

3.1. Phase 1: The extended STPA

The STPA was performed in a workshop with industry participants and risk analysts to facilitate the analysis. The goal was to identify unsafe control actions for an autonomous cargo ship. The main focus was on the machinery system, and how the switching between different modes (see above) can lead to grounding or impacts with ships or obstacles. The workshop had 13 participants and went over three days in the winter of 2019. The participants have thorough knowledge and experience with ship control systems, risk analysis, and system verification. The workshop was conducted as a discussion between the participants where STPA was used to identify unsafe control actions.

3.1.1. Define the system

The system described in Section 3, is first modeled as a hierarchical control structure; as shown in Fig. 2. The system consists of three main control levels; supervisory control, guidance and optimization, and control execution. The case study focuses mainly on the SRC and its responsibilities:

(a) Set ship operating (SO) mode for the Autonomous Navigation System (ANS)
(b) Set reference parameters, such as max speed for the ANS to follow
(c) Set machinery system operating (MSO) mode for the Autonomous Machinery Management System (AMMS)

The SRC has a set of process variables that are used to make decisions:

- PV-1: Active MSO-mode
- PV-2: Available power and thrust
- PV-3: Machinery system status
- PV-4: Active SO-mode
- PV-5: Ship navigational states
- PV-6: Weather conditions
- PV-7: Traffic conditions
- PV-8: Route information

3.1.2. Identify hazardous events and system level hazards

The case study focuses on two system-level hazardous events:

- HE1: The ship collides with a ship
- HE2: The ship allides with another object

The corresponding system-level hazard is

- H1: The ship violates the minimum distance of separation to an obstacle

The relationship between the hazard and hazardous event depend on factors such as the type and size of obstacle/ship, what control the obstacle/ship has, and impact speed (DNVGL, 2003).

To structure the analysis more clearly, the hazardous event “collision” is subdivided into two: the first is that the ship collides with another ship, and the second is allision with other objects. This makes it easier to define the consequences. For this case study, the main focus is on the first hazardous event (A1) and first system-level hazard (H1).

3.1.3. Identify unsafe control actions

The STPA workshop identified a total of 60 unsafe control actions (UCA) for the whole control system. Five of these are chosen for further use in the case study as shown in Table 1. The number of UCAs used in the BBN are limited to avoid an unnecessary complex model. The STPA seek to identify all UCAs that can affect the ship, but many of these are caused by the same RIFs, such as sensor failures in the navigation system. A BBN with more nodes will also have a negative effect on the computation time when updating the model as the ship is sailing, and affect the time necessary to define the BBN. When choosing how many and what UCAs to include, the challenge is to have a sufficient number to get a good enough situational awareness, but limit the time necessary for both building and using the BBN in the controller.

The first step to limit the number of UCAs is to only consider UCAs where the SRC is giving a command, since the purpose of the BBN is to enable the SRC to make decisions. Of the 60 UCAs identified in the workshop, 15 are commands where the SRC give a command leading

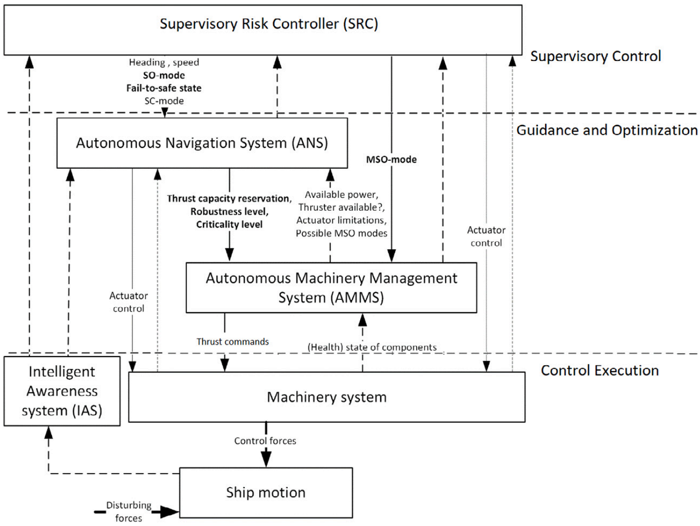


Fig. 2. Hierarchical control structure.

Table 1
Unsafe control actions.

UCA	Description
UCA-1	A command is given to change MSO-mode to PTO when a fault inhibits the machinery from producing the necessary thrust
UCA-2	A command is given to change MSO-mode to Mech when the main engine does not function
UCA-3	A command is given to change MSO-mode to PTI, resulting in insufficient power for the main propulsion
UCA-4	A command is given to change SO-mode to transit when uncontrolled motion may cause violation of the minimum safe distance to shore or objects
UCA-5	A command is given to change SO-mode to maneuvering when the speed is higher than the maximum maneuvering speed which may result in loss of motion control

the system-level hazard. Of these 15, four changes MSO-mode to PTO, five to Mech, and two to PTI. All these are caused by a failure in the machinery system or inaccurate estimation of the power necessary. Since the same factors affect all the UCAs, it is sufficient for the SRC to have one UCA for each MSO-mode and still have a good situational awareness. Two of the UCAs change SO-mode to transit and two change to DP. Both UCAs that changes to transit are scenarios where the ship need more accurate motion control. Either of these can therefore be used in the BBN as they both have the same causes. For changing to DP, the scenario is either caused by switching with to much speed, or not enough power available. Since power is already included in the BBN, wrong speed is more important to include in the BBN.

3.1.4. Develop scenarios

The next step in the STPA is to develop scenarios that can lead to unsafe control actions. A total of 11 scenarios are developed in this case study, where all UCAs have two scenarios and UCA-2 has three potential scenarios. The scenarios are shown and described in Table 2.

3.1.5. Analyze consequences

For the risk model to be useful, it is necessary to find out more about the consequences related to the accidents. Consequences are identified and categorized based on information in DNVGL (2003) and Kristiansen (2005). These also give information about what conditions affect how serious the different consequences are. The damage to the ship and the object/ship the ship collides with will (for example) depend on factors such as impact speed, type of object, and size of object (DNVGL, 2003).

In this case study, the consequences are:

- Harm to humans
- Damage on other ships/objects
- Damage on own ship

The consequences are analyzed and divided into three categories (IMO, 2018). Severe consequences are fatalities or serious injuries to humans, damage to the ship where it is necessary with assistance to get back to shore and receive extensive repairs, or extensive damage to other ships/objects where extensive repairs are also necessary. Significant consequences are less serious/minor injuries to humans, and damage to the ship or other ships/objects that need extra repairs outside of planned maintenance, but it is not necessary with extra assistance to get back to shore. Minor consequences are insignificant/no injuries to humans, and damage to the ship or other ships/objects that can be fixed during the next planned maintenance. The IMO (2018) manual also include catastrophic consequences, but these are considered unacceptable, and therefore not relevant for the SRC.

3.2. Phase 2: Online risk model

3.2.1. Define end-nodes and UCA nodes

The goal, or top node, in the BBN is the expected risk calculated from Eq. (2).

The BBN includes consequences that are divided into severe, significant, minor, and no consequences. Each of these have a corresponding cost, and the overall cost (i.e., the quantitative risk) is calculated as shown in Eq. (2).

The cost of severe consequences is set to 45 000 000NOK, significant to 4 500 000NOK, minor to 450 000NOK and no consequences give zero cost. These are estimated costs for each category of consequences based on EfficienSea (2012), The Norwegian Agency for Public and Financial Management (2018), and IMO (2018). The highest cost is limited to 45 000 000NOK because costs above this level are unacceptable. In situations with potential consequences in the highest category, the SRC should choose the configuration with the lowest possible expected

Table 2
Scenarios.

Scenario	Description	UCA
SC-1	MSO changed to PTO because PTI delivers insufficient amount of power, but a failure in the ME or propeller shaft results in loss of propulsion.	UCA-1
SC-2	MSO changed to PTO because this is more efficient given the current operational conditions, but a failure in the ME or propeller shaft results in loss of power.	UCA-1
SC-3	MSO changed to Mech because PTI is not producing sufficient power, but a failure with the main engine leads to loss of propulsion.	UCA-2
SC-4	MSO-mode is changed to Mech to have higher margin on power in, a more challenging navigational situation, but a failure in the main engine results in loss of propulsion power	UCA-2
SC-5	MSO changed to Mech because this is more efficient given the current operational conditions, but a failure in the main engine results in loss of propulsion power.	UCA-2
SC-6	MSO-mode is changed to PTI because inaccurate/incorrect measurements leads to underestimated power-need for propulsion.	UCA-3
SC-7	MSO-mode is changed to PTI because the main engine is shut down by another system, resulting in insufficient power for propulsion.	UCA-3
SC-8	SO-mode is changed to transit to early after leaving harbor due to inaccurate/incorrect measurements of the ship states	UCA-4
SC-9	SO-mode is changed to transit when inaccurate/incorrect information about the navigational area leads to underestimation of the navigational complexity.	UCA-4
SC-10	SO-mode is changed to maneuvering when the navigational situation makes it necessary to have better control of the vessel, but the speed is not sufficiently low enough when making the switch.	UCA-5
SC-11	SO-mode is changed to maneuvering as the ship approaches harbor and an inaccurate/incorrect speed measurement results in to early switching	UCA-5

Table 3
Risk influencing factors.

RIF	Description	Scenario(s)
RIF-1	Estimation of necessary thrust	SC-1, SC-3
RIF-2	Power optimization	SC-2, SC-5
RIF-3	Navigational complexity/situation	SC-4
RIF-4	Measurement/estimation of ship's navigational states	SC-6, SC-8, SC-11
RIF-5	Engine control system	SC-7
RIF-6	Route description/information	SC-9
RIF-7	Machinery system status	SC-1, SC-2, SC-3, SC-4, SC-5

risk cost, or minimum risk condition. In this case study, this means a speed of 1 m/s, PTO as MSO-mode, and DP as SO-mode.

$$c = Pr(severe)C_{severe} + Pr(significant)C_{significant} + Pr(minor)C_{minor} + Pr(no)C_{no} \tag{2}$$

The BBN has one node for collision with other ships, and one for allision with other objects. The system-level hazard is hazard H1 in Section 3.1.2 where the ship violates the minimum distance of separation to a ship/obstacle.

3.2.2. Identify high-level RIFs

The high-level RIFs are identified based on the scenarios developed in Section 3.1.4. A total of seven high-level RIFs are identified as in Table 3.

3.2.3. Identify input RIFs

With the high-level RIFs identified, the next step is to identify the input and intermediate nodes. These are causal factors that describe the high-level RIFs, how the hazard lead to unwanted consequences, or decisions nodes for the different decisions available in the SRC.

The causal factors are identified by going through the high-level RIFs and assessing what may affect these, or how the system-level hazard can lead to different consequences. For example, the machinery system status is dependent on the propulsion system and the power system. The propulsion system in turn depends on the different propulsion components. The consequences will (for example) depend on the impact speed, whether the impact is with another ship or another object, and the amount of humans on the other ship/objects that might be harmed in the impact.

By organizing the BBN in this way, the amount of parent nodes can be limited. This also makes it easier to define states and conditional probability tables (CPT) because these depend on the number of parent nodes and states in the parent nodes.

The system has three decision nodes: MSO-mode switch choosing which MSO-mode to run the machinery in, SO-mode switch to select the active controller, and speed reference to set the reference used in the controller. The input nodes in the BBN can be divided into three categories; Machinery system (M), Environment (E), and Control system/planning (C). The category of each node is shown in Table 4. Weather affects the model in two different ways; ship motions and visual conditions. Ship motions are affected by wind and currents. Wind can be everything from zero wind to hurricane. Current can also vary between zero current and very strong currents where the ship is unable to maintain control. The visual conditions is affected by wind, rain, fog, and snow. High wind combined with snow or rain, or fog give poor visibility that can affect sensors aboard the ship. The area around the ship is described by the node navigational area complexity. This node is affected by ship density, obstacle density, and what type of area the ship is sailing in. Another node that should be explained further is the reliability of own ship's navigational states. This node represents the quality and accuracy of sensor measurements for the ship, which can be affected by faulty sensors, incorrect setup or tuning, or disturbances. A full list of nodes are shown in Table 4. A similar list with the connections for each node are given in Tables 6–8. The full BBN is shown in Fig. 3.

Table 4
BBN Nodes.

Node description	Type	States
Cost	Output	Cost
Consequences	Top-level consequences	Severe/Significant/Minor/None
Damage to others property	Sub-level consequences	Severe/Significant/Minor/None
Damage to own ship	Sub-level consequences	Severe/Significant/Minor/None
Harm to humans	Sub-level consequences	Severe/Significant/Minor/None
HE1-The ship collides with a ship	System-level hazardous event	Yes/No
HE2-The ship allides with another object	System-level hazardous event	Yes/No
H1-The ship violates the minimum distance of separation to an obstacle	System-level hazard	Yes/No
UCA1-A command is given to change MSO-mode to PTO when a fault inhibits the machinery from producing the necessary thrust	UCA	Yes/No
UCA2-A command is given to change MSO-mode to Mech when the main engine does not function	UCA	Yes/No
UCA3-A command is given to change MSO mode to PTI, resulting in insufficient power for the main propulsion	UCA	Yes/No
UCA4-A command is given to change SO-mode to transit when uncontrolled motion may cause violation of the minimum safe distance to shore or objects	UCA	Yes/No
UCA5-A command is given to change SO-mode to maneuvering when the speed is higher than the maximum maneuvering speed which may result in loss of motion control	UCA	Yes/No
RIF1-Estimation of necessary thrust	RIF	Incorrect/Imprecise/Correct
RIF2-Power optimization	RIF	Poor/Sufficient/Good
RIF3-Navigational complexity/situation	RIF	High/Medium/Low
RIF4-Measurement/estimation of ship's navigational states	RIF	Incorrect/Imprecise/Correct
RIF5-Engine control system	RIF	Poor/Sufficient/Good
RIF6-Route description/information	RIF	Poor/Sufficient/Good
RIF7-Machinery system status	RIF	Failed/Ok
Propulsion system state	Intermediate	Failed/Ok
Power system state	Intermediate	Failed/Ok
Weather conditions	Intermediate	Poor/Sufficient/Good
Visual conditions	Intermediate	Poor/Sufficient/Good
DP propulsion	Intermediate	Failed/Ok
Auto-pilot propulsion	Intermediate	Failed/Ok
PTO	Intermediate	Failed/Ok
Mech	Intermediate	Failed/Ok
PTI	Intermediate	Failed/Ok
Control of ship	Intermediate	Poor/Sufficient/Good
Controller performance	Intermediate	Poor/Sufficient/Good
Ship speed	Intermediate	High/Medium/Low
Navigation area complexity	Intermediate	High/Medium/Low
Controllable speed	Intermediate	No/Yes
Impact speed	Intermediate	High/Medium/Low
Category of obstacle	Intermediate	Ship/Other
MSO-mode switch	Decision	PTO/Mech/PTI
SO-mode switch	Decision	Auto-pilot/DP
Speed reference	Decision	1–8 m/s
Power management system function	Input(C)	Poor/Sufficient/Good
Obstacle density	Input(E)	Low/medium/High
Traffic density	Input(E)	Low/medium/High
Ship safety system function	Input(C)	Poor/Sufficient/Good
Reliability of own ship's navigational states	Input(C)	Poor/Sufficient/Good
Route information	Input(C)	Poor/Sufficient/Good
Bow thruster state	Input(M)	Failed/Ok
Aft thruster state	Input(M)	Failed/Ok
Main propeller state	Input(M)	Failed/Ok
Steering system state	Input(M)	Failed/Ok
ME state	Input(M)	Failed/Ok
Genset 1 state	Input(M)	Failed/Ok
Genset 2 state	Input(M)	Failed/Ok
HSG state	Input(M)	Failed/Ok
Current velocity	Input(E)	High/Medium/Low
Auto-pilot performance	Input(C)	Poor/Sufficient/Good
DP-controller performance	Input(C)	Poor/Sufficient/Good
Wind speed	Input(E)	High/Medium/Low
Fog	Input(E)	High/Medium/Low
Rainfall	Input(E)	High/Medium/Low
Snowfall	Input(E)	High/Medium/Low
Area type	Input(E)	Harbor/Coastal/Open
Speed of ship/obstacle	Input(E)	High/Medium/Low
Control of ship/obstacle	Input(E)	Low/Medium/High
Type of ship/obstacle	Input(E)	Ship/Fish farm/ Oil installation/Wind-farm/ Markers/Containers/Other
Crew and passengers	Input(E)	Many/Normal/Limited/No
Size of ship/obstacle	Input(E)	Big/Medium/Small

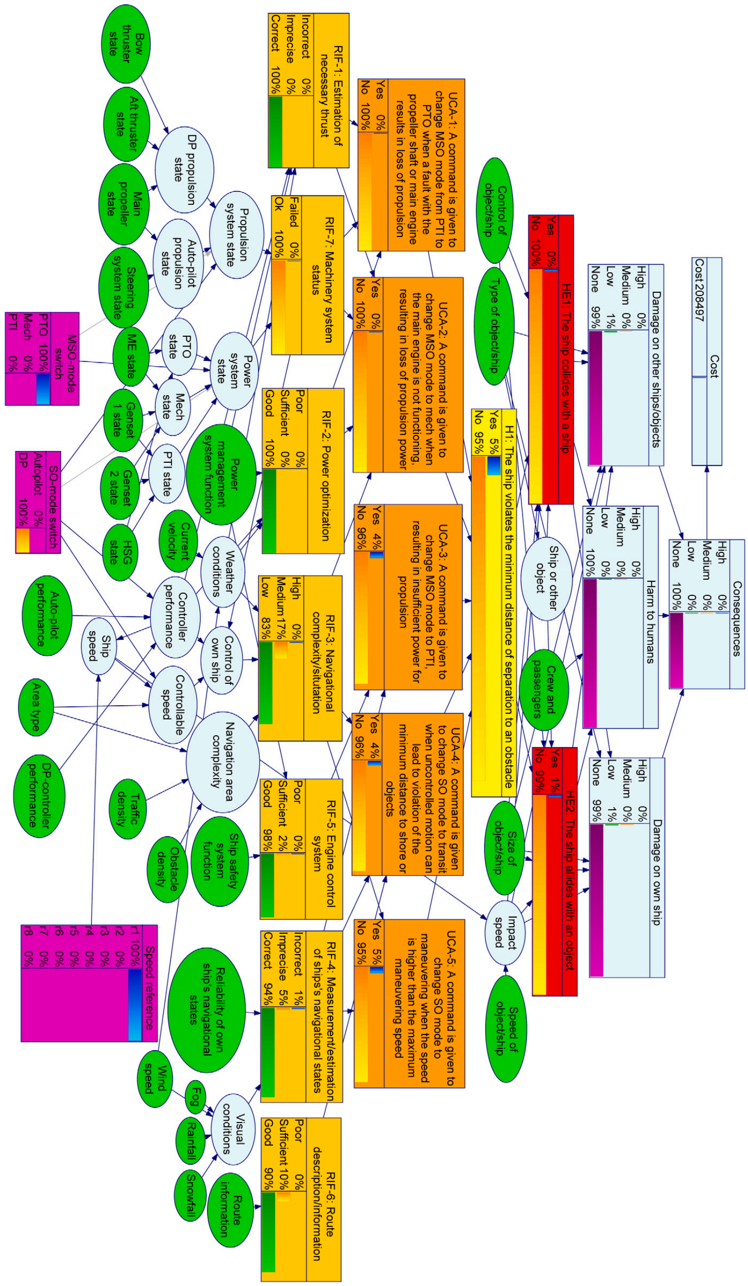


Fig. 3. Online risk model.

3.2.4. Identify states and build CPTs

The next part of building the BBN is defining states and building the CPTs for each node. States are defined such that each node provide sufficient information to the BBN, while keeping the number of states reasonably low. Limiting the number of states in each node makes it easier to define the CPTs because they depend on the number of parent nodes and number of states for each of these. CPTs are constructed based on available information about the ship and the environment (DNVGL, 2003; SINTEF, NTNU, 2015; Marine Traffic, 2021; Norwegian Meteorological Institute, 2021; Norwegian Mapping Authority, 2021).

The data from SINTEF, NTNU (2015) is used directly to describe the likelihood of component failures in the machinery system. The information in DNVGL (2003) is used differently based on what node it is used for. To describe the machinery components, it is used to check that the data from SINTEF, NTNU (2015) can also be used for

Table 5
Input probabilities for simulations.

Node	Situation	States	Probabilities	Source
ME state	All systems functioning	Failed/ok	9e−07/ 0.9999991	DNVGL (2003), SINTEF, NTNU (2015)
ME state	Main engine fails after 200 sec	Failed/ok	1.0/0.0	DNVGL (2003), SINTEF, NTNU (2015)
ME state	HSG failed fails after 200 s	Failed/ok	9e−07/ 0.9999991	DNVGL (2003), SINTEF, NTNU (2015)
HSG state	All systems functioning	Failed/ok	9e−07/ 0.9999991	DNVGL (2003), SINTEF, NTNU (2015)
HSG state	Main engine fails after 200 s	Failed/ok	9e−07/ 0.9999991	DNVGL (2003), SINTEF, NTNU (2015)
HSG state	HSG fails after 200 s	Failed/ok	1.0/0.0	DNVGL (2003), SINTEF, NTNU (2015)
Area type	Before way-point four	Harbor/ Coastal/Open	0.0/0.5/0.5	DNVGL (2003) Norwegian Mapping Authority (2021)
Area type	After way-point four	Harbor/ Coastal/Open	1.0/0.0/0.0	DNVGL (2003) Norwegian Mapping Authority (2021)
Obstacle density	Before way-point two and after way-point three	High/Medium/ Low	0.1/0.5/0.4	DNVGL (2003) Norwegian Mapping Authority (2021) Marine Traffic (2021)
Obstacle density	Way-points two - three	High/Medium/ Low	1.0/0.0/0.0	DNVGL (2003) Norwegian Mapping Authority (2021) Marine Traffic (2021)
Traffic density	Before way-point two and after way-point three	High/Medium/ Low	0.1/0.5/0.4	DNVGL (2003) Norwegian Mapping Authority (2021) Marine Traffic (2021)
Traffic density	Way-points two - three	High/Medium/ Low	1.0/0.0/0.0	DNVGL (2003) Norwegian Mapping Authority (2021) Marine Traffic (2021)
Speed of obstacle	Before way-point two and after way-point three	High/Medium/ Low	0.2/0.7/0.1	DNVGL (2003) Norwegian Mapping Authority (2021) Marine Traffic (2021)
Speed of obstacle	Way-points two - three	High/Medium/ Low	1.0/0.0/0.0	DNVGL (2003) Norwegian Mapping Authority (2021) Marine Traffic (2021)
Crew and passengers	Before way-point two and after way-point three	Many/Normal/ Limited/None	0.0/0.1/0.3/0.6	DNVGL (2003) Norwegian Mapping Authority (2021) Marine Traffic (2021)
Crew and passengers	Way-points two - three	Many/Normal/ Limited/None	1.0/0.0/0.0/0.0	DNVGL (2003) Norwegian Mapping Authority (2021) Marine Traffic (2021)

components that are not directly listed. For the node describing the control system and sensors, the data is processed such that they have three states instead of two. Some of the data has also been used as a basis for deciding how CPTs differ between a manned and autonomous ship, such as the control system and sensors. Since the human operator is not present on the ship, the CPTs describing controllers and sensors are changed slightly compared to ships with full crew. Marine Traffic (2021) and Norwegian Mapping Authority (2021) are used to find out how much traffic and obstacles are typical for coastal sailing along the Norwegian coast, both open waters, more coastal areas with islands and more traffic, and highly congested waters with very limited space and much traffic. Marine Traffic (2021) is also used to find how many ships sailing along the coast have passengers and estimate the size of these ships. Norwegian Meteorological Institute (2021) is used to find historical data about weather conditions along the Norwegian coast.

In addition to literature and available data, expert judgment is also used to both build the BBN, assign states, and build CPTs. The experts are deck and technical officers on board ships, and engineers designing ship control systems. The discussions with deck and technical officers have focused on how ships are operated today and how this can change with increased autonomy, such as what SO and MSO-modes should be used in different situations. The control engineers have given input on design and setup of the control system, and how to change this from a manned to more autonomous ship.

3.2.5. Converting the BBN into an online risk model

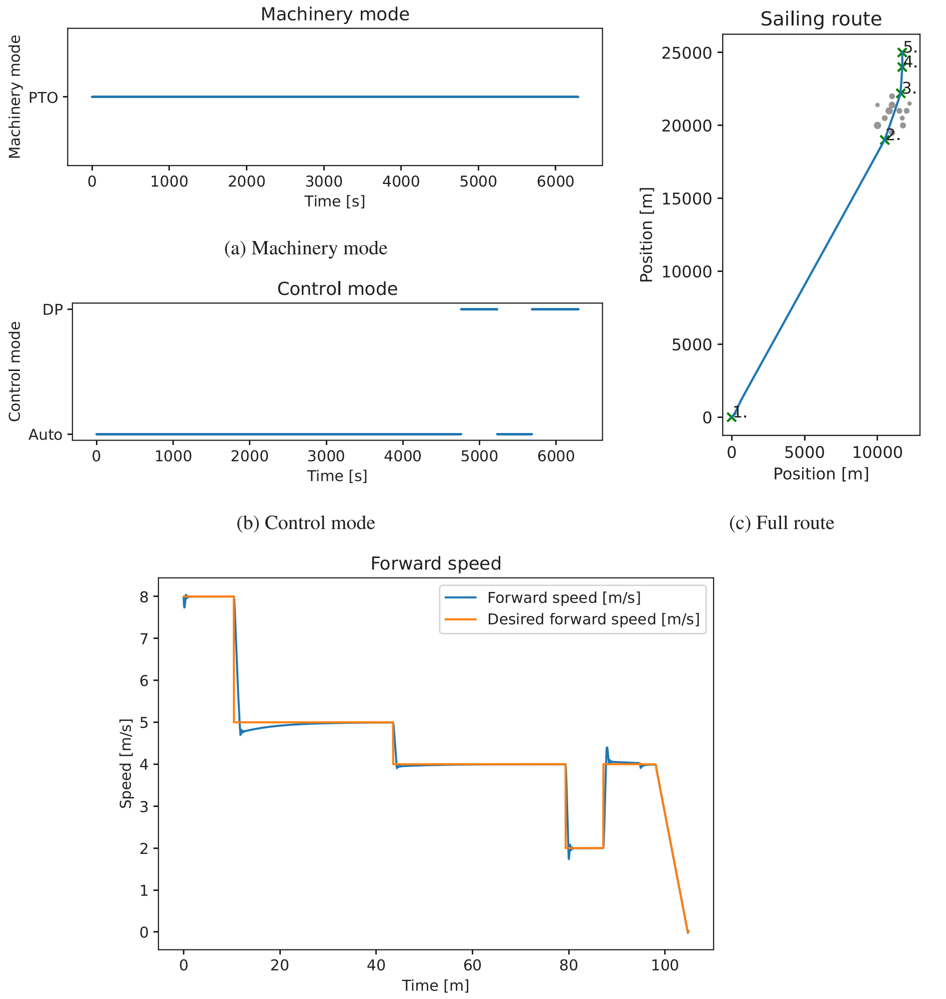
The BBN is converted to an online risk model for use in the SRC, including both probabilities for the nodes' states and the potential consequences. Developing the online risk model includes identifying what nodes that should be updated with data from the ship as it is sailing such that the BBN represent the actual situation.

The risk model in this paper has been tested in simulations to check that the SRC functions and is able to control the ship. The simulated scenario is that the ship is sailing and has five way-points left on a pre-planned route. At first, the conditions around the ship describe a normal situation for ships sailing along the Norwegian coast, based on data from DNVGL (2003), SINTEF, NTNU (2015), Marine Traffic (2021), Norwegian Meteorological Institute (2021) and Norwegian Mapping Authority (2021). Between way-points two and three, the traffic and obstacle density is increased to see if the control can handle situations with more ships and more obstacles around the ship, more similar to high traffic areas such as the English channel. More ships and objects around also increases the amount of people, both crew and passengers, that might be harmed in accidents. After way-point three, the ship is again back in normal conditions, before it reaches the area where it should dock next to the fish farm.

Other input probabilities and CPTs are based on the same sources (DNVGL, 2003; SINTEF, NTNU, 2015; Marine Traffic, 2021; Norwegian Meteorological Institute, 2021; Norwegian Mapping Authority, 2021), combined with expert judgment, such that the BBN represent the actual type of ship and conditions this sail in.

3.3. Phase 3: The supervisory risk controller

The SRC optimizes the decisions, d, based on the risk cost from the risk model, $R(d)$, and the expected cost of running the machinery in the current configuration, $C(d)$, for the remaining distance to the last way-point. The risk cost is taken directly from the risk model based on



(a) Machinery mode

(b) Control mode

(c) Full route

(d) Forward speed

Fig. 4. All systems functioning.

Eq. (2). The machinery cost is calculated based on the expected cost of running the machinery in each configuration for the remaining sailing time (Eq. (3)). This cost will therefore decrease as the ship gets closer to the final way-point because it is a function of the remaining sailing time.

The cost of fuel consumption is calculated using the price per kWh for LNG and marine gas oil (DNV, 2021). The load is taken as the expected mean load percentage times the available power for the remaining sailing time. This gives a good estimation of the fuel cost that can be compared to the risk cost from the BBN with the information available.

$$C(d) = c_{fuel} \times (t_{cruise} \times P \times \eta_{cruise} + t_{dock} \times P \times \eta_{dock}) \tag{3}$$

$$M(d) = R(d) + C(d) \tag{4}$$

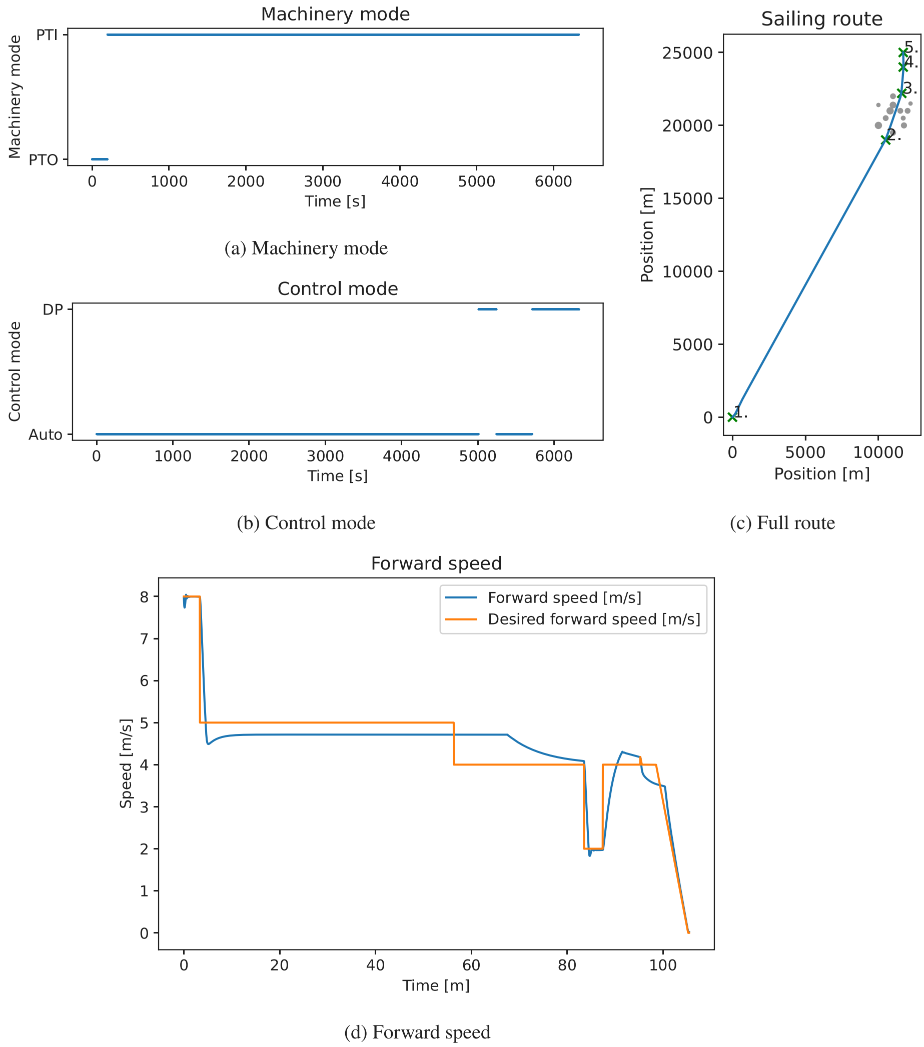
The SRC is implemented such that the optimum set of decisions is checked every 10 s to limit the number of times that the risk model has to be checked. It also avoids chattering, where the SRC is just switching back and forth.

4. Results and discussion

4.1. Results

The SRC is tested in three different simulations to test how the risk model affects the control of an autonomous ship. The case study shows the last part of a route, approximately 27 km over five way-points. Around 2 km, between way-points two and three, there are more traffic and islands. This makes it necessary to lower the speed of the vessel to maintain sufficient control. The input values that change in the simulations are shown in Table 5.

All of the simulations show that the SRC reacts when it becomes more difficult to navigate safely with an increased amount of ships and obstacles around. The speed is then lowered to maintain sufficient control of the ship (Figs. 4(d), 5(d), and 6(d)). The simulations also show that the ship, with the current setup, is more risk averse than similar manned ships because the speed in the normal conditions is lower than a typical cruising speed of 8 m/s. This also mean that the ship uses more time before it reaches the goal.



(a) Machinery mode

(b) Control mode

(c) Full route

(d) Forward speed

Fig. 5. Main engine failed.

Fig. 4 show the simulation with all machinery systems functioning. The ship then operates in PTO because this is the most efficient mode for the ship. The ship uses 105 min from the start point before it has stopped at the final way-point. The ship lowers the speed to 5 m/s after around 10 min, and lowers it further down to 4 m/s after around 40 min. The speed is reduced when the distance to the final way-point is low enough that the reduction in risk cost is lower than the increase in fuel cost. When it reaches the area with more traffic and obstacles, the speed is not immediately reduced because the speed is already at 4 m/s. As the ship gets closer to the final way-point, the speed is reduced further to 2 m/s, and then increased to 4 m/s again when the traffic and obstacle density is reduced. When the speed is reduced to 2 m/s, the SO-mode is changed to DP (Fig. 4(b)) because the speed is then so low that it is difficult to control the ship with only the main propeller and rudder. When it increases back to 4 m/s, it switches back to auto-pilot because the tunnel thrusters have less effect at higher speeds.

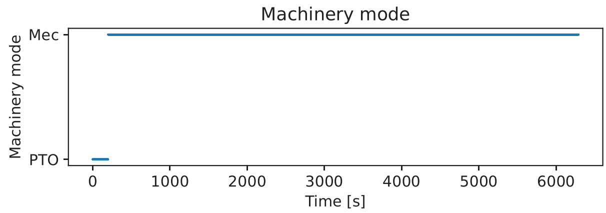
Fig. 5 shows a simulation where the main engine fails after 200 s The ship then goes over in PTI because this is the only available MSO-mode (Fig. 5(a)). This also reduces the maximum speed to 5 m/s because PTI is unable to produce sufficient propulsion power for higher speeds. This increases the total sailing time slightly to 107 min. The rest of the simulation is similar to the simulation with PTO. The speed is lowered when the traffic and obstacle density increases. When the speed is lowered to 2 m/s, it switches to DP.

Fig. 6 show a simulation where the HSG fails after 200 s, which means that the ship must switch MSO-mode to Mech to have power (Fig. 6(a)). The rest of the simulation is the same as when the ship operates in PTO (Fig. 4).

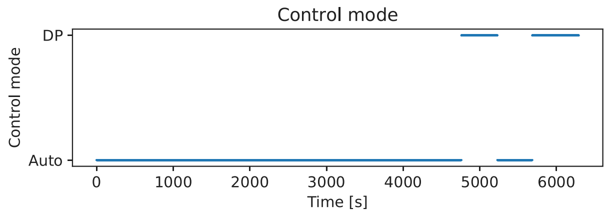
4.2. Discussion

4.2.1. STPA and the online risk model

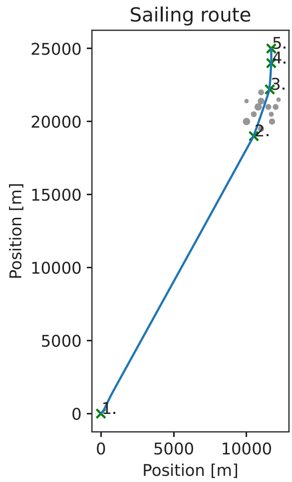
One of the most important parts for an SRC is information about how the control decisions affect the risk level for the ship. To find this information, STPA is useful to identify hazards and system losses, with a focus on how control actions can lead to these and what causal factors



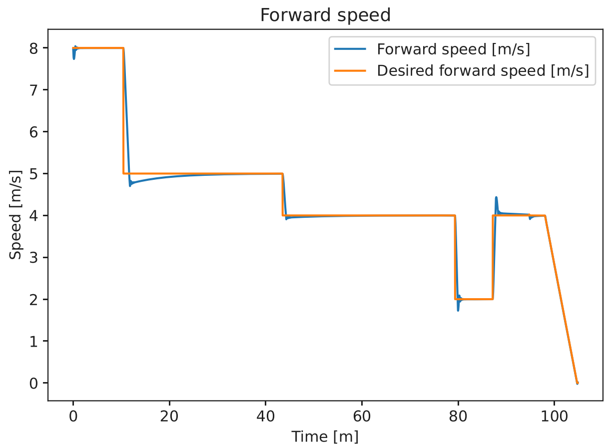
(a) Machinery mode



(b) Control mode



(c) Full route



(d) Forward speed

Fig. 6. HSG failed.

affect this. But STPA only gives qualitative information, which is very difficult to use directly in a controller. Furthermore, consequences are not explicitly identified and analyzed in the general STPA. Hence, this was a necessary extension and additional step of the STPA method, and the controller implemented in this paper addresses this problem by including consequences from the losses and an expected cost from these (see Section 3.2.1). Consequences are divided into four categories; high, medium, low, and no consequences. Deciding what cost to give to each category of consequences is one of the biggest challenges and it has a considerable affect on the overall performance. These numbers are therefore based on both literature, previous work, expert judgment, and trial and testing with the BBN to get the desired behavior.

The STPA results are further used as the basis for the development of the BBN risk model. As shown in this paper, this give an online risk model that can be used in the control system where the risk cost can be combined with operation costs. STPA provides qualitative information about causal factors that lead to UCAs and hazards, but no quantitative information. The STPA also provides limited information about the consequences and their cost. In the case study, both CPTs and information about costs are based on a limited amount of reports and the external sources describing them. This makes it difficult to find sufficient information to build the BBN with sufficient detail. A more structured way to find this could make this process easier and give a more accurate risk model.

The BBN risk model is useful to get a good overview over the situation and the risk level for the ship. With good available software tools, BBNs can also be combined with other computer-based control systems. This makes it easy to update the BBN as a new input become available. It also makes it easy to use the output directly in an SRC. The main challenge with using BBNs for this application is constructing the BBN, especially deciding states for each node and building up CPTs. The STPA provides information about how different nodes are connected, but provides very little information for defining states and CPTs. Based on the case study in this paper, both states and CPTs must weigh accuracy against the purpose of the risk model. The amount of states will also directly influence the size of the CPTs, and can also affect the time necessary to evaluate the BBN.

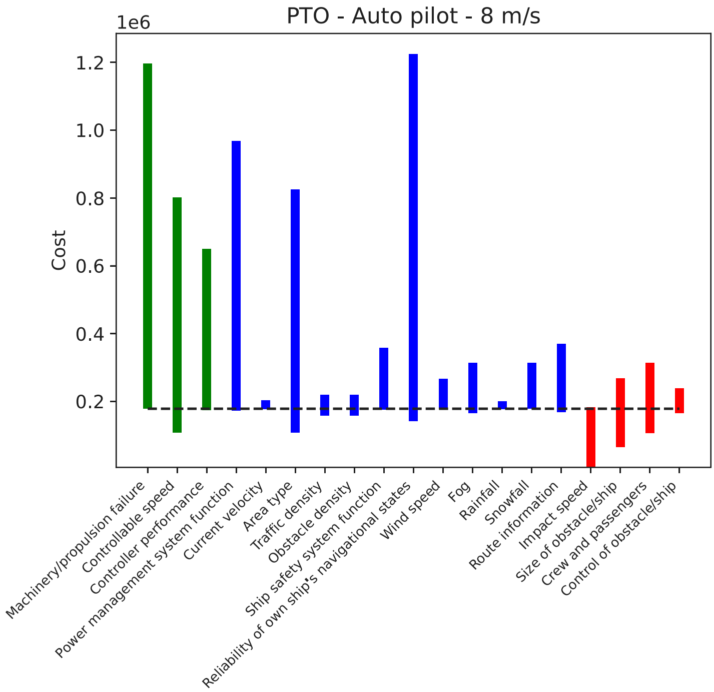


Fig. 7. Sensitivity analysis. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Some states can be found directly from the use an type of node, such as decisions, sensor measurements, or limitations for both the control system and the ship. For other nodes, it might be information available. However, some states will most likely be changed as the system is tested because they influence the risk slightly different than initially expected. It can also be necessary to change states later because they make other nodes too complex to define. CPTs should be defined such that top level node gives an accurate picture of the risk, and changes when conditions or decisions change. To do this, both expert judgment, previous analysis, and specifications for the control system can be used. In the case study, the initial values are set based on a mix of literature and expert judgment, and are then tuned slightly to get the desired output and behavior. Because there is no complete literature on how to make the BBN and define different nodes, it is necessary to make some changes in CPTs based on the testing. By doing this in an iterative process, the ship behaves as expected and as intended but it also increases the overall uncertainty in the model.

4.3. Sensitivity and uncertainty

The BBN is assessed by performing a sensitivity analysis (Fig. 7). Given that the BBN is based on both literature, expert judgment, and testing, this provides useful information about the effect that each node has on the cost. The base cost is operating the ship in PTO with auto pilot and a reference speed of 8 m/s. This gives a base cost of 178 712 NOK with the same initial values for all nodes as in the simulations. The BBN is then checked to find out how much the cost depend on each node. The three first bars (Green bars) in Fig. 7 show how the cost depend on the machinery and propulsion state, whether the speed is controllable, and the controller's performance. These show how the cost changes if the decisions, MSO-mode, SO-mode, and reference speed are wrong. A wrong decision would mean a failed MSO-mode, or a combination of speed and SO-mode where the ship is difficult to control. The machinery status is the most sensitive of these, followed by the speed and the SO-mode. The next bars (Blue bars) show the sensitivity of the input nodes that affect the high-level RIFs. The three most sensitive of these are the reliability of the navigational states, the power management system, and the type of area the ship is sailing in. The four last bars (Red bars) show how the input nodes to the consequences affect the final cost.

The sensitivity analysis show that the sensitivity differs significantly between the different nodes. Some nodes have very little effect on the overall cost, such as rain or current velocity, and others, such as the navigational states and power management system affect the cost much more. The most sensitive nodes are important when assessing the uncertainty in the model as they have higher effect on the end result. Most of the nodes with high sensitivity relate to the reliability of hardware components or the control system. The data used to define these is based on multiple literature sources, which limits the uncertainty from these nodes. But, these should still be addressed further to reduce the overall uncertainty in the model. The base cost is taken in good conditions with good control of the ship. Changing the state of the nodes to the most positive value will therefore have little effect on reducing the cost, except for lower speed and the fewer obstacles around the ship.

4.3.1. The supervisory risk controller in the case study

The purpose of implementing an SRC is to make safer and more efficient control of autonomous systems. By including an online risk model in the control system, the control system should be able to make more informed decisions compared to existing control systems. In the case study, the SRC is tested with three different decisions: selecting SO-mode, MSO-mode, and setting the reference speed for the ship. The case study shows how the SRC enables the control system to select the best combination of these three, considering both operational costs and risk. Other than the SRC, the control system tested is the same type as many ships use today. A DP controller for station-keeping and low speed maneuvering, and a heading and speed auto pilot for use at higher speeds. However, the operators decide MSO-modes, SO-modes, and speed references on existing ships.

This extra functionality comes with both advantages and some challenges compared to existing systems. One of the main advantages is the higher flexibility and functionality in the control system. To get the same type of behavior from existing ships, without human input when sailing, the same decisions must planned ahead of time. Some might be possible to plan ahead, such as switching from auto pilot to DP when the ship is a certain distance from the dock, but this is much less flexible and efficient. If the conditions change before the ship reaches this point, then it might be possible to have a higher speed for longer or it might be necessary to lower the speed and change to DP earlier to ensure sufficient control. Failing to do this would either mean a higher cost in the operation of the ship or increased risk for both the ship owners, environment, the public, and others who might be affected if the ship has an accident. An alternative could be to define rules for how the decisions should be made that also account for changes in the environment. A rule could (for example) say that wind speeds lower than a certain limit make it safe to keep a higher speed longer. But with ships, this would be very complex. In the case study, the BBN contains 27 input nodes that describe either the ship or the environment and situation around the ship. Some rules could be very simple binary rules, such as not leaving dock if the wind is at hurricane force, but most rules would depend on multiple conditions. Even if a rule might not depend on all 27, this would be almost impossible to do based on the number of possible combinations. Uncertainty will also be a problem where it is very difficult to say how rules should depend on different conditions. The SRC still has a certain degree of uncertainty, but the cost is now less dependent on one specific condition but rather a combination of multiple nodes in the BBN. This makes it less likely for the SRC to make critical mistakes compared to specific rules for each condition.

The case study indicates how the SRC behaves when the information is updated as conditions changes. For the SRC to be tested with constantly updated input, it is necessary with more detailed datasets and extend the control system. A potential approach for doing this could be logging data on existing ships on specific routes. By logging detailed weather data, machinery data, position, speed, and what decisions the crew make, the SRC could be tested through simulation and field trials with autonomous platforms in the same conditions. Comparing decisions made by the SRC and crew can then be used to assess how the SRC performs. Another approach is to test if the SRC is able to satisfy a set of constraints for safe and efficient operation in on the same routes and conditions, such as minimum distance to land and max time from start to finish. Assessing the SRC against both human operators and more formal constraints can be used to verify the model and controller. For the BBN model itself, it can also be compared to other models in the literature and be discussed further with experts to verify that it give an good representation of the actual system.

5. Conclusion

The main purpose of this paper is to demonstrate how online risk models and ship control systems can be integrated for improved intelligence and decision support for autonomous ships. This is shown by implementing a supervisory risk controller (SRC), and combining this with existing ship control systems. The SRC is based on an online risk model, combined with operational costs. This enables us to make decisions that consider both risk and operational costs.

The online risk model is based on qualitative information from an extended STPA, including an additional step consisting of identifying and analyzing consequences. This is necessary to enable the SRC to make decisions. The online risk model is represented by a BBN, which is developed based on the results of the extended STPA.

Table 6
BBN nodes.

Node description	Parent node(s)
Cost	Consequences
Consequences	Harm to humans, Damage on other ships/objects, Damage on own ship
Damage on other ships/objects	HE1, HE2, Impact speed, Type of ship/obstacle, Size of ship/obstacle
Damage on own ship	HE1, HE2, Impact speed, Type of ship/obstacle, Size of ship/obstacle
Harm to humans	HE1, HE2, Crew and passengers
HE1	H1
HE2	H1
H1	UCA-1,UCA-2,UCA-3,UCA-4, UCA-5
UCA-1	RIF-1,RIF-2,RIF-7
UCA-2	RIF-1,RIF-2,RIF-3,RIF-7
UCA-3	RIF-4,RIF-5
UCA-4	RIF-3,RIF-4,RIF-6
UCA-5	RIF-3,RIF-4
RIF-1	Power management system, Controller performance, Weather conditions
RIF-2	Power management system, Controller performance, Weather conditions
RIF-3	Navigation area complexity, Weather conditions, Control of ship
RIF-4	Reliability of own ship s navigational states, Visual conditions
RIF-5	Power management system, Ship safety system
RIF-6	Route information
RIF-7	Propulsion system state, Power system state

The SRC is tested in a case study of an autonomous cargo ship, where the purpose is to select the best MSO-mode, SO-mode, and reference speed based on both risk and operational costs. The ship follows a planned route, where the traffic conditions and area around the ship changes along the route. The case study shows that the SRC adjusts the speed with more traffic and obstacles around the ship, even though this reduces the efficiency. When the situation changes again and the risk is reduced, the speed is increased again. As the ship approaches the final way-point where it should dock, the SRC changes SO-mode to DP such that the ship has better control with lower speed.

The case study also shows that the SRC is able to handle failures in the machinery system and then select the most efficient MSO-mode without using a failed component. The SRC is able to make these decisions while the ship is sailing, without the need for adjusting the controller or human input to the system. This increases the functionality of the control system and reduces the need for human control. For autonomous ships to operate, this capability of assessing risk versus cost and comparing these in a good way is necessary for both safe and efficient operation.

Further work on this type of controller should consider how it can be integrated with different types of controllers. For SRC to be a useful tool for different types of ship, and other autonomous systems, it is important to know that it works with different types of control systems. The risk model itself should also be investigated further, to check how detailed this must be for the system to still function to see if this can make it both more efficient and easier to implement. The risk model may also be expanded with more real-time data such that more nodes change (e.g., machinery components and controller

Table 7
cont.BBN nodes.

Node description	Parent node(s)
Propulsion system state	SO-mode switch, DP propulsion, Auto pilot propulsion, MSO-mode
Power system state	SO-mode switch, MSO-mode, PTO, Mech, PTI
Weather conditions	Current velocity, Wind speed
Visual conditions	Wind speed, Fog, Snowfall, Rainfall
DP propulsion state	Main propeller, Aft thruster, Bow thruster
Auto-pilot propulsion state	Main propeller, Steering system
PTO	ME, HSG
Mech	ME, Genset1, Genset2
PTI	HSG, Genset1, Genset2
Control of own ship	Controllable speed, Controller performance, RIF7
Controller performance	SO-mode switch, Auto pilot performance, DP controller performance
Ship speed	Speed reference, Controller performance
Navigation area complexity	Traffic density, Obstacle density, Area type
Controllable speed	SO-mode switch, Ship speed, Area type
Impact speed	Ship speed, Speed of obstacle
Category of obstacle	Type of obstacle
MSO-mode switch	Decision
SO-mode switch	Decision
Speed reference	Decision
Power management system function	None
Obstacle density	None
Traffic density	None
Ship safety system function	None
Reliability of own ship's navigational states	None
Route information	None
Bow thruster state	None
Aft thruster state	None
Main propeller state	None
Steering system state	None
ME state	None
Genset 1 state	None
Genset 2 state	None
HSG state	None
Current velocity	None
Auto-pilot performance	None
DP-controller performance	None
Wind speed	None
Fog	None
Rainfall	None
Snowfall	None
Area type	None

performance). Further work should also address the uncertainty by testing for a wider variation of input parameters to assess how the behavior changes in a wider range of situations.

CRediT authorship contribution statement

Thomas Johansen: Conceptualization, Methodology, Software, Investigation, Data curation, Writing – original draft, Visualization. **Ingrid Bouwer Utne:** Conceptualization, Writing – review & editing, Supervision, Funding acquisition.

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.

Table 8
cont.BBN nodes.

Node description	Parent node(s)
Speed of ship/obstacle	None
Control of ship/obstacle	None
Type of ship/obstacle	None
Crew and passengers	None
Size of ship/obstacle	None

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Appendix. BBN connections

Tables with an overview of child/parent nodes for the BBN. (See Tables 6–8).

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Article 3:

Development and Testing of a Risk-based Control System for Autonomous Ships

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Development and testing of a risk-based control system for autonomous ships

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ABSTRACT

This paper presents a method for designing and verifying a control system with risk-based decision-making capabilities to improve its intelligence and enhance the safe operation of autonomous systems. The decision-making capabilities are improved, compared to existing control systems, using a Bayesian Belief Network (BBN) that is derived from the systems theoretic process analysis (STPA) as a foundation for an online risk model, which represents the operational risk for an autonomous ship. Combined with an electronic navigational chart (ENC) module to get accurate information about the environment, this enables the ship to operate in a safe and efficient manner. In addition, the control system is verified against safety and performance requirements using a formal verification method, based on temporal logic and Gaussian processes. The proposed methodology is tested in a case study where the system's behavior is compared with an existing conventional (manned) ship on experimental data from two routes along the coast. The case study shows that the performance of the Supervisory Risk Controller (SRC) with respect to the autonomous ship speed and maneuvering is similar to how the existing ship is operated. This means that the proposed methodology shows promising results with respect to developing autonomous ships with control systems and leads to intelligent and safe behavior.

1. Introduction

Although conventional ships have control systems for navigation, maneuvering, and power management, they are designed to rely on human input and supervision onboard. For example, Dynamic Positioning (DP) systems are used to maintain a ship's position or to maneuver the ship at low speeds with good accuracy. Nevertheless, a human operator must specify the mission and be ready to take over control if the automatic system fails. Power management systems (PMS) also have a high degree of automation to control electric power generation, power distribution, and prevent blackouts on ships.

There is currently no automation system that monitors or controls the complete ship's operation, replacing the crew onboard. For example, engine control systems may monitor the engine and shut it down if there is a failure, even if this compromises the safety and integrity of the ship. An example is the Viking Sky incident, where the diesel generators were automatically shutdown due to low lubrication oil levels in a severe sea state, which led to a complete blackout and nearly caused the cruise ship with almost 1400 people onboard to ground in storm conditions [1]. In general, for a ship to operate safely and autonomously, its control systems must be able to assess risk (currently the task of the crew onboard conventional ships). Hence, Utne et al. [2] propose a control system framework that can assess and manage risk, replacing some of the cognitive judgements that the crew would normally make while sailing to improve the autonomous ship's decision making. Thieme et al. [3] describe how risk analysis methods can be integrated with control systems and identify four areas for implementing this. Another approach is further demonstrated in Johansen and Utne [4]. A risk model represented by a Bayesian Belief Network (BBN), which is based on a systems theoretic process analysis (STPA), assesses navigational risks for an autonomous cargo ship while sailing as part of a supervisory risk controller (SRC) for high-level control of the ship. This risk model provides information that can be used as a basis for selecting the control mode, machinery mode, and setting control objectives while sailing. Bremnes et al. [5,6] presented a similar control system for autonomous underwater vehicles (AUVs) for under ice operations. In this case, the SRC was used to set the altitude set-point, velocity set-point, and control strategy such that the AUV could avoid collision while performing under-ice mapping with sufficient accuracy.

Relevant risk factors have also been discussed in Fan et al. [7]. A framework to identify navigational risk factors for autonomous ships is presented, but without any further application. Chang et al. [8]

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Nomenclature

AIS	Automatic Identification System
AMMS	Autonomous Machinery Management System
ANS	Autonomous Navigation System
AP	Autopilot
API	Application Programming Interface
AUV	Autonomous Underwater Vehicle
BBN	Bayesian Belief Network
CONOPS	Concept of Operations
CPT	Conditional Probability Table
DP	Dynamic Positioning
ENC	Electronic Navigational Chart
FMEA	Failure Mode and Effects Analysis
GNSS	Global Navigational Satellite System
GP	Gaussian Process
H-RIF	High-level Risk Influencing Factor
HiL	Hardware-in-the-Loop
HSG	Hybrid Shaft Generator
I-RIF	Input Risk Influencing Factor
LNG	Liquefied Natural Gas
Mech	Mechanical
MPC	Model Predictive Control
MSO	Machinery System Operating
PMS	Power Management System
PTI	Power Take In
PTO	Power Take Out
RIF	Risk Influencing Factor
ROC	Remote Operation Center
SLAM	Simultaneous Localization and Mapping
SO	Ship Operating
SRC	Supervisory Risk Controller
STL	Signal Temporal Logic
STPA	System Theoretic Process Analysis
UCA	Unsafe Control Action
USD	United States Dollar
VHF	Very High Frequency

combine Failure Mode and Effects Analysis (FMEA) with evidental reasoning and Bayesian Networks to quantify the risk level of major hazards related to autonomous ships. Johansen and Utne [9] propose to use STPA to identify potential hazards for autonomous ships and discuss some methods for finding additional quantitative data to use in a risk model, but without building and using the model. STPA is also used in Valdez Banda et al. [10] for hazard analysis on autonomous passenger ferries. This paper suggests safety controls to mitigate the identified hazards when designing the ship. Wróbel et al. [11] use STPA to develop a model to analyze safety and make design recommendations for autonomous vessels. Chaal et al. [12] propose a framework to model the ship control structure, based on STPA that can be useful to describe the functionality of the system.

Risk models have also been used to predict the loss of AUVs during missions [13–15] and to manage uncertainty in these missions [16]. However, none of these models are connected or implemented as part of the control system. Other papers have discussed risk as part of collision avoidance but use risk in a very general term and lack a direct link to risk analysis and risk modeling [17–22]. Combining some selected risk aspects with Model Predictive Control (MPC) has also been proposed for collision avoidance systems [23,24] and emergency management but the risk metrics that are used in these studies are not based on risk assessment and are simplified so that they can be used in an MPC application [25].

A quantitative risk model can provide good and useful information got an autonomous control system if it includes reliable information about the ship's position and its surroundings. One option is to use tools such as Simultaneous Localization and Mapping (SLAM) that can be used for AUVs [26–28] operating in areas where localization and mapping are challenging. Mapping the environment is unnecessary for autonomous ships because position data are available from global navigational satellite systems (GNSSs), such as position and speed measurements, and electronic navigational charts (ENC) are available. GNSS measurements are already used in control systems, such as in DP controllers to provide position and speed measurements. ENC data have been used in decision making systems, such as path planners, for ship navigation [29]. The data can then be used directly in the planner, with limitations on extracting and presenting the data. To address these limitations, Blindheim and Johansen [30] developed an open-source application programming interface (API) to process and display the data with high accuracy and in short computation time. Their paper shows how the API can be used for certain tasks, such as path planning based on a dynamic risk optimization. A simple risk metric based on wind speed and direction, and the distance to land is used when planning the route.

Developing better control systems is an important step towards realizing autonomous ships, which in turn is expected to improve safety at sea [31,32]. However, it is important to demonstrate that these ships are safe in operation to achieve approval from the authorities and public acceptance. This means that autonomous ships need to be tested in various scenarios and environmental conditions. Today, verification, validation, and certification in the maritime industry depend on type of ship and operation. On advanced offshore installations and ships, the ship and control system are thoroughly tested through simulations, scale testing, sea-trials, and Hardware-in-the-Loop (HiL) testing. Extensive and thorough tests are necessary to get the systems approved by class societies and coastal states [33]. Suppliers usually test individual components on less advanced ships during commissioning and sea-trials.

The shift towards autonomous ships presents several challenges with respect to verification and testing. Both the complexity and criticality of the software systems increase. In addition, the control system interacts with a highly dynamic and unstructured operative environment, which causes the span of possible scenarios to become enormous. Autonomous systems typically use machine-learning software to some extent, which introduces its own set of challenges (see Torben et al. [34]). Therefore, there is a need for new methodology to formalize and scale the verification and testing efforts to new levels.

Several recent works have aimed to address these challenges. For example, Pedersen et al. [35] propose a test system for autonomous navigation systems (ANSs) and show how it can be used to verify the performance of a collision avoidance system. Torben et al. [36] present an Autonomous Simulation-based testing framework and show how it can be used to verify a collision avoidance system. Xiao et al. [37] propose a quantitative evaluation method to evaluate obstacle avoidance methods for unmanned ships. These studies indicate that although the test systems work, they only work through testing a very limited part of the control system. They also lack a description of how the testing should be integrated into the design process for autonomous ship control systems.

To summarize the gaps identified in the current literature, it is necessary integrate risk with control systems intended for autonomous ships to improve its high level decision making. In addition, these control systems need access to data from ENCs, and they need to be verified in a formal and systematic manner to ensure the necessary safety and performance. Hence, the overall objective of this paper is to present a novel and interdisciplinary methodology to develop an SRC for high level control of autonomous ships that bridges risk modeling, optimization, ENC, and formalized verification to achieve safer and more intelligent performance of autonomous ships.

The proposed methodology is tested and compared to an existing conventional-manned ship for different coastal routes to assess how the SRC handles failures in the ship's machinery and propulsion system. The main scientific contribution is the demonstration of how the intelligence of an autonomous control system can be improved by combining thorough risk analysis and modeling, detailed data from navigational charts, and novel verification methodology. Compared to existing control systems, this new approach makes it possible to handle a wider range of operations and situations, which reduces the need for human intervention and supervision. Even though the application in this paper is focused on autonomous surface ships, it is expected that the methodology will have relevance for other autonomous applications. A similar methodology might also be used to assist operators by providing additional decision support by assessing how the risk level changes leading to safer ship operations.

The rest of this paper is organized as follows. Section 2 presents the methodology for building and setting up the controller. Section 3 describes the case study. Section 4.1 and Section 4.2 present the results from the case study. Sections 4.3–4.7 discuss how risk can be included in control systems, how to use ENC data, how to test the system, and it also describes some uncertainties in the controller and risk model. Section 5 concludes this paper and outlines further work towards highly autonomous ships.

2. Method

The SRC controller is developed through a five-step process, as shown in Fig. 1. The SRC enables the controller to make risk informed decisions that emphasize both safety and efficiency when operating the ship. These decisions can (for example) determine the ship's operating machinery mode, control mode, or the speed reference for the proposed control system.

The ship and the operation are first described in detail and analyzed using an extended STPA to identify hazardous events that need to be included in the risk model. Thus, the STPA results are used as the basis for building the online risk model in step 2, which is represented here in terms of a BBN. The justification for using STPA combined with BBN is presented in Utne et al. [2]. For situation awareness, the risk model uses data from the ship's sensors and the control system to assess the current conditions. The ENC module is used to extract data from navigational charts with information about the area surrounding the ship. The ENC model is set up in step 3 based on the design requirements to provide the necessary data to the risk model and SRC. The SRC is then developed in step 4 based on the requirements identified in the system analysis and the STPA (step 1), and using data from both the risk model and ENC. Finally, the controller is verified against the performance requirements using the automatic simulation-based testing methodology.

2.1. Step 1: System description and STPA

To setup and build the control system, the ship and operation have to be described and analyzed, such as in terms of a CONOPS (concept of operations). This starts by clearly describing the ship, how it is controlled, its technical condition, and characterization of the operation that it is used for. In terms of control, it is important to know what type of controllers the ship has or will have, how they are connected, and their different responsibilities. Human operators or supervisors (e.g., onshore in a control center) must also be described with information about how they can control or affect the ship. Describing the ship's operation requires a clear statement of why and where the ship is sailing, as well as its operating modes. For example, a coastal cargo ship sailing along the Norwegian coast may be very different to a passenger ferry sailing between islands in the Mediterranean Sea.

The decisions or control actions relevant for the SRC must also be specified. These are important to consider because they are the only options for the SRC to affect the control of the ship. After describing the ship, STPA can be used to identify potential hazards, causal factors, and safety constraints. The STPA follows the steps defined in Leveson [38] but is expanded to also explicitly consider the consequences of the hazardous events and system-level hazards as follows:

(a) Define the system
(b) Identify hazardous events and system-level hazards
(c) Identify unsafe control actions (UCAs)
(d) Develop loss scenarios
(e) Analyze consequences

The description of the ship can be used as a basis for the first step of STPA, and is a basis for defining the control structure and assigning responsibilities to the different controllers in the system. The next step is to identify hazardous events and to identify UCAs. These are subsequently described in loss scenarios that may lead to UCAs. Scenarios also include how decisions, such as selecting the wrong control mode or using machinery systems with failures, can lead to UCAs. The decisions are included in the same way as risk influencing factors (RIFs). The final part is to describe and classify the potential consequences of the hazardous events (e.g., through cost estimations).

2.2. Step 2: Online risk model

The online risk model is built based on the STPA results and follows the emerging top-down structure, like the results of the analysis, as shown in Fig. 2. The BBN has six main types of nodes:

- Consequences
- Hazardous events
- System-level hazards
- UCAs
- RIFs
- Decisions

The end node in the BBN is the consequences. These are caused by the hazardous events, under given conditions. The hazardous events are caused by one or more system-level hazards identified in the STPA. The next is the UCAs that lead to system-level hazards. UCAs get an input from RIFs that describe the loss scenarios and the conditions where hazardous events have negative consequences. RIFs can be both high-level RIFs (H-RIFs) and input RIFs (I-RIFs), as shown in Fig. 2. For a more detailed description of mapping STPA results to a BBN, the reader is referred to Utne et al. [2] or Johansen and Utne [4]. For a detailed description of BBNs in general, the reader is referred to Fenton and Neil [39].

The BBN is converted to an online risk model by deciding how to update the BBN as the ship sails with online information. This links specific nodes to sensors and systems onboard the ship, and then decides which data are necessary, including the ENC module. Decisions made in the SRC are also included in the BBN to model how they affect the risk picture and consequences. The BBN can also have intermediate nodes to group I-RIFs and decisions to reduce the number of nodes that are connected to each H-RIF. This is more important for larger and more complicated BBNs.

2.3. Step 3: ENC module

The ENC module extracts and manipulate data from electronic navigational charts. These data are necessary in the risk model to

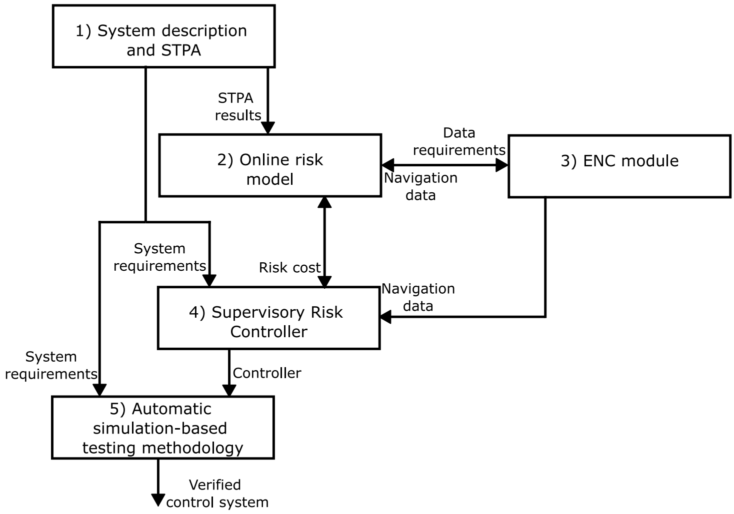


Fig. 1. Methodology flowchart.

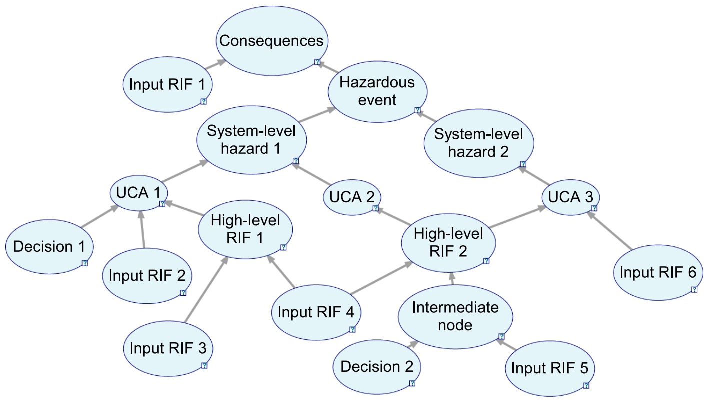


Fig. 2. Example BBN structure, showing how the STPA is linked to the BBN and how different nodes are related .
Source: Adopted from Utne et al. [2].

describe the surroundings and conditions around the ship. The ENC module is based on the open-source Python package SeaCharts [30]. This package use FGDB 10.0 data sets with 2D data of the relevant areas. These are then processed as the application starts, so that they can be stored as shapefiles, where only the relevant depth layers and land areas are stored. This allows for much faster processing because it reduces the time necessary for computation and/or querying. The data is stored as polygons for various water depths and land areas. The stored shapefiles can then be queried to find the distance to points where the ship can collide or ground, and assess how much space the ship needs to maneuver.

The ENC module is set up by first loading the necessary maps for the relevant area. The next step is to define and load relevant layers for the ENC module, depending on the ship and data needed in the control system. This is achieved by defining the minimum water depth that the ship must maintain for safe sailing. To avoid unnecessary quantities of information in the risk model, a planning horizon is set in the ENC to decide how far the ENC should look ahead of the ship. This limits the data size that the ENC must query and reduces the computation time. Connecting the ENC module with the risk model is done by connecting the relevant nodes and updating them with data from the ENC, such as distance to land and shallow areas, combined with position and speed measurements from the GNSS system.

The current ENC module does not account for navigation markers, as this is not currently implemented in the SeaCharts package. This is discussed more in Section 4.5. For a detailed description of the package and all functions, the reader is referred to Blindheim and Johansen [30].

2.4. Step 4: Supervisory risk controller

The controller is set up as an SRC to make high-level decisions or set control objectives. One option is to use costs as a means for implementing the inputs from the risk model into the decision making. For other potential options, see Thieme et al. [3].

For an autonomous ship controller, decisions can be made based on four costs: the risk cost from the online risk model, fuel cost based on the expected fuel consumption, operation costs (other than fuel), and the cost of not starting new missions. The total cost is calculated using Eq. (1) as a function of the decisions, d, such as setting the speed reference and deciding how the machinery should be operated:

$$C(d) = R(d) + F(d) + O(d) + L(d) \tag{1}$$

The risk cost, $R(d)$, gives the expected cost from the consequences described in the risk model and account for factors such as weather conditions, ship speed, traffic conditions, etc. Fuel cost, $F(d)$, describes the expected cost of fuel of operating the ship under the current conditions. Operation cost, $O(d)$, describes the costs of operating the ship, outside of fuel cost, such as maintenance, insurance, and manning costs. $L(d)$ describes the potential loss of future income caused by the time used. The cost function is set up such that fuel cost, operation cost, and potential loss of future income increase if the ship takes a longer time to reach the final way-point.

The controller checks each possible set of decisions to find the set with the lowest cost. The decisions can vary depending on the ship and can include selecting what machinery mode to use, how the ship should be controlled, and which speed reference to follow. The SRC configures the control of the ship according to the set with the lowest cost.

2.5. Step 5: Automatic simulation-based testing methodology

Step five verifies the controller against a set of design requirements related to safety and efficiency. The verification process is performed using the automatic simulation-based testing methodology from Torben et al. [36]. This methodology automatically runs simulations where the vessel is sailing along its planned route, while varying scenario parameters. The methodology formulates requirements using the Signal Temporal Logic (STL) formal specification language, which enables automatic evaluation of the simulations against the requirements [40]. The result of evaluating a simulation against an STL requirement is an STL robustness score that describes how robustly the requirement is satisfied. If the STL score is greater than zero, then the requirement is satisfied. If it is less than zero, then the requirement is violated.

The methodology selects the simulations to run from a test space that is defined by a set of scenario parameters with corresponding parameter spaces. The test space can, for example, be based on scenarios that are identified in the STPA [41–43] to test the controller in specific situations. A Gaussian Process (GP) model [44] is used to predict the STL robustness score as an unknown function of the test case parameters. The GP model estimates the expected value and the uncertainty of STL robustness over the entire parameter space of a test case. The GP model is iteratively updated by running simulations and observing the resulting STL robustness score. The estimates of the GP model are then used to adaptively guide the test case selection towards cases with low STL robustness or high uncertainty. This results in efficient coverage of the parameter space or alternatively efficient falsification if the controller does not satisfy the requirements.

The testing terminates in a verified state if the lower confidence interval of the GP is greater than zero for the entire parameter space. For example, using 99% confidence intervals, a verification would indicate that there is at least a 99% probability that the system satisfies the requirement for the entire test space of the test case. Alternatively, if a test case that does not satisfy the requirements is identified, then the verification terminates in a falsified state, returning the corresponding counter-example. For a more detailed explanation of the automatic simulation-based testing methodology, the reader is referred to Torben et al. [36].

3. Case study: Supervisory risk control of an autonomous cargo ship

The method for building the SRC is tested in a case study that simulates an autonomous ship operating along the Norwegian coast to assess how the SRC manages and controls the ship in comparison to an existing conventionally-manned ship. The first part of the case study will analyze how the SRC adjusts the speed and configures the ship to maintain control. This is then compared performance-wise to a conventional ship in similar conditions, using position and speed data from the ship navigation system. The second part will study how the SRC handles failures in the machinery and propulsion system.

In the case study, it is assumed that the chart and GNSS measurements are sufficiently accurate to be used in the control system. It is also assumed that the time necessary to start up machinery can be neglected. There are still some delays and thruster dynamics included, such that engines and generators cannot change the load immediately. This is deemed sufficient to show how the SRC functions. Some of the potential ways to include these aspects in the SRC will be discussed in Section 4.3.

The ship simulation uses a simplified kinetic model without wave forces. This makes it easier to simulate and test the system, while it also changes the ship's movement such that the ship drifts more. This makes it more difficult to control the ship, especially in tight turns, without reducing the speed much more than conventional ships. Although the focus in this paper is the design and testing of the SRC, it still provides sufficient results to show that the proposed methodology works.

3.1. Step 1: Describing the ship and operation

The autonomous ship that is considered in the case study is an 80 m long and 16 m wide cargo ship that is sailing along the Norwegian coast. Although the ship is operated unmanned, it has a human supervisor onshore that can monitor and take control remotely if necessary. The ship has an autonomous control system, as shown in Fig. 3, with an SRC as the high-level controller, an ANS to control the navigation, and an autonomous machinery management system (AMMS) to manage the machinery. The ANS has two ship operating (SO) modes: (i) DP and (ii) autopilot (AP), with a corresponding controller for each mode. The DP controller is used during low-speed maneuvering and station keeping, while the AP controller is used for transit at higher speeds. When the ship is operated in DP-mode, it utilizes the main propeller, bow tunnel thruster, and aft tunnel thruster to control the ship's speed, position, and heading. The AP controller uses the main propeller and rudder to control the ship.

The ship is equipped with a Liquefied Natural Gas (LNG) fueled main engine, a hybrid shaft generator (HSG), and two diesel generators. The HSG can be used as a generator to produce electricity when the main engine is used or an electric engine when diesel generators can be used to produce electricity.

The AMMS is used to control the machinery system depending on the machinery system operating (MSO) mode. The ship has three MSO-modes: power take out (PTO) mode, where the main engine provide propulsion and the HSG is used as a generator to provide electricity; power take in (PTI) mode, where the diesel generators produce electricity, and the HSG is used as an electrical engine to propel the ship; and the mechanical (Mech) mode is where the main engine provides propulsion and the diesel generators produce electricity.

The SRC is responsible for selecting SO-modes and MSO-modes. It also sets the reference speed for the ANS to follow.

The STPA in the case study is based on a workshop with 12 relevant system experts who identified UCAs for the autonomous cargo ship. The participants have 5–30 years of experience from academia and industry working with risk assessment, testing, verification and validation, marine technology and maritime operation, and ship control system design. The workshop where conducted over three sessions. The first two where used to identify UCAs that were discussed and processed by the participants in the third. The result from the workshop was a report sent out to the participants. The main purpose of the workshop was to not only identify how switching between different machinery modes can lead to insufficient power capacity and power losses but also to identify when the wrong SO-mode used by the ANS could lead to accidents.

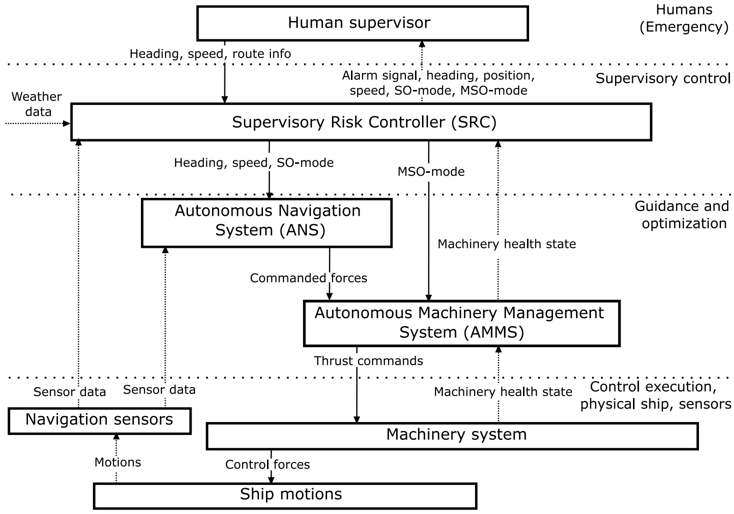


Fig. 3. Hierarchical control structure.
Source: Adopted from Johansen and Utne [4].

The STPA in the workshop considered a slightly different control structure with a remote operation center (ROC) that is responsible for planning, monitoring, and supervising the ship. The ANS and AMMS determine the SO- and MSO-mode, respectively, according to the sailing plan. An SRC in the control system was not included. The results from the workshop have therefore been developed further to account for the different ship control structure considered in this case study.

This case study assumes that the human supervisor plans the mission and the SRC then executes this plan. The human supervisor is also responsible for taking remote control of the ship if notified by the SRC. Selecting SO- and MSO-mode is now done by the SRC, and not the ANS and AMMS. The ANS controls the ship in either AP- or DP-mode depending on the SO-mode. The AMMS manages the machinery system according to the MSO-mode decided by the SRC. The AMMS also contains thrust allocation that computes individual thrust commands, based on the commanded forces from the ANS.

Since the workshop did not include an SRC, the control structure is modified to include this with the associated control actions. However, because setting SO-mode, MSO-mode, and the ship speed were considered when identifying UCAs in the workshop, the results can still be used with some modifications to account for the differences.

The SRC has a set of process variables that are used to make decisions, as follows:

- PV-1: Active MSO-mode
- PV-2: Available power and thrust
- PV-3: Machinery system status
- PV-4: Active SO-mode
- PV-5: Ship's navigational states
- PV-6: Weather conditions
- PV-7: Traffic conditions
- PV-8: Route information

The case study focuses on the following hazardous event (HE) and system-level hazards (H), as follows:

- HE1: The ship grounds or has contact with the seafloor
- H1: The ship violates the minimum separation distance to the shore
- H2: The ship sails in water that is too shallow

Table 1
Unsafe control actions.

UCA	Description
UCA-1	A command is given to change MSO-mode to PTO when the health state of the ME is reduced
UCA-2	A command is given to change MSO-mode to Mech when the diesel generators do not function, or are unable to provide the rated power to the DC bus
UCA-3	A command is given to change MSO-mode to PTI, resulting in insufficient power for the main propulsion
UCA-4	A command is given to change SO-mode to transit/AP when the ship is in harbor/tight areas
UCA-5	A command is given to change SO-mode to maneuvering/DP when the speed is higher than the maximum maneuvering speed

The workshop identified a total of 60 UCAs. However, including all these would make the risk model more complicated to build and evaluate. Therefore, the case study focuses on five different UCAs, as shown in Table 1, to reduce the size and complexity of the risk model. These are chosen to have a good basis for specifying scenarios where the decision making in the SRC, such as setting SO-mode or speed reference, can lead to hazardous events and identify RIFs that affect this.

Nine scenarios are defined to describe the situations that can cause UCAs and hazards, as presented in Table 2.

The extended STPA in this paper also considers the consequences from the hazardous event and the expected resulting costs. The consequences are divided into damage to own ship, damage to others' property, and harm to humans. Consequences are classified as either severe, significant, minor, or no consequences [45]. Fatalities or serious injuries to humans or extensive damage to the ship or other ships/objects where assistance is necessary are considered severe consequences. Less serious/minor injuries to humans and damage that needs repairs outside of planned maintenance are considered significant consequences. Insignificant or no injuries to humans and damage that can be fixed in the next planned maintenance are considered minor consequences. Severe consequences cost 4 550 640 USD, significant 455 064 USD, minor 45 506.4 USD, and no consequences lead to zero

Table 2
Scenarios.

Scenario	Description	UCA
SC-1	MSO changed to PTO because PTI delivers insufficient amount of power but the health state of the ME is reduced, leading to insufficient power production	UCA-1
SC-2	MSO changed to PTO because the extra power in Mech is not necessary but the health state of the ME is reduced, leading to insufficient power production	UCA-1
SC-3	MSO changed to Mech because PTO is not producing sufficient power for propulsion but the diesel generators fail or provide less power than expected, leading to insufficient power on the DC bus	UCA-2
SC-4	MSO-mode is changed to from PTO to PTI due to an underestimate of the power necessary, leading to insufficient power to the ship	UCA-3
SC-5	MSO-mode is changed to from Mech to PTI due to an underestimate of the power necessary, leading to insufficient power to the ship	UCA-3
SC-6	SO-mode is changed to transit while still in harbor due to inaccurate/incorrect measurements of the ship states	UCA-4
SC-7	SO-mode is changed to transit while still in harbor due to wrong understanding of the area around the ship	UCA-4
SC-8	SO-mode is changed to maneuvering with too high speed due to faulty speed estimates/measurements	UCA-5
SC-9	SO-mode is changed to maneuvering with too high speed due to a wrong limit set in the controller	UCA-5

Table 3
Risk influencing factors.

High-level RIF	Description	Scenario(s)
H-RIF-1	Machinery health state	SC-1,SC-2,SC-3
H-RIF-2	Estimation of necessary power	SC-1,SC-2,SC-3,SC-4,SC-5
H-RIF-3	Navigational complexity/situation	SC-1,SC-2,SC-3,SC-4,SC-5
H-RIF-4	Measurement/estimation of the ship's navigational states	SC-6, SC-8, SC-9
H-RIF-5	Situation awareness	SC-7, SC-8
H-RIF-6	Reliability of the ship's control system	SC-9

cost. The costs are estimated based on EfficienSea [46], The Norwegian Agency for Public and Financial Management [47], and IMO [45].

3.2. Step 2: Building the online risk model

The STPA is used as the basis to build the online risk model based on the methodology in Utne et al. [2], as shown in Fig. 4. The output from the risk model is the expected cost from the consequence. The BBN has four nodes describing the consequences: one general consequence node and one for damage to own ship, damage to others property, and harm to humans; one node describes the hazardous event, and one node describes each of the system-level hazards. The two system-level hazards depend on the five UCAs considered in the STPA. Each of these correspond to one node in the BBN.

The nine scenarios described in the STPA are used as the basis to define the six H-RIFs in the BBN. The list of H-RIFs, with the corresponding scenarios are show in Table 3. Each of the high-level RIFs are analyzed further to find I-RIFs, as shown in Table 4.

In addition to the I-RIFs and decisions in Table 4, the type of seabed and shore affect the consequences directly. Intermediate nodes are used between I-RIFs/decisions and H-RIF nodes to reduce the number of inputs to each node. This reduces the size of conditional probability tables (CPTs) and makes it easier to define these. CPTs and states

Table 4
Input to H-RIFs.

High-level RIF	Description	Input RIF/Decision
H-RIF-1	Machinery health state	ME state, HSG state, DG1 state, DG2 state, BT state, AT state, MP state, ST state, MSO-mode (Decision node), SO-mode (Decision node)
H-RIF-2	Estimation of necessary power	PMS, AP performance/accuracy, DP performance/accuracy, SO-mode (Decision node)
H-RIF-3	Navigational complexity/situation	Traffic, Obstacles, Current, Distance to grounding hazard, Wind speed, Wind direction, SO-mode (Decision node) Speed reference (Decision node)
H-RIF-4	Measure-ment/estimation of ship's navigational states	GNSS system, Radar, AIS, SO-mode (Decision node) AP performance/accuracy DP performance/accuracy
H-RIF-5	Situation awareness	GNSS, Radar, AIS, Visual conditions
H-RIF-6	Reliability of the ship's control system	SO-mode (Decision node), AP performance/accuracy DP performance/accuracy, Ship design process

are defined based on the work in Johansen and Utne [4], DNVGL [48], Hassel et al. [49], discussions with crew working on different ships, and control engineers from Kongsberg Maritime. A full list of all nodes, with parent nodes, is shown in Table 5.

The BBN is converted to an online risk model by linking I-RIFs to the control system so they can be updated as the ship sails. Nodes describing the state of machinery parts are updated with information from the AMMS. If the machinery is well functioning and well maintained, then the probability of failure is very low, $9 \cdot 10^{-7}$. In future works, this is intended to be updated as the ship sails since machinery components are more likely to fail as components age, but this is not modeled in the current case study.

Nodes describing the control system and sensors are given a static value based on Johansen and Utne [4], DNVGL [48], Hassel et al. [49]. Weather nodes are linked to sensors where these exist, such as wind and current, or weather forecast and historical data [50]. These nodes are designed to be updated in real-time depending on the available data. Traffic use data is drawn from the automatic identification system (AIS), which is used to transmit the identity, position, course, and speed to nearby vessels using the very high frequency (VHF) band. Obstacle density and distance to grounding hazards are taken from the ENC. The seabed and shore are described with data from Norwegian Mapping Authority [51] over the relevant area. The values used in input nodes describe the probability over the planned mission.

3.3. Step 3: Setting up the ENC module

The ENC module is setup to extract data from electronic navigational charts for use in the online risk model and the rest of the control system. The ENC module here includes charts covering the areas around Brønnøysund and Rørvik in Norway, which are relevant for the type of ship in the case study. The module is set up to consider everything shallower than 5 m as shallow areas or land where the ship cannot navigate safely. The rest of the chart is divided into layers of 10 m, 20 m, 50 m, 200 m, 350 m, and 500 m. This distribution is considered a reasonable combination of chart resolution and efficiency in the control system.

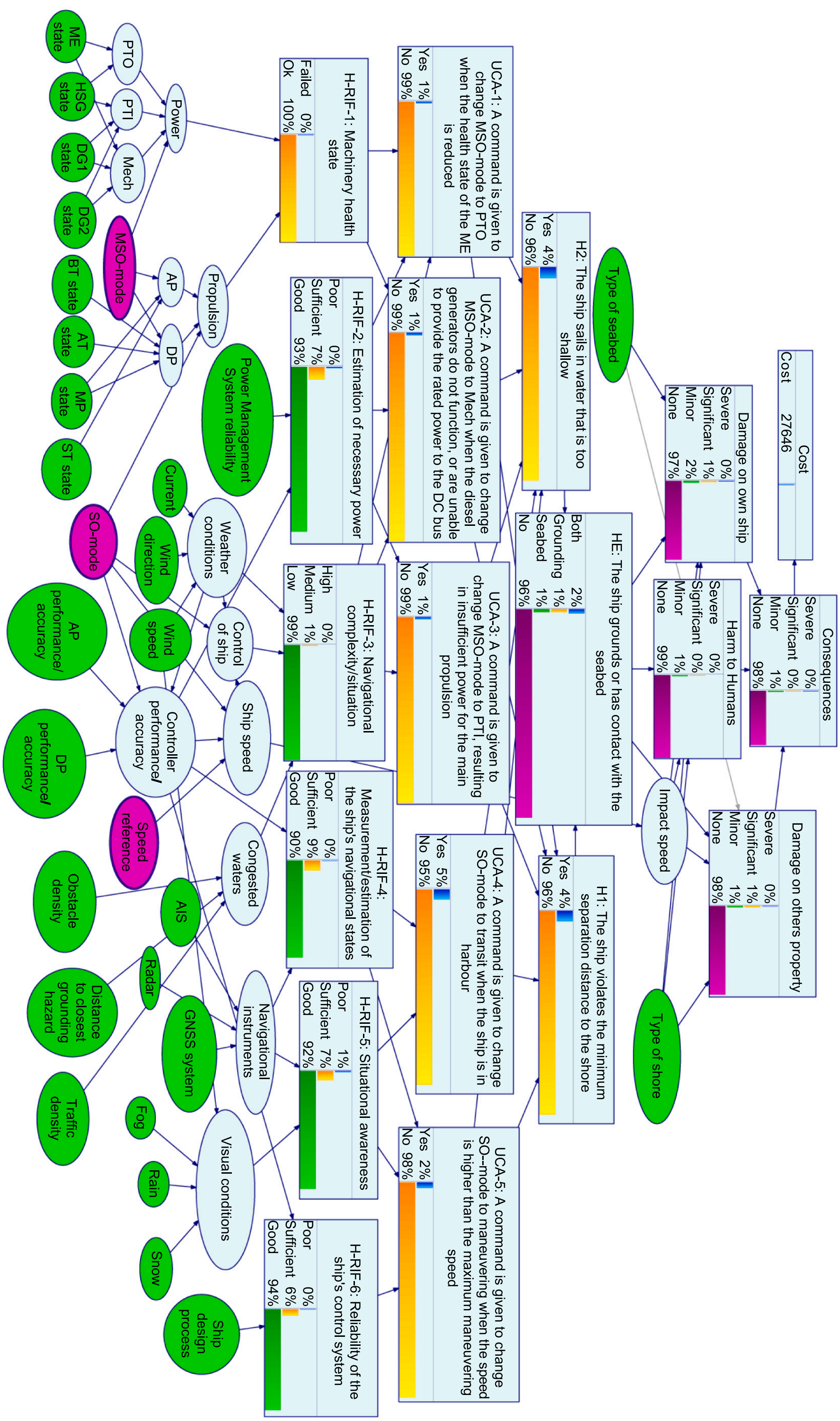


Fig. 4. BBN risk model showing an example of the risk cost. For more detailed information about the BBN, please contact the corresponding author.

The obstacle density is based on the distance to the closest shallow point (i.e., areas with less than 5 m water depth) and the percentage of obstructed water around the ship. The water depth of 5 m is the same as the max draft of the ship. Using this water depth is considered sufficient for assessing the portion of obstructed water in this work. Shallow areas are consequently areas with too little water depth for the ship to sail, which should be avoided with sufficient safety margins. The percentage of obstructed water is calculated by considering a disk with radius 1400 m and finding the portion of the disk with land and shallow water. The radius is set through testing to ensure that the disk gives a good picture of the sea area surrounding the ship, without being unnecessarily large.

The ENC module checks the area around the ship every 15 s and updates the input to the online risk model. Updating every 15 s ensure that the control system has updated data, while limiting the computation time necessary to check the ENC module.

3.4. Step 4: Building the supervisory risk controller

The SRC is the high-level controller that manages and controls the ship. The SRC uses data from the risk model and ENC, combined with operational measurements from the ANS and AMMS, such as position, speed, and machinery status to make decisions. The SRC has four main objectives: selecting the SO-mode, selecting the MSO-mode, setting the reference speed for the ship to follow, and notifying the human supervisor when the situation becomes too severe to continue.

The SRC is implemented as a switch that checks the cost function, as shown in Eq. (1), for each set of decisions. The risk cost is calculated using Eq. (2). This takes the probability of the different consequences, $Pr()$, estimated in the online risk model described, multiplied with the expected cost for each consequence, $C_{()}$, as described in Section 3.1:

$$R(d) = Pr(severe)C_{severe} + Pr(significant)C_{significant} + Pr(minor)C_{minor} + Pr(none)C_{none} \quad (2)$$

The fuel cost is calculated as the specific fuel cost (SFC) multiplied by the expected sailing time. The SFC is taken from a look-up table, depending on wind speed, ship speed, current speed, and MSO-mode. The look-up table is made by simulating the machinery under different conditions to estimate how much fuel is used to sail a set distance. The fuel prices are taken from Ship & Bunker [52] at 1 343.5 USD/ton for LNG and 684.5 USD/ton for diesel. This table provides a cost per distance that is multiplied with the planned sailing distance, as shown in Eq. (3):

$$F(d) = SFC(wind, speed, current, machinery) * distance \quad (3)$$

Operation costs are calculated using Eq. (4). This includes manning in the ROC, maintenance from wear and tear on the machinery, insurance of the ship, lubrication oil, spare-parts, and logistics. These are estimated based on conventional ships of the similar size and type, and using data from Stopford [53] to be 341.3 USD/h for the current ship. This is similar to the fuel cost in normal transit with a speed of 5–7 $\mathrm{m/s}$ (9.7–13.6 knots):

$$O(d) = Cost_{operating} * distance/speed \quad (4)$$

The cost of potential future loss is calculated with Eq. (5). This cost is the loss of income if the ship is unable to take on any new missions before finishing the current route, which is set to 910.1 USD/h:

$$L(d) = Cost_{futureloss} * distance/speed \quad (5)$$

The cost function, including the ratio between the different terms, is discussed in Section 4.7. The controller estimates the cost of sailing a distance equal to the initial route distance. This is constant for the whole route which keeps the weight between the different cost terms constant.

The alarm is implemented so that a human supervisor can take over control remotely of the ship if necessary, but unnecessary alarms also need to be avoided. To achieve an acceptable balance, the alarm trips if either the risk cost exceeds 9 267.70 USD, or the probability of the hazardous event exceeds 0.5. The cost limit is set between minor and significant consequences because it is better to have the human supervisor check the ship having an emergency later on. The SRC is implemented to lower the speed to limit the risk cost because impact speed directly affects the consequences. However, this can cause situations where the probability of a hazardous event is too high to continue due to environmental conditions, even though the risk cost is low because the speed is reduced to the minimum. Thus, a probability limit of 0.5 is used to notify the human supervisor in these situations.

If the SRC changes the ship's control configuration, then it is paused for 30 s before checking again. Implementing a time delay in the switching logic ensures that the controller reacts to changes but avoids situations where it gets stuck switching between different modes (e.g., DP and AP) without stabilizing, which is also called chattering [54].

3.5. Step 5: Verifying the control system

After setting up the SRC, verification is done by first determining how to test the system and which requirements to verify against. The autonomous ship should follow the route through Brønnøysund that is shown in Fig. 5. The route follows the same path as a conventional ship and those described in Norwegian Hydrographic Service [55]. This is used to check the ship in situations where the controller is expected to adjust the speed reference, without using much longer time than conventional ships. The ship has to lower the speed reference early enough to slow down when entering narrow and tight areas, and increase it when it opens up again.

To test safety, the ship should maintain a minimum distance of 5 m to shallow areas or provide an alarm to the human supervisor at least 5 min before the minimum distance is violated. Having a minimum distance of 5 m is not realistic for a real ship. However, to account for extra drift caused by simplifications in the simulator this is used to get results reasonable results that can be compared to conventional ships. These assumptions are discussed further in Section 4.8. The following verification focus on wind and how this affect the ship. However, the process is the same for other disturbances, such as current.

To verify that the controller is efficient, the ship should at maximum use 140 min on the whole route segment under consideration in the case study or provide an alarm to the human supervisor. This time limit is set based on the time existing manned ships used on the same route. Both the safety and efficiency requirements are tested in wind speeds ranging from no wind to 20 $\mathrm{m/s}$ and from all directions. Other factors (e.g., current, waves, and machinery failures) are not considered in the verification. This simplifies the verification but still gives sufficient results for further testing of the control system. The route is chosen to get a good variation between open water and more narrow straights with tight turns.

The verification is performed using the automatic simulation-based testing methodology that was introduced in Section 2.5. This methodology selects and simulates interesting combinations of wind speed and wind direction to verify or falsify the system. The system is verified to satisfy the safety requirement (minimum distance to shallow) in 161 simulations, and the efficiency requirement (maximum allowed sailing time) in 97 simulations. The STL robustness surfaces for safety and efficiency are shown in Figs. 6(a) and 6(b), respectively. The STL robustness score is normalized to the interval $[-1, 1]$. Fig. 6(a) shows that the robustness score in the case study is always above 0. Similarly, Fig. 6(b) shows that the robustness is always above 0 and is close to 1 when it reaches the final way-point early or trips an alarm because the risk cost or grounding probability becomes too high.

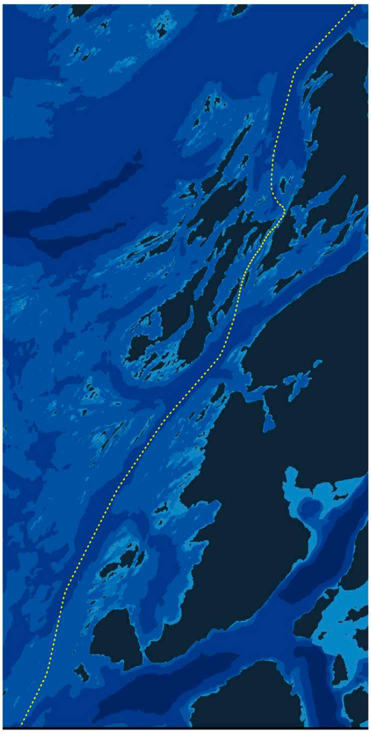


Fig. 5. Route used in the verification process.

The verification shows that the control system makes the autonomous ship follow the route and it also reaches the end of the route in reasonable time in wind speeds of up to 8 m/s. Above this, the planned route forces the ship very close to land in certain spots, which means that it notifies the human supervisor. When the wind speed exceeds 10 m/s, the route leaves too little space for the ship to maneuver. This can cause problems with certain wind conditions. However, the control system provides an alarm to the human supervisor with enough time to pass the safety requirement. Overall, the verification shows that the proposed control system works in the planned route but it is limited by not being able to change the route in accordance with the environmental conditions.

4. Results and discussion

4.1. Comparing the controller with the maneuvering of a conventional ship

After building and setting up the controller, the autonomous ship is simulated along two different routes to compare it against an existing conventional ship. The first route is through Rørvik and the second is through Brønnøysund. The route through Brønnøysund is similar to the one used in the verification (Fig. 5) but with different start and end points. The start and end points are changed because the GNSS data from the conventional ship is only available for part of the route. The purpose is to see how the SRC sets the speed reference, MSO-mode, and SO-mode, and compare this to how conventional ships operate along the same routes in similar weather conditions. The existing ship is equipped with a similar machinery and control system as the autonomous ship but with a crew who decides MOS-mode, SO-mode, and speed reference.

The conventional ship sailed through Rørvik and Brønnøysund in the fall of 2021 with a wind speed between 5–7 m/s. The routes followed by the conventional ship are plotted with GNSS data taken from the control system aboard the conventional ship. The route through Rørvik is planned by placing way-points along the route that the autonomous ship can follow. The GNSS data for Brønnøysund contain some measurements that place the route over land. The cause of these are not certain but it only affects the data between point 0.5 and 0.7. Therefore, the route was re-planned by placing way-points along the same route into Brønnøysund but following the route recommended in Norwegian Hydrographic Service [55] through and after Brønnøysund. The routes are shown in Fig. 7 for route one and Fig. 10 for route two with the conventional ship in red and the autonomous ship in yellow.

To compare the two ships, the risk model and SRC need position, speed, MSO-mode, and SO-mode from the conventional ship. Position and speed are recorded in the ship's control system. Ship speed is fed directly to the SRC to find the expected fuel cost and is used as input to the risk model. Position data is used in the ENC module to get the distance to the closest grounding hazard and obstacle density. MSO-mode is set to PTO and SO-mode to AP after discussing how the conventional ship is operated with the crew. This provides a cost that can be compared to the autonomous ship. The SRC uses a constant distance when calculating costs, as explained in Section 3.4. The plots therefore show the costs of sailing a distance equal to the distance of the whole route, d_0, estimated at each point.

4.1.1. Comparison on route one through rørvik

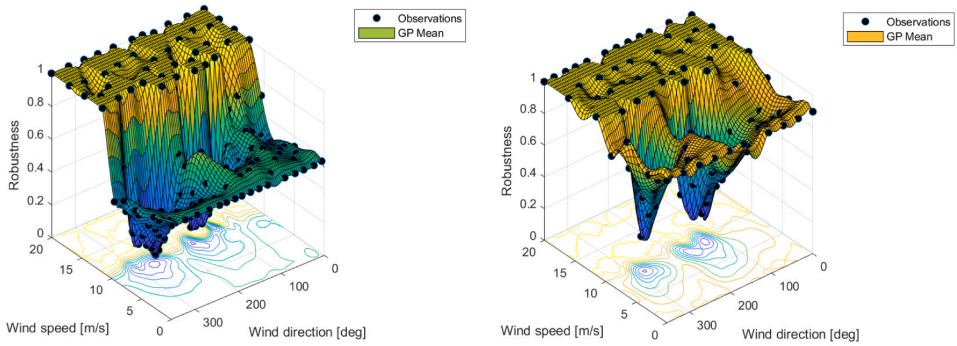
On route one, the conventional ship starts with a speed of 5.25 m/s, before increasing to 6.5 m/s. The speed is then maintained at 6.5–6.75 m/s the rest of the distance. The autonomous ship starts with a speed of 5 m/s. This is later increased to 7 m/s as the ship sails into more open water. Along the rest of the route, the speed varies between 5 m/s and 7 m/s as it passes through more narrow parts of the route and in more open areas. Overall, the autonomous ship varies the speed more as the environmental conditions change, compared to the conventional ship.

The cost is shown in Fig. 8 for the conventional ship and in Fig. 9 for the autonomous ship. The plots show the expected costs of sailing the full route, d_0. The conventional ship has a higher risk cost (blue line) because it maintains a higher minimum speed. Fuel (yellow line), operation (green line), and potential future loss (red line) costs are almost the same but they vary more for the autonomous ship because the expected time varies more corresponding to more changes in the speed. For the conventional ship, both fuel and operation costs are almost constant because the speed is kept more or less constant along the whole route. In contrast, the speed of the autonomous ship is changed more, which leads to more changes in fuel and operation costs. The conventional ship uses 96 min on the whole route and the autonomous ship uses 103 min.

4.1.2. Comparison on route two through brønnøysund

The routes differ slightly more through Brønnøysund, due to the errors in the position data from the conventional ship. This means that the autonomous ship sails around 1 km longer. The conventional ship maintains a speed of around 6.75 m/s before it reaches the narrow parts of the route between 0.5 and 0.6 on the route shown in Fig. 10. In the narrowest part, the speed is reduced to 3 m/s, it is then increased to 6.75–7 m/s as the area opens up. The autonomous ship has a speed of 7 m/s in open water. This is reduced to 5 m/s when it reaches the first narrow straits between points 0.4 and 0.5. It then returns to 7 m/s for a short time in the more open area, before it is reduced to 4 m/s through the narrow harbor area. Overall, the autonomous ship makes more changes to the speed, but maintains a higher minimum speed.

The cost is shown in Fig. 11 for the conventional ship and Fig. 12 for the autonomous ship. Fuel (Yellow line), operation (Green line), and potential future loss (red line) costs are virtually the same along



(a) Safety verification

(b) Efficiency verification

Fig. 6. Robustness surfaces resulting from the two verification runs.

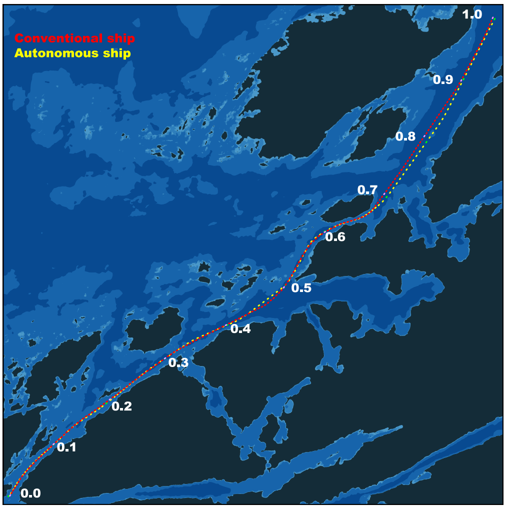


Fig. 7. Map of route one through Rørvik. The conventional ship's route is shown in red and the autonomous ship's route is shown in yellow.

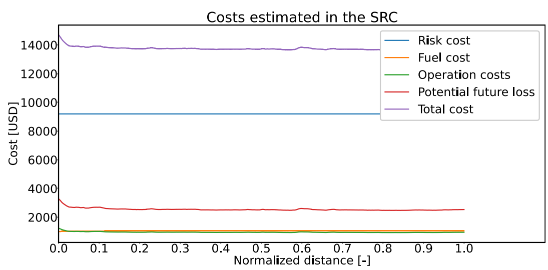


Fig. 8. Conventional ship's costs on route one.

the whole route. The risk cost is similar along the first part where both ships follow the same route, but is much higher for the conventional ship in the middle part of the route. This is caused by the inaccuracies in the GNSS data collected on the conventional ship showing the ship sailing very close and over land, and the conventional ship not reducing the speed between points 0.4 and 0.5. This combination results in a

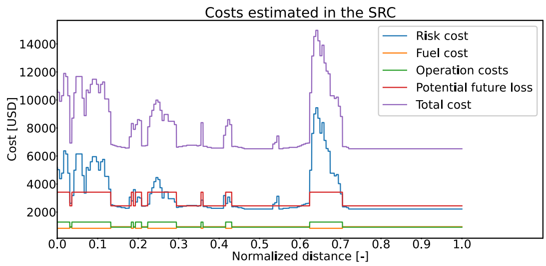


Fig. 9. Autonomous ship's costs on route one.

significantly higher risk cost compared to the autonomous ship. Fuel cost is similar for both ships with a reduced fuel consumption when the speed is reduced in the most challenging part of the route. Operation cost is also similar, but with a higher top for the conventional ship since because reduces the speed more.

4.2. Controlling the ship with machinery and propulsion failures

The second part of the case study tests how the control system manages the autonomous ship when the health of the main engine and steering system is worsened. This is modeled by increasing the probability of failure for these elements in the risk model. The SRC then chooses the best way to operate the ship based on this information. The routes are the same as shown in Fig. 7 for route one and Fig. 10 for route two. The weather is also the same, which ensures that the results can be compared to how the ship is managed when all systems function.

4.2.1. Machinery and propulsion failures on route one through rørvik

In both cases, the failure happens when the ship has sailed approximately 8% of the route, close to point 0.1 on the figures. When the main engine fails, the SRC changes MSO-mode to PTI, which only uses the HSG and diesel generators for power production. The speed reference is also reduced to 4 m/s because the diesel generators produce less power than the main engine. This ensures that the ship still has sufficient power to maneuver. The SO-mode is AP along the whole route in this case.

When the steering machinery fails, the speed is lowered significantly such that the tunnel thrusters can provide steering for the ship and SO-mode is changed to DP. The MSO-mode is Mech for the whole route. The speed reference switches between 2 m/s and 3 m/s, depending on the number of islands and obstacles around the ship.

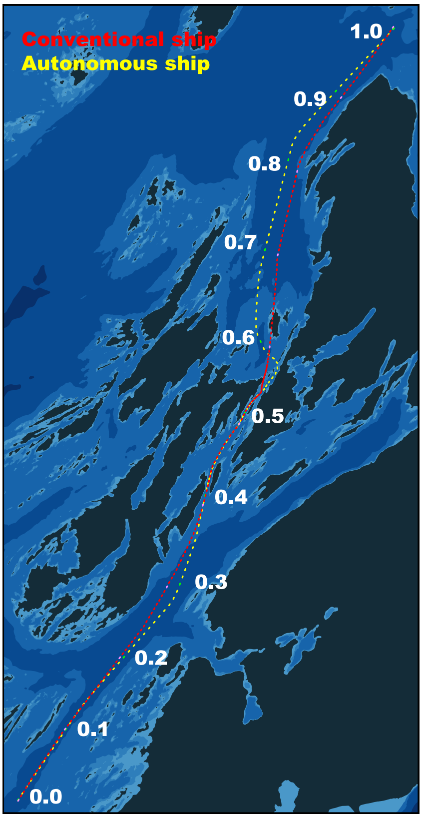


Fig. 10. Map of route two through Brønnøysund. The conventional ship's route is shown in red and the autonomous ship's route is shown in yellow.

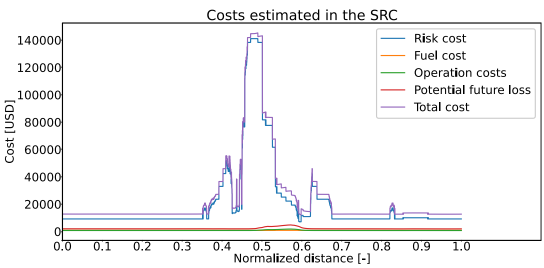


Fig. 11. Conventional ship's costs on route two. The risk cost is here significantly higher since the position data used to estimate the costs include some incorrect measurements placing the ship both very close and on land as shown in Fig. 10, as well as having a .

Figs. 13 and 14 show the costs calculated by the SRC. Overall, the cost is maintained at a similar level as when everything is working by adjusting how the speed is operated. The risk cost is controlled by reducing the speed, compared to how the ship is operated when all systems function as intended, and by switching to MSO-modes and SO-modes with functioning components. Operation and potential future loss is increased because the ship uses a longer time with lower speed.

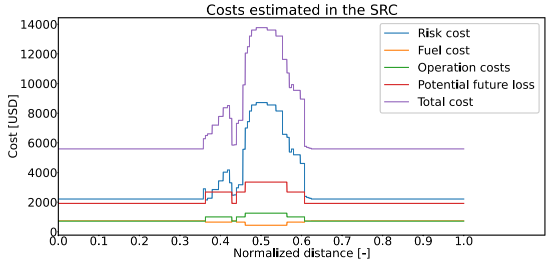


Fig. 12. Autonomous ship's costs on route two.

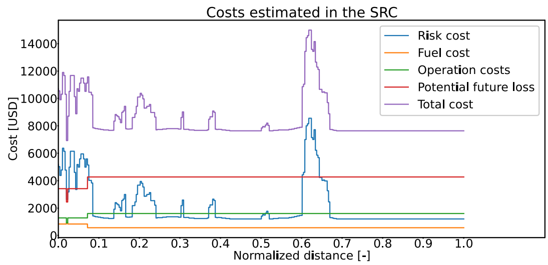


Fig. 13. Costs with failure on main engine on route one.

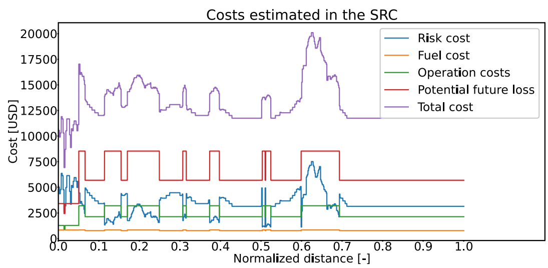


Fig. 14. Costs with failure on steering machinery on route one.

4.2.2. Machinery and propulsion failures on route two through brønnøysund

The main engine fails between point 0.3 and 0.4, and the steering machinery fails between point 0.2 and 0.3. When the main engine fails, the speed is reduced significantly to account for the reduced power production. MSO-mode is also changed to PTI, which do not use the main engine. The SO-mode is AP along the whole route.

When the steering machinery fails, the speed is reduced to 2 m/s and SO-mode is changed to DP, to get more effect from the tunnel thrusters and maintain control of the ship. When the ship has passed the narrowest parts of the route, the speed is increased to 3 m/s.

Similar to route one, the costs that are shown in Fig. 15 for the main engine and Fig. 16 are similar as when everything is functioning by reducing the speed and changing MSO-mode and SO-mode. The biggest difference compared to the cost when all systems function is the time used to finish the route. The time and the time dependent costs, operation costs and potential future loss increase when the ship sails at a lower speed. This is most visible after the ship has finished with the most challenging parts of the route, around 0.4–0.5. However, because the speed was reduced in the narrow and tight parts with all systems functioning as well, the max cost is still at the same level.

Data from conventional ships operating with failures but switching to modes that function without the failed components are limited,

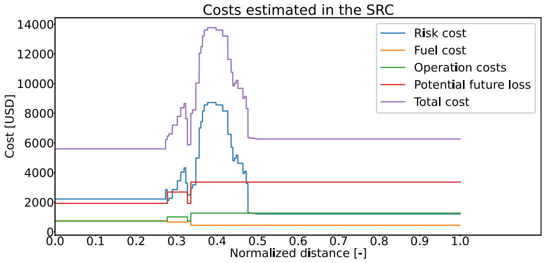


Fig. 15. Costs with failure on main engine on route two.

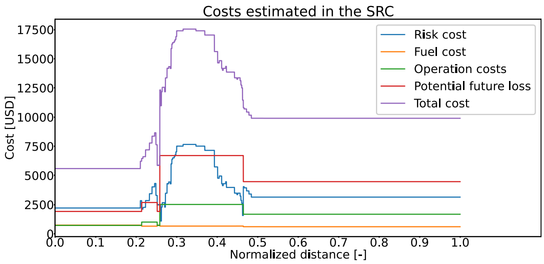


Fig. 16. Costs with failure on steering machinery on route two.

although this is a logical way to mitigate failures. In a conventional ship, the failed components can be fixed by the crew or the ship can be maneuvered to the closest harbor for repairs. On an autonomous ship without a crew, the only option is to maneuver to harbor and get it fixed there or in case of severe failures transport a repair crew to the ship offshore. Because this route change is not included in the SRC and the redundancy of the machinery systems onboard the autonomous ship was not compromised entirely, the ship continues to sail towards the final way-point. With the current control system, this is a reasonable solution. Deviating from the planned route to get to shore and repair damaged equipment, which would be viable solutions in case of critical machinery failures and total loss of propulsion, and notifying the human supervisor are topics for further research that could improve the control system further.

4.3. Risk modeling and implementation in the control system

The proposed control system uses a BBN-based risk model to assess the risk. The model is based on an extended STPA of the ship. STPA provides a systematic way to analyze the ship and identify causal factors that can lead to hazardous events. The results of the STPA also provide a logical way to build and structure the BBN. However, the results depend on the data used and the quality of the analysis.

Another potential challenge using STPA is to decide the refinement level. The refinement level generally depends on the purpose of the STPA. More details mean more data, but it can also make the risk model and the corresponding calculations too time consuming. In this current work, the analysis considers one hazardous event only, two system level hazards, and five UCAs. The scenarios include causal factors, such as wind, obstacles, and the main parts of the machinery system. The scenarios could have been more detailed and could have included information about how machinery parts fail. However, because the purpose of the analysis in this paper is to build an SRC, the level of detail is considered to be sufficient because the controller does not provide detailed control actions to the different parts of the machinery systems. An example of this could be saying that the main engine can only produce limited power because the cooling system is only partially functioning, although in this situation limited power is necessary to maintain control of the ship. Enabling the controller to make such decisions would be an interesting topic for further research to continue to develop the control system.

When building the BBN risk model, the overall structure is determined by the STPA. However, because the STPA is qualitative, it provides very little data for setting up states defining CPTs. Hence, they are generally based on other sources, such as literature, previous works, and expert judgement. The CPTs can also be adjusted later to put more weight on specific risk factors. Given that the CPTs are based on different sources, they contain a certain degree of uncertainty, as discussed in Section 4.7.

To convert the risk model into an online risk model, the risk model is connected to the rest of the control system. This means that all of the nodes in the BBN that can be measured by the control system or sensors should be updated when the ship is sailing. The risk model should be updated often to describe the current sailing conditions. However, updating it too often increases the computation time in the control system. There is also a limit to how quickly the controller can update the decisions. In the case study, the risk model and SRC is paused for 30 s if the SO-mode, MSO-mode, or speed reference is changed. This delay allows the controller to evaluate if the decisions influence the ship and to avoid chattering, where the controller is stuck switching back and forth between different decisions, such as DP and AP.

The control system can be expanded further by including more dynamics in the ship model. The case study assumes that machinery parts can be started immediately, which is not the case. Although the specific time necessarily varies for different engines, it will have to be included when making decisions. This type of dynamics could be included in the control system as limits to how often decisions can be changed. The risk model can also be modified to include starters for the different machinery parts. For example, for the main engine to function, both the starter and engine would be necessary.

Similar dynamics can be included for changing load on the machinery and the speed of the ship. In particular, reducing the speed of the ship takes time, depending on the size of the ship. The ship simulator includes a time delay on load changes and uses some time to change the speed of the ship. However, the SRC does not account for this specifically when it makes decisions. Therefore, including more dynamics in the control system and risk model is an interesting topic for further research.

4.4. Challenges with measuring risk in cost function

The proposed control system uses a cost function to make decisions about MSO-mode, SO-mode, and speed reference. This cost function estimates the cost of operating and sailing the ship, and the potential cost of hazardous events. The cost of sailing and operating the ship is straightforward to calculate and use in a cost function because it is already measured as cost. However, to combine this with risk cost is a bigger challenge. The STPA analysis can identify potential hazardous events but is only a qualitative analysis that does not consider likelihood of these events or the following cost.

This work addresses this problem by extending the analysis to consider consequences and classifying these in terms of cost. The STPA results and consequences are modeled in a BBN to give a likelihood of the consequences. The likelihood is multiplied with the consequence cost to give a risk cost to use in the cost function. Decisions are then made based on the current time, without considering how this can change in the future. Risk could be alternatively assessed by simulating how changing conditions and decisions affect the cost over a longer time. This would make the SRC more like an MPC, which could find the optimum set of decisions to minimize the cost over a longer time period. However, this would mean running a lot of simulations to check all potential combinations. Investigating this further could be subject for further research.

4.5. Risk modeling and integration with the ENC module

In the proposed control system, information about grounding obstacles is important for the risk model because it allows the model to assess the area around the ship. This information, and other data about the relevant area, is available in ENCs. The ENC module is an efficient tool for extracting and filtering this information to enable it to be used to describe the navigation area in the risk model. The control system uses the distance to the closest area where the ship can ground and the density of such areas as inputs to the risk model. Together with weather and traffic data, this determines how challenging it is to maneuver the ship.

The ENC module used in this work do not account for navigational markers, as this is not currently implemented in SeaCharts. For an autonomous ship, knowing where different navigational markers and their meaning is an important part of operating safely. The proposed control system itself can utilize this information in the risk model to get a better understanding of the environment when this become available with the SeaCharts package. However, the current ENC module is still considered sufficient to demonstrate that the proposed control system works.

The ENC module also provides an efficient way to plot the ship during testing, and is used when testing the control system to see how well the ship follows the route and identifies problems in specific areas. Compared to just using the position data, without grounding obstacles and land, this approach makes it much easier to understand and/or verify how the ship maneuvers.

Data from the ENC module can also be used to add more functions to the control system, such as route planning. In addition, a planning algorithm can use the ENC module to check if the route maintains the necessary distance to land and grounding obstacles. When combined with AIS data, this can enable the planner to account for other ships and use this information to avoid collisions. This is an interesting extension of the control system that would reduce the need for human supervision and control even further. This point is left open as a relevant topic for further research.

4.6. The efficiency of testing and verification of control systems in operation

In this work, the proposed control system is verified against the design requirements using the automatic simulation-based testing framework that was introduced in Section 2.5. Using this approach significantly increases the efficiency of building sufficient verification evidence for the control system. [36] show that this reduces the number of simulations necessary to verify the scenario compared to a regular grid search, which is a large time saver when doing several design iterations and verifying the scenario after each iteration.

The robustness surface resulting from a verification run with the automatic testing framework enables us to quickly get an overview of the performance of the SRC system at different regions of the scenario space. This overview is actively used in the design process to iteratively adjust the control system. Compared to the alternative of running simulations manually and evaluating the resulting time series, this offers a significant reduction in the workload. Furthermore, using STL to evaluate the system also gives a robustness score to show not only that it is verified but also how well the system performs.

It is also worth noting that the verification process considers a specific route and area. These can be planned such that the route includes different environments, such as open water, coastal waters with many islands, or tight harbor areas. The results from the verification should then be valid for other routes with similar characteristics, as shown in the case study. However, if the system is only tested in a distinct environment, such as open water without obstacles, then it cannot say anything about how the controller handles other environments.

An interesting extension of the automatic testing framework is to also use it in an online setting and integrate it more closely with the SRC system. This online verification system could repeatably start verification runs at fixed time intervals. A verification run would attempt to verify safe operation for a finite time-horizon ahead and for a set of uncertain scenario parameters, such as environmental conditions, traffic, or internal components failures. It would achieve this by running simulations with the current situation as an initial condition and then intelligently selecting the scenarios to simulate using the Gaussian process model. The simulator should have an exact (software-in-the-loop) replica of the SRC system, thereby also evaluating how future choices of the SRC system will affect the performance in the different scenarios. The result from a verification run would be used as a robustness map for future scenarios. This robustness map, when combined with data on the probability of the different scenarios, could then be used by the SRC system to make risk-based decisions. The concept of an online verification system operating in closed loop with the SRC system appears to be very interesting because it enables the SRC system to consider multiple future scenarios and at the same time evaluate how its decisions would affect future behavior.

Another interesting extension is to use the STPA directly to define safety requirements and simulation scenarios; see, for example, Rokseth and Utne [41],Rokseth et al. [42]. In the current work, the scenarios are set up to test the ship in a wide range of wind conditions and in very different areas. However, testing similar scenarios to those that the STPA identified when controlling the ship is challenging. Therefore, testing in more specific scenarios based on the STPA is left for further research.

4.7. Uncertainties and sensitivity in the data and models in the case study

The proposed control system combines existing control systems, such as DP and autopilots, with an online risk model in an SRC. The DP and autopilot are well described in the literature and are used on conventional ships. However, the use of an online risk model in an autonomous ship system and the concept of a cargo ship sailing without humans onboard is a novel concept. This means that data describing this is very limited, and mostly based on concepts and plans for these types of ships.

To get sufficient data in the case study, a combination of data from traditional manned ships, concepts for autonomous ships, geographic, and weather data is used. The quality of geographical and weather data is good with little uncertainty. However, the case study considers a simplified environment and not all conditions that a real ship would experience. For example, the wind measurements are taken over a long period but only at a general location. The wind is therefore assumed to be the same along the whole route, even though it will likely vary significantly between different locations. Similarly, the charts that are used are the same as ships use for navigation today but are simplified to only consider shallow areas and land, and not other ships or navigational marks. Although these simplifications make it possible to test the system, they also lead to uncertainties in the results (e.g., how the system can handle more obstacles such as other ship traffic and more local variations in wind conditions).

The STPA used in the paper is based on a workshop with academic industry experts. This helps to identify relevant information for the case study, but the quantitative risk models and corresponding calculations could still have limitations affecting the risk costs.

The input uncertainty will have a different effect on the overall uncertainty, depending on the sensitivity of each input node. If a node has high sensitivity, then changing it will change the risk cost more compared to nodes with lower sensitivity. Nodes with high sensitivity have the same effect on the uncertainty in the risk cost. Fig. 17 shows the effect that each node has on the risk cost when setting the node in the best and worst state. This shows that the weather conditions have the biggest potential effect on the risk cost. Other input nodes with a noticeable effect on the risk cost are GNSS accuracy, machinery status, controller performance, and obstacles. However, it is important

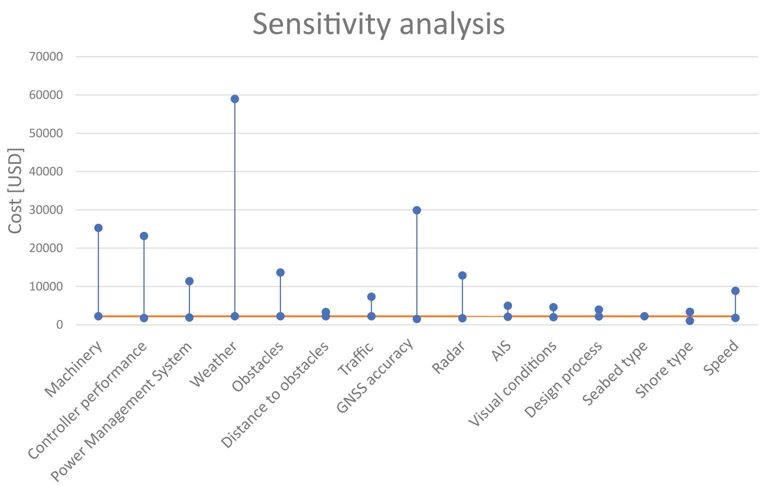


Fig. 17. Sensitivity analysis, showing the effect on the risk cost of setting nodes in the best and worst states.

to note that other factors than weather still give a high risk cost, especially combinations of multiple factors. Fig. 11 shows that the risk cost increases a lot when the GNSS data puts the ship very close to land without reducing the speed. The machinery and control system data are based on multiple sources that describe the system's reliability, and thus have less uncertainty. For weather and obstacles, the main source of uncertainty is the previously mentioned simplifications.

Another source of uncertainty in the risk model is the sensitivity of each input, or how much each input affect the risk cost. It is difficult to say how much weight should be on each input but it is possible to make some general remarks about it based on Fig. 17. For an autonomous ship to function properly, it needs well-functioning machinery, power, and control system. It also makes sense that sensors providing situation awareness influence the ship, and that weather and obstacles affect the decision-making process. The sensitivity analysis and case study show that all these have a significant effect on the risk cost.

The fuel cost, operation cost, and loss of future income also affect the uncertainty in the case study. Because the SRC makes decisions based on the total cost, the balance between different cost elements affect the decisions and the results. The fuel cost is calculated using a lookup table of how much fuel the ship uses in different environmental conditions and speeds. The table is made by simulating the ship to derive the fuel consumption. These simulations use simplified models of the machinery system, but they still give numbers similar to those for existing ships and engines. Both operation costs and loss of future income are estimated based on the type of ship and operation.

Based on the tests, the balance between safety and efficiency is good. The balance between the different costs is also reasonable. Fuel and operation costs are at the same level. The potential loss of future income is slightly higher than the sum of fuel and operation costs because the ship should have a higher income than just covering the expenses. The results can be improved further by advancing the models, and by getting more and better data, but this is left for future work.

4.8. Simplifications in the ship simulator and testing

The proposed methodology and control system is tested using a simplified ship simulator. The simulator is based on the models given in Fossen [56]. This provides a good tool to test the ship's control systems. However, the models include simplifications that affect the ship's behavior and control. Not including wave forces is one such simplification. The most commonly used approach to include waves takes a 3D model of the ship and tests it in a hydrodynamic program. However, the data to make this 3D model is missing for the ship in the case study, and therefore the ship is simulated without waves. Similarly, the simulations consider a simplified propulsion system and use approximations in the kinematic and kinetic equations.

In testing, the simulator works sufficiently to test the proposed methodology and SRC. However, the ship is difficult to control when turning, especially using the autopilot. Therefore, the minimum distance used in the safety verification, Section 3.5, is only 5 m. In real life, the ship should stay further away from land. This would also add more safety margins to the ship draft and more clearance under the keel. Although the system has been tested with a larger minimum distance, it then fails the safety verification at much lower wind speeds. The ship can be operated in DP-mode, which offers much better control at lower speeds using the tunnel thrusters to both control heading and sideways position. However, this would mean sailing at unreasonable low speeds when compared to the conventional ship. To get comparable data, the autonomous ship is allowed to operate with smaller margins in the simulations. Given that the focus of the paper is the method for developing the SRC and how this make high level decisions, this is deemed sufficient. Testing with more accurate ship models is left for further work.

Accuracy in the position data is another challenge when testing the proposed methodology. The case study assumes that the GNSS data is accurate for use in the ship control system. However, GNSS accuracy can be a challenge for autonomous ships, especially when sailing between tall mountains where the signal quality can be affected by bad satellite coverage and signals reflecting off the mountains. How accurate the data is will vary depending on the location, but is something that should be addressed when setting the limits in the system verification and the control system. However, it is still sufficient for testing the SRC and the methodology for building this. Combining GNSS measurements with other sensors, such as radar, LIDAR, sonar, and cameras is an option for improving the accuracy by measuring the distance to land and other objects, instead of just using the GNSS position. However, this is considered to be outside the scope of this paper and is left for further work.

5. Conclusions

This paper presents a control system with risk-based decision-making capabilities to enable the smarter and safer operation of autonomous systems. The proposed control system uses an online risk model, which is represented by a BBN, to evaluate the operational risk, through an SRC. An ENC module is used to provide accurate data of the environment to both the risk model and the rest of the control system. The online risk model provides decision support in the SRC, which can make high level decisions. The control system has been verified against design requirements for safety (minimum distance) and efficiency (maximum time) using a novel formalized verification method. The combination of the SRC with ENC and formalized verification leads to a risk-based control system that can control autonomous ships in a safe and efficient manner, which currently does not exist.

The proposed control system is first compared to experimental data from an existing conventional ship in a case study along two coastal routes. This shows that the novel controller makes similar decisions to adjust the speed and maintain safe operation as the conventional ship, without using significantly more time to reach the end destination. It also shows that the controller took less risk than the conventional ship, mainly by adjusting the speed earlier when maneuvering in narrow areas, while maintaining a higher minimum speed than the conventional ship. This will make a bigger difference for routes that changes a lot, such as the route through Rørvik. However, it will still have an effect on routes with less variation between open water and narrow straits. The second part of the case study tests how the SRC handles failures in the machinery and propulsion system. This shows that the SRC changes MSO-mode and SO-mode to continue safely to the final way-point.

Further work includes adding more functions to the control system to increase autonomy, such as safe and reliable auto-docking. This will enable the ship to leave harbor, sail to a second location/harbor, deliver goods, and then return and dock in harbor again. This would be a typical cargo ship or passenger operation and would thus be an important step towards achieving highly autonomous ships. Route planning to enable the control system to change route depending on the risk level and environmental conditions, and looking at how a similar system can be used for decision support to human operators are also parts of the future work.

CRediT authorship contribution statement

Thomas Johansen: Writing – original draft, Software, Methodology, Investigation, Data curation, Conceptualization. **Simon Blindheim:** Writing – original draft, Visualization, Software, Conceptualization. **Tobias Rye Torben:** Writing – original draft, Software, Investigation, Conceptualization. **Ingrid Bouwer Utne:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization. **Tor Arne Johansen:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization. **Asgeir J. Sørensen:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization,.

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.

Data availability

The authors do not have permission to share data.

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Table 5
BBN Nodes, Input-RIFs are only listed as parent nodes.

Node description	Parent node(s)
Cost	Consequences
Consequences	Harm to humans, Damage on own ship, Damage on other ships/objects
Damage on other ships/objects	HE, Impact speed, Type of seabed, Type of shore
Damage on own ship	HE, Impact speed, Type of seabed, Type of shore
Harm to humans	HE, Impact speed, Type of shore
HE	H1, H2
H1	UCA-1, UCA-2, UCA-3, UCA-4, UCA-5
H2	UCA-1, UCA-2, UCA-3, UCA-4, UCA-5
UCA-1	H-RIF-1, H-RIF-2, H-RIF-3
UCA-2	H-RIF-1, H-RIF-2, H-RIF-3
UCA-3	H-RIF-2, H-RIF-3
UCA-4	H-RIF-4, H-RIF-5
UCA-5	H-RIF-4, H-RIF-5, H-RIF-6
H-RIF-1	Power, Propulsion
H-RIF-2	Power management system reliability, Controller performance/accuracy
H-RIF-3	Weather conditions, Control of ship, Congested waters
H-RIF-4	Controller performance/accuracy, Navigational instruments
H-RIF-5	Navigational instruments, Visual conditions
H-RIF-6	Controller performance/accuracy Ship design process
Power	PTO, PTI, Mech, MSO-mode
Propulsion	AP, DP
Weather conditions	Current, Wind direction, Wind speed
Control of ship	Weather conditions, SO-mode, Ship speed, Propulsion
Congested waters	Obstacle density, Distance to closest grounding hazard, Traffic density
Controller performance/accuracy	AP performance/accuracy, DP performance/accuracy, SO-mode, Weather conditions
Ship speed	Controller performance/accuracy, Speed reference
Navigational instruments	AIS, Radar, GNSS system
Visual conditions	Wind speed, Fog, Rain, Snow
PTO	ME state, HSG state
PTI	HSG state, DG1 state, DG2 state
Mech	ME state, DG1 state, DG2 state
AP	MSO-mode, MP state, ST state
DP	MSO-mode, MP state, BT state, AT state
Impact speed	Ship speed

Appendix. BBN connections

Tables with an overview of child/parent nodes in the BBN shown in Fig. 4.

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Article 4:

Human-autonomy Collaboration in Supervisory Risk Control of Autonomous Ships

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Human-autonomy collaboration in supervisory risk control of autonomous ships

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ABSTRACT
This paper presents a method for developing and testing a risk-based control system, as a first step towards including the human supervisor explicitly in the design of the system. The result is a control system with improved decision-making capabilities compared to existing control systems. The methodology presented in the paper uses the Systems Theoretic Process Analysis (STPA) to analyze the risks of an autonomous ship within its concept of operations (CONOPS), and a Human-STPA (H-STPA) is used to analyze human responsibilities and involvement. The STPA results are then used to construct a Bayesian belief network (BBN)-based risk model to assess the operational risk of the ship. This is represented as a risk cost, describing the expected cost of consequences caused by potential hazardous events. This cost is combined with fuel costs, operations costs, and the potential loss of income if new missions are not undertaken using a supervisory risk controller (SRC). The SRC is capable of making decisions about how the ship should be safely operated and notifies the human supervisor in due time when it is necessary for them to take control. The last part of the methodology presented in this paper is testing the control system using a set of verification objectives based on results from the STPA and H-STPA. A case study involving an autonomous cargo ship with a human supervisor located in a remote operation center (ROC) is included; it shows that the proposed control system can operate the ship safely in different conditions and situations. By designing the SRC to notify the human supervisor before it reaches its operational limit, the ship is able to operate in a wider range of conditions compared to when just the autonomous control system is in charge. Hence, the proposed methodology shows promising results and provides useful insights related to shared control for autonomous ships.

KEYWORDS
Autonomous Systems; Risk Modeling; Ship Control Systems; Human-Autonomy Collaboration; Systems Theoretic Process Analysis; Bayesian Belief Networks

1. Introduction

Ship control systems have advanced from early autopilots to dynamic positioning (DP) systems, and currently they are moving towards control of autonomous ships. Autonomous ships are expected to improve general safety at sea (Wróbel et al. 2017;

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Abbreviations

AIS	Automatic Identification System
AMMS	Autonomous Machinery Management System
ANS	Autonomous Navigation System
AP	Autopilot
API	Application Programming Interface
AUV	Autonomous Underwater Vehicle
BBN	Bayesian Belief Network
CONOPS	Concept of Operations
CPT	Conditional Probability Table
DP	Dynamic Positioning
ENC	Electronic Navigational Chart
GNSS	Global Navigational Satellite System
GP	Gaussian Process
H-RIF	High-level Risk Influencing Factor
HiL	Hardware-in-the-Loop
HMI	Human Machine Interface
HSG	Hybrid Shaft Generator
I-RIF	Input Risk Influencing Factor
LNG	Liquefied Natural Gas
LoA	Level of Autonomy
Mech	Mechanical
MPC	Model Predictive Control
MRC	Minimal Risk Condition
MSO	Machinery System Operation
PID	Proportional Integral Derivative
PMS	Power Management System
PTI	Power Take In
PTO	Power Take Out
RIF	Risk Influencing Factor
ROC	Remote Operation Center
SLAM	Simultaneous Localization and Mapping
SO	Ship Operation
SRC	Supervisory Risk Controller
STL	Signal Temporal Logic
STPA	Systems Theoretic Process Analysis
UAV	Unmanned Aerial Vehicle
UCA	Unsafe Control Action
USD	United States Dollar
VHF	Very High Frequency

de Vos et al. 2021) by reducing the number of humans at risk. In general, much work has been done on identifying different risk factors and performing risk assessments of autonomous ships. Fan et al. (2020) present a framework for identifying navigational risk factors for autonomous ships. Johansen and Utne (2020) suggest using the Systems Theoretic Process Analysis (STPA) as the basis for building risk models describing autonomous ships and discuss additional methods for finding more data. Chaal et al. (2020) propose using the STPA to model the ship control structure in order to describe the system functionalities. Valdez Banda et al. (2019) use the STPA for the hazard analysis of autonomous passenger ferries. The STPA is also used in Wróbel et al. (2018) to develop a model for analyzing safety and providing recommendations for designing autonomous vessels. However, none of these papers use the results of the risk analyses to control autonomous ships. Other works have proposed using risk models to predict the loss of AUVs (Brito and Griffiths 2016; Loh et al. 2020a,b) or to manage uncertainty in AUV missions (Brito 2016). Risk is also included in multiple papers discussing collision avoidance (Hu et al. 2017; Wang et al. 2019; Woo and Kim 2020; Lyu and Yin 2019; Li et al. 2021; Gil 2021), but at a more general level.

Even with the continuous development and improvement of ship control systems, it is expected that humans will remain important in the safe and efficient operation of autonomous systems (Ramos et al. 2020b,a). Therefore, an important issue when developing autonomous ships is designing control systems that support the safe transition between autonomous and human control.

Ramos et al. (2020b) present a method for analyzing cooperation between humans and autonomous ships called the Human-System Interaction (H-SIA) method. The method is used in a case study to analyze a collision scenario. Ramos et al. (2020a) present a generic approach for analyzing failures in the interaction between the system and humans and demonstrate this approach by analyzing an autonomous ship. Hogenboom et al. (2021) discuss how the available time affects risk when humans must take over control in DP operations. Parhizkar et al. (2020) propose a risk management framework for DP operations to provide decision support to human supervisors and test the framework in a case study on DP drilling operations. Wu et al. (2022) summarize and review techniques for analyzing human and organizational factors related to maritime accidents, and they provide ideas for further development, with a focus on humans. All these papers discuss important aspects of human-system cooperation for ships, but they do not discuss how to include humans as a part of the control system or specify the responsibilities of a human supervisor in shared control scenarios.

Huang et al. (2020) present a collision avoidance system that is focused on human-machine interaction. The collision avoidance system is designed such that the decision-making process is easy to follow and interactive for human supervisors. However, the control system is limited to only considering collision avoidance and is not a more high-level control system. Liu et al. (2022) discuss multiple issues and challenges related to human-machine cooperation with autonomous ships. They also discuss unsolved problems that should be tackled as part of further development and therefore provide ideas for further work. Rødseth et al. (2021) propose an operational envelope that includes sharing control responsibilities between humans and the control system. They show how this can be done in a general way to account for most geographical areas and operations, but they do not demonstrate how this information can explicitly be used to design the control system.

Porathe (2021) discusses how to design the autonomous control system to provide better decision support for human supervisors of autonomous ships. The paper suggests having a copy of the control system running in a remote operation center (ROC) such that data are readily available to human supervisors. However, the paper lacks a description of the actual control system and how the human supervisor should be included. Dittmann et al. (2021) describe how to design a control system complying with international regulations on watch-keeping with a remote control center as part of the control system. They discuss how to design the system to share information with human supervisors and how to transfer control between the system and human supervisors. A control structure is suggested but how the different parts function is not specified.

Utne et al. (2020) propose using risk models in the control system, i.e., a supervisory risk controller (SRC), to improve the decision-making capabilities and intelligence of the system. Thieme et al. (2021) describe how to use risk analysis methods to design control systems and propose four areas where this can be implemented. Johansen and Utne (2022) propose a control system using Bayesian belief network (BBN)-based risk models and show how this implementation can contribute to high-level decisions, such as selecting the optimal machinery and control mode to ensure the safe and efficient operation of an autonomous ship. Similar control systems have been proposed for autonomous underwater vehicles (AUVs) performing under-ice mapping (Bremnes et al. 2019, 2020). Yang and Utne (2022) present a set of criteria for an online risk model for autonomous marine systems and discuss potential methods for building the model. All these works show how risk modeling can be used to improve control systems, but they lack the perspective of shared control and the inclusion of the human supervisor and his/her responsibilities in the system and operations for different levels of autonomy.

In general, previous works on control systems for autonomous ships focus either on the control system or human control. A limited number of papers discuss collaboration but without discussing how to design the control system to support and interact with the human supervisor. Safe and efficient collaboration between the human supervisor and the autonomous system is decisive for safe operation. Hence, the objective of this paper is to present a methodology for designing and testing a risk-based control system, focusing on both the autonomous control system and the human supervisor. The control system is designed to notify the human supervisor to provide them with time to react and make alternative plans when necessary. The proposed control system is tested in a case study involving an autonomous coastal cargo ship. This paper is the first attempt to include both the autonomous control system and the human supervisor in the SRC to ensure safe ship operation.

Table 1. Summary of key aspects of the proposed control system compared to existing control systems

	Proposed control system	Existing control systems
Main features/tasks	High-level risk-based decision making. Optimum control of autonomous ships.	Control of specific functions and subsystems. Optimizing energy consumption.
Integration with humans	Controller designed to notify human supervisor in case of emergencies.	Human supervisor/operator assumed to constantly monitor control system in case of emergencies.
Possible application areas	Control of autonomous ships. Decision support system for human operators and supervisors.	Control of autonomous ships. Decision support system for human operators and supervisors.
Limitations and challenges addressed	Including risk and safety in optimum control of ships. Inclusion of human supervisors.	Automation of ship control systems. Optimum control of ship subsystems.

2. Background

2.1. Level of autonomy

The level of autonomy (LoA) is used to describe the functionality of autonomous systems and how they are related to the human operator/supervisor. In this paper, four LoAs are used; they are based on Utne et al. (2017) and shown in Table 2.

Level one describes an automated system in which the human operator has full control of the system. The system is dependent on human supervisors who monitor and control the system. The human operator and the system can be located in different places. In level two, the system has more automation, but it still needs a human operator to make decisions about how it should operate. At level three, the system can follow a plan. If the operation deviates from the plan, the system can suggest changes to the plan, but the human supervisor must accept these changes. If the operation goes according to plan, the human supervisor is "out of the loop." At level four, the system operates without human control. Humans can be informed about the progress of the system, but the system is operating independently. The human supervisor has limited or no ability to take control of the ship, but they may provide input to the system. It is important to note that a system may switch between different LoAs in operation,

Table 2. Levels of autonomy, adopted from Utne et al. (2017)

LoA	Type	Description
1	Automatic operation / Remote control	The system operates automatically with a remote human operator. The human operator has full control of the system. The system can have pre-programmed functions implemented.
2	Management by consent	The control system can make recommendations about specific parts of the operation. The human operator still controls the operation. The system can perform many tasks independently, if they are approved by the human operator.
3	Management by exception	The system automatically executes the mission plan and has the ability to make small changes when the available time is too short for human intervention. The human supervisor can take control of the system or change the plan. The human supervisor is notified by the system when it is necessary to take over or update the plan.
4	Highly autonomous operation	The system automatically plans and executes the operation. The system can change and alter the plan during operation. Humans can be informed about the operation, but the system operates independently.

i.e., high and low LoAs, and the system may also include sub-systems operating at different LoAs at the same time.

This paper focuses on an autonomous ship operating at LoA 3. The ship can follow preplanned routes, choose which preplanned route to follow, and change the speed, machinery mode, and control mode. To make bigger changes to the plan, such as deviating from the preplanned routes due to weather conditions, the human supervisor must assess the situation and agree to the new route proposed by the control system. To support the decision-making abilities of the human supervisor, the control system should be designed to provide enough time and information for human intervention. If the human supervisor need to react, the controller should still maintain the ship in a safe condition by for example maintaining its current position using DP. Collision avoidance is considered outside the scope of this work due to the complexity of building a control module for handling this. It is also assumed that collision avoidance would function otuside the control system proposed in this paper due to the criticality of such decisions and the time available to avoid collisions with other ships.

2.2. Human-autonomy collaboration

The ship considered in this paper is an unmanned cargo ship operating along the Norwegian coast. The ship has no crew aboard but is connected to a remote operation center (ROC). In the ROC, a human supervisor has access to the same information and data as the control system on the ship, but he/she also has the ability to remotely take control of the ship. The human supervisor, however, is not monitoring the ship during normal operation. Only after a notification will the human supervisor take control of the ship, and therefore they need some amount of time to obtain a sufficient awareness of the situation and react appropriately.

There are three main types of notifications sent from the control system to the human supervisor. First, the control system sends a notification when it is unable to maintain the safe operation of the ship or when it determines that it is likely to lose control in the near future. The control system is designed to go into a ”minimal risk condition” mode if it determines that it is unsafe to continue and it also notifies the supervisor. To exit this mode, the human supervisor has to take remote control of the ship or indicate that the control system can continue to operate. Second, the control system will notify the human supervisor of potential problems that he or she can contribute to avoiding or mitigating. The final type of notification is sent when the control system loses control, and it is impossible to avoid an accident. In these cases, the human supervisor's role is to start coordinating rescue operations to limit negative consequences and salvage the ship.

Control systems for autonomous ships are designed to reduce the need for human control while still operating in a safe and efficient manner. However, humans are still expected to be involved in operating the ship, especially when the situation exceeds the autonomous capabilities of the ship. Humans will then function more as supervisors who monitor the ship and assist when necessary rather than as operators or crews onboard responsible for the daily operation of the ship.

Since the autonomous ship in this paper is operating at either LoA 3 or LoA 1, the human supervisor receives these three types of notifications only. These notifications are mainly caused by failures or conditions that exceed the operational limits or safety constraints of the control system. In any case, the amount of time (Hogenboom et al. 2021) and information available to the human supervisor are important for a successful intervention. If the amount of time is too short or information is missing, there is less of a chance for the human supervisor to successfully take control and handle the situation. Providing a detailed analysis of human reaction times, human reliability, risk-based decision support for the supervisor, and human-machine interaction is, however, outside the scope of this paper and should be the subject of future work.

To reduce the likelihood of hazardous events, the control system has the option to enter a minimal risk condition (MRC) mode when the risk becomes too high. ISO (2020) defines the MRC as "a condition to which a user or an automated driving system may bring a vehicle after performing the minimal risk manoeuvre in order to reduce the risk of a crash when a given trip/voyage cannot be completed." For the autonomous ship in this paper, it is very difficult to eliminate all risk, but the risk can still be reduced to a level that is as low as reasonably practicable (ALARP). For further information on the definition of ALARP, please see HSE (2001).

3. Methodology

The proposed methodology extends and further develops the work in Utne et al. (2020), Johansen and Utne (2022), and "Johansen et al. (2023) by adding more advanced functionalities to the controller, such as the ability to select different routes to follow, and adding a specific MRC mode that the ship can enter when the risk becomes too high. Furthermore, interaction with the human supervisor is considered; it is not included in the above-mentioned studies. Specifically, the SRC in this paper is a high-level controller that can manage the ship control system. The SRC makes decisions, such as selecting the control mode for the navigation system and selecting how the machinery system should be operated. The methodology proposed for developing the SRC in this paper is a five-step process:

- Perform an STPA of the ship and a fault tree analysis (FTA) of critical subsystems.
- Extend the STPA with a Human-STPA (H-STPA).
- Develop an online risk model and assign inputs for the different nodes, such as sensor measurements and data from electronic navigational charts (ENCs).
- Set up the SRC and integrate it with the rest of the control system, including the motion and machinery controllers.

- Verify the control system in scenarios based on the STPA and H-STPA.

The STPA is used to get a good overview of unsafe control actions related to the ship and control system within its concept of operations (CONOPS). This forms the basis for building the risk model, deciding what data need to be extracted from ENCs to use in the control system, and setting up the SRC. To ensure a safe interaction between the human supervisor and the autonomous system, an H-STPA is performed. The results from this analysis are also used when setting up the control system to enable the human supervisor to interact with the control system in a safe and efficient manner. Then, the system is tested in different scenarios, which are formulated based on the STPA and H-STPA results, to verify that it functions as intended. The testing should include both easy and challenging scenarios.

3.1. Extended STPA and fault tree analysis

The STPA is based on Leveson (2011), and the extended STPA proposed in Johansen and Utne (2022) includes consequences as part of the analysis. In the traditional STPA, losses are defined as a starting point, which to some extent indicates the consequences. When developing control systems, however, it is necessary to include consequences in more detail. Hence, "losses" are here called hazardous events, and consequences are explicitly described. This is also in line with the bow-tie model (Rausand and Haugen 2020). The STPA starts by describing the ship and the CONOPS, including the machinery, propulsion, and control system. The CONOPS should provide information about the intended routes and/or area of operation, potential cargo aboard the ship, schedule, and limitations concerning when and where the ship can sail.

The STPA then defines hazardous events that, under certain conditions, can cause negative consequences for the ship. The rest of the analysis follows the normal STPA process by identifying system-level hazards, unsafe control actions (UCAs), loss scenarios, and causes.

Critical systems related to power, propulsion, and navigation sensors that emerge from the STPA are then analyzed using a qualitative FTA. The reason for this is that such systems are monitored, and the FTA provides information about whether the ship still has the necessary redundancy to continue or if it should notify the human supervisor about the situation to obtain assistance and enter the MRC.

3.2. Human-STPA

A Human-STPA is used to identify causal factors that affect the human supervisor's ability to intervene. This is done using an STPA by modeling the human supervisor as a human controller, as proposed by France (2017). Each possible action from the human supervisor is a control action that can be analyzed. The focus in this step is on how the control system should be designed to make it as safe and efficient as possible for a human supervisor to take control of the ship and to make decisions.

The analysis uses the same control structure as the regular STPA but it focuses on the human supervisor instead of the SRC. The rest of the analysis follows the same approach and considers the same hazardous events and system-level hazards. As with the SRC, the human supervisor has a set of available control actions that is analyzed to identify UCAs and specify scenarios in which these UCAs may occur.

3.3. Building the online risk model

The STPA results are used as the basis for building the BBN risk model. A detailed description of this process can be found in Utne et al. (2020). The BBN is made into an online risk model by connecting input risk influencing factors (RIFs), i.e., by connecting parent nodes to the control system, and deciding when to update nodes with new information. This includes describing the data required from electronic navigational charts (ENCs), which are required for the path planning and safe navigation of the ship.

An important source of data for the online risk model is ENCs. These contain navigational information about the area, such as the water depth, land, and navigational marks. However, the charts contain so much data that these data need to be processed to be useful in both the online risk model and the rest of the control system. The ENC module used in this paper is based on the work of Blindheim and Johansen (2022). The ENCs provide necessary information about the area around the ship so that the SRC can include this information in its decision-making process. The module is based on SeaCharts, an open-source Python package for displaying and manipulating charts. The module uses FGDB 10.0 charts with 2D data concerning the relevant areas. These data are processed and filtered to avoid giving irrelevant data to the control system. The relevant data are stored in shapefiles for different water depths and land. This makes it easier to find the water depth and the distance to points where the ship can ground.

The ENC module is set up based on the required data from the online risk model and the SRC. The data are then used to describe how much open water is around the ship, how much room the ship has to maneuver, and other relevant information to improve the decision-making process of the SRC.

3.4. Setting up the supervisory risk controller (SRC)

The SRC combines the risk cost, fuel cost, operation cost, and a penalty cost for the potential future loss of income and delays:

$$Cost(d) = R(d) + F(d) + O(d) + L(d). \tag{1}$$

The expected risk cost, $R(d)$, is taken directly from the risk model. The expected fuel cost, $F(d)$, is derived for the remaining route. The operation cost, $O(d)$, describes the additional operation costs (not fuel). The potential future loss, $L(d)$, represents the extra time used because the ship is not sailing full speed all the time and potentially misses deadlines because it is not able to follow the planned schedule. Notifications to the human supervisor are included based on the results from the H-STPA. The SRC is also implemented with a route checker to see if the ship is able to follow the route. If not, the SRC can either switch to an alternative route or notify the human supervisor. Changing the route is possible if an alternative route is provided and the ship has not passed the point where the alternative route starts.

3.5. Verification of the control system

The fifth step is to verify that the control system works as intended, focusing on its functional behavior, performance (Pedersen et al. 2022), and safety to ensure that it is ready for further use. This is done by simulating the ship in different scenarios within the CONOPS using verification objectives identified from the STPA and H-STPA. Verification objectives are formulated using a modified version of the method proposed in Rokseth et al. (2018).

In Rokseth et al. (2018), causal scenarios are used to specify safety constraints that, if violated, can lead to UCAs. Safety constraints are also used to derive verification objectives. Objectives are then processed to verify that the proposed control system can operate as intended without violating the safety constraints.

The verification objectives are processed in this study by simulating the ship in various scenarios to see if the objectives are satisfied. This is done by setting up a set of simulations and checking that all objectives are satisfied. An alternative method involves using an automated testing framework, as proposed in Torben et al. (2022).

4. Case study: Autonomous coastal cargo ship

The purpose of the case study is to test the methodology and assess if the SRC will make reasonable decisions compared to a conventional ship. The role of the human supervisor is to make the overall plan for the SRC to follow. Furthermore, notifications from the SRC are received in the ROC, where the human supervisor is located; they have a communication link to the ship and the ability to assess the situation and intervene if necessary. This is the first step towards the design and implementation of human-in-the-loop control systems for autonomous ships.

4.1. Step 1: Extended STPA with FTA

The ship in the case study is 80 m long and 15 m wide. It is equipped with a liquid natural gas (LNG)-powered main engine (ME), two diesel generators (DGs), and a hybrid shaft generator (HSG) for power production. The HSG can be used as a generator to obtain electrical power from the ME or as an electric engine powered by the DGs. The propulsion and steering system consists of a main propeller, two electric tunnel thrusters, and steering machinery controlling the rudder. The control system consists of an autonomous navigation system (ANS), an autonomous machinery management system (AMMS), and the SRC. The ANS handles the navigation and motion control, the AMMS controls the power production and propulsion, and the SRC makes high-level decisions for the rest of the control system to carry out. The full STPA control structure of the autonomous ship is shown in Figure 1. Collision avoidance is considered outside the scope of this work and therefore not included in the STPA control structure.

The ANS has a DP controller, an autopilot (AP) controller, and an observer for data processing. The DP controller is used for low-speed maneuvering and for station-keeping, while the AP controller is used to control the ship at higher speeds. The DP controller provides the required surge, sway, and yaw forces to control the position, heading, and speed of the ship. The AP controller is a line-of-sight (LoS) guidance controller that provides a heading reference based on the route and current ship position. The observer is used to process and check the data coming from navigation sensors, such as the GNSS. The data coming from these sensors must be filtered to remove noise and checked to confirm that these data are valid and do not contain measurement errors.

The AMMS consists of a power management system (PMS), thrust allocation (TA),

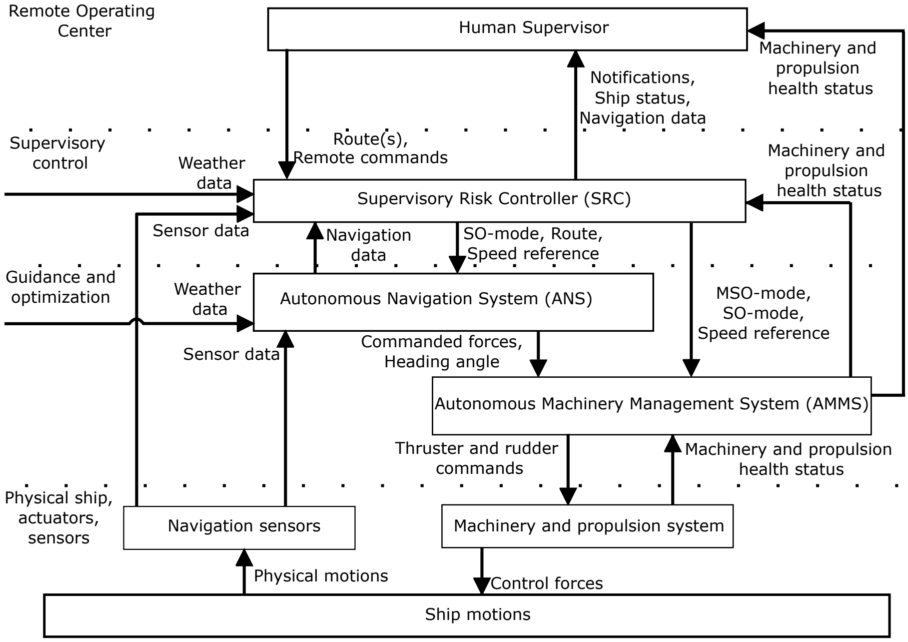

Figure 1. Control structure (adapted from Johansen and Utne (2022) and "Johansen et al. (2023))

a speed controller, and a rudder controller. The PMS is responsible for power production. Thrust allocation is used to convert the force commands from the DP controller into individual thrust commands for the propulsion system. The speed controller is used to control the load on the main propeller according to the speed reference, and the rudder controller converts the heading angle to a rudder angle for the steering machinery.

The SRC consists of the BBN risk model, ENC module, fuel consumption estimator, and controller. The SRC can select two different ship operation modes (SO-modes): DP-mode and AP-mode. When the ship is operated in AP-mode, the ANS uses the LoS controller to send a heading reference to the rudder controller in the AMMS. The speed reference is sent directly to the speed controller in the AMMS. The speed controller outputs a load percentage for the main propeller to maintain the desired speed, and the rudder controller provides a rudder angle to maintain the necessary heading angle. In AP-mode, the main propeller provides forward thrust, and the rudder controls the heading.

When operating in DP-mode, the DP controller calculates the force necessary to follow the desired route or maintain a certain position when it is used for station-keeping. The general force demand is mapped to individual thruster commands in the TA. In DP-mode, the main propeller provides thrust (surge), and the two tunnel thrusters control the sway and yaw. Since each degree of freedom (DOF) can be controlled directly, the DP-mode provides more accurate control of the ship than the AP-mode, but only at low speeds at which the tunnel thrusters are still efficient.

There are three different machinery system operation modes (MSO-modes), namely power take out (PTO), power take in (PTI), and mechanical (Mech). In PTO, the ME drives the main propeller. The HSG is used as a generator to produce electricity. In PTI, the two DGs produce electricity, and the HSG is used as an electric engine to power the main propeller. Mech uses the ME to power the main propeller and DGs to produce electricity.

The SRC is designed to manage the ANS and AMMS by setting the MSO-mode, SO-mode, and speed reference. It also has the option to enter an MRC, notify the human supervisor when necessary, and switch to an alternative route. The selection of modes and the speed reference is done using an optimization algorithm that calculates the cost of operating the ship and selects the set with the lowest total cost. The MRC is entered when the risk cost becomes too high for the ship to continue sailing or when the ship loses redundancy in critical systems. When this happens, the ship will begin station-keeping and use the DP-controller to maintain its current position. The MRC is not included explicitly in the risk model since model updates are paused when this condition is triggered and remain paused until the situation is assessed by the human supervisor. Route changes are not directly linked to the risk model; instead, they are based on how much the ship drifts and deviates from its course in different weather conditions.

The STPA in this paper is based on a workshop with 12 participants that focused on risk analysis, ship control systems, and the verification of control systems. The experts have 5–30 years of experience in both academia and industry. The workshop was conducted in three sessions. The first two sessions were used to identify different UCAs, which were discussed and analyzed in the third session. The sessions focused on the ship's machinery system and grounding and collision, but they also considered how selecting the wrong SO-mode could lead to hazardous events. The control structure, shown in Figure 1, includes the SRC and control responsibilities, as described above, in addition to the AMMS and the ANS. As the SRC is a novel functionality, the results from the workshops have been used as a basis for the analysis in this paper, but with some modifications to account for the changed control structure and control responsibilities due to the SRC. The STPA considers two hazardous events:

- HE1: The ship collides/allides with a ship/obstacle.
- HE2: The ship grounds or has contact with the seafloor.

Three system-level hazards can lead to these hazardous events:

- H1: The ship violates the minimum distance of separation to a ship/obstacle.
- H2: The ship violates the minimum distance of separation to shore.
- H3: The ship sails in too-shallow water.

The next step in the STPA is identifying UCAs. In this case study, UCAs are used to identify scenarios that should be checked during the verification process. Three types of UCAs are used in the case study: not providing a control action, providing an unsafe control action, or providing a control action at the wrong time (too late/early). The STPA also includes a fourth type of UCA, i.e., a signal lasts too long or stops too soon. However, since all signals considered in this case study are discrete, this is not relevant here. To build the BBN risk model, the relevant control actions are setting the MSO-mode, SO-mode, and speed reference, since these are decisions made by the SRC. In this work, changing the route is considered relevant for verification purposes but not for building the risk model since this decision is not made based on the risk cost. Instead, this decision is based on how much space the ship needs to maneuver with different wind and current conditions. Entering the MRC is also a different type of control action since this action is triggered when the ship is unable to continue sailing

Table 3. UCAs identified in the STPA

Control action	Type	Context
MSO-mode	Providing a control action	Selecting an MSO-mode using failed machinery
MSO-mode	Providing a control action	Selecting an MSO-mode that produces a max. power that is too low
MSO-mode	Not providing a control action	Not selecting a different MSO-mode when machinery parts fail
MSO-mode	Not providing a control action	Not selecting a different MSO-mode when the current MSO-mode produces too little power
SO-mode	Providing a control action	Selecting an SO-mode using failed propulsion parts
SO-mode	Providing a control action	Selecting an SO-mode unable to control the ship with the current speed reference
SO-mode	Not providing a control action	Not selecting a different SO-mode when propulsion parts fail
SO-mode	Not providing a control action	Not selecting a different SO-mode when the speed reference is too high or low for the current mode
Speed reference	Providing a control action	Setting the speed reference too high when the ship has limited space to maneuver
Route selection	Not providing a control action	Not changing to an alternative route when the ship is unable to follow the initial route
Route selection	Providing a control action too late	Changing to an alternative route after passing the point where it was possible to change the route
MRC	Providing a control action	Entering the MRC when the ship is unable to maintain the current position due to propulsion failures
MRC	Providing a control action too late	Not entering the MRC when the traffic or conditions become too difficult for the ship to continue

and continues until the human supervisor has assessed the situation. However, these actions are still important to consider when verifying the resulting control system.

Table 3 shows 13 different UCAs: four for selecting the MSO-mode, four for selecting the SO-mode, one for setting the speed reference, two for changing which route to follow, and two for entering the MRC. These UCAs are grouped together into six more general UCAs, as shown in Table 4. This makes the analysis easier to follow since it limits the number of UCAs describing the same type of situation.

Table 4. UCAs for the case study

UCA	Description	Hazard(s)
UCA-1	The SRC changes to an MSO-mode that depends on failed parts of the machinery system.	H1, H2, H3
UCA-2	The SRC changes to an MSO-mode that is unable to produce the necessary power.	H1, H2, H3
UCA-3	The SRC changes to an SO-mode that depends on failed parts of the machinery system.	H1, H2, H3
UCA-4	The SRC changes to an SO-mode that is unable to maintain sufficient control of the ship.	H1, H2, H3
UCA-5	The SRC fails to change to an alternative route when the ship is unable to follow the original route.	H1, H2, H3
UCA-6	The SRC fails to enter the MRC when the situation makes it necessary.	H1, H2, H3

Setting the speed reference is not explicitly included in the list of UCAs since it will impact the other UCAs as an RIF. UCA-1 and UCA-3 focus on failures that cause the machinery and propulsion system to be unable to function as intended. UCA-2 is related to the maximum power available in each mode, depending on the machinery parts used, and the ability to predict how much power the ship needs in different situations. UCA-4 is related to the ability to control the ship with respect to the SO-mode, speed reference, and conditions around the ship. Based on the six different UCAs shown in Table 4, the scenarios shown in Table 5 are specified.

Table 5. Scenarios that could lead to UCAs

Scenario	Description	UCA
Sc-1	The SRC selects PTO as the MSO-mode when a fault in the ME results in a loss of power.	UCA-1
Sc-2	The SRC selects PTO as the MSO-mode when a fault in the HSG results in a loss of electric power.	UCA-1
Sc-3	The SRC selects Mech as the MSO-mode when a fault in the ME results in a loss of propulsion power.	UCA-1
Sc-4	The SRC selects Mech as the MSO-mode when a fault with t he DGs results in a loss of electric power.	UCA-1
Sc-5	The SRC selects PTI as the MSO-mode when a fault in the HSG results in a loss of propulsion power.	UCA-1
Sc-6	The SRC selects PTI as the MSO-mode when a fault with the DGs results in a loss of power.	UCA-1
Sc-7	The SRC selects PTO as the MSO-mode when the load on the main propulsion system is higher than the power the ME can produce when it is also powering the HSG.	UCA-1
Sc-8	The SRC selects PTI as the MSO-mode when the total load on the machinery is higher than the power the DGs can produce.	UCA-2
Sc-9	The SRC selects AP as the SO-mode when a fault in the steering machinery results in a loss of steering for the ship.	UCA-3
Sc-10	The SRC selects AP as the SO-mode when a fault with the main propeller results in a loss of propulsion for the ship.	UCA-3
Sc-11	The SRC selects DP as the SO-mode when a fault with the main propeller results in a loss of propulsion for the ship.	UCA-3
Sc-12	The SRC selects DP as the SO-mode when a fault with the tunnel thrusters results in a loss of steering for the ship.	UCA-3
Sc-13	The SRC selects AP as the SO-mode when the speed is too low for the rudder to control the ship.	UCA-4
Sc-14	The SRC selects AP as the SO-mode when the ship is maneuvering in very tight areas where the AP-controller is unable to provide sufficient control.	UCA-4
Sc-15	The SRC selects DP as the SO-mode when the speed is too high for the tunnel thrusters to produce the necessary thrust to maneuver the ship.	UCA-4
Sc-16	The SRC fails to change the route, because the control system underestimates the current conditions.	UCA-5
Sc-17	The SRC fails to enter the MRC while it can still do so safely because the current conditions are underestimated.	UCA-6
Sc-18	The SRC enters the MRC when it is unable to maintain its position due to a failure with the tunnel thrusters.	UCA-6

The final part of the extended STPA is analyzing the consequences of the hazardous events. This is necessary in order to be able to quantify the input data used for the optimization of the control system. The consequences are first divided into either damage to the ship, damage to other ships/objects/structures, and harm to humans. Based on IMO (2018), these consequences are either severe, significant, minor, or nonexistent. Severe damage to the autonomous ship means that the ship is unable to continue without assistance and that it needs extensive repairs.

Significant damage means that the ship can get back to shore without assistance but will need extensive repairs before it can sail again. Minor damage must be repaired during the next planned maintenance period, but the ship can still sail with the damage that has been sustained. Severe damage to other objects/structures means that it needs immediate extensive repairs. Significant damage requires bigger repairs but is not as time critical. Minor damage should be repaired during the next planned maintenance period. Fatalities or serious injuries to humans are considered severe consequences. Less serious injuries are considered significant consequences, and insignificant injuries such as scratches and bruises are minor consequences.

The qualitative fault tree analysis focuses on three critical sub-systems identified in the STPA as being especially important for operating the ship:

- The machinery system;

- The propulsion system;
- The navigation sensors and communication system.

These sub-systems are analyzed in more detail to identify when the ship is unable to continue sailing because one of these systems fails or because redundancy is lost so that the control system can notify the human supervisor and make alternative plans. A fault tree analysis, even though it is a qualitative analysis, provides information about what components are necessary to operate the ship in the different SO- and MSO-modes. The same fault trees are used to identify situations in which the ship loses redundancy in the same systems.

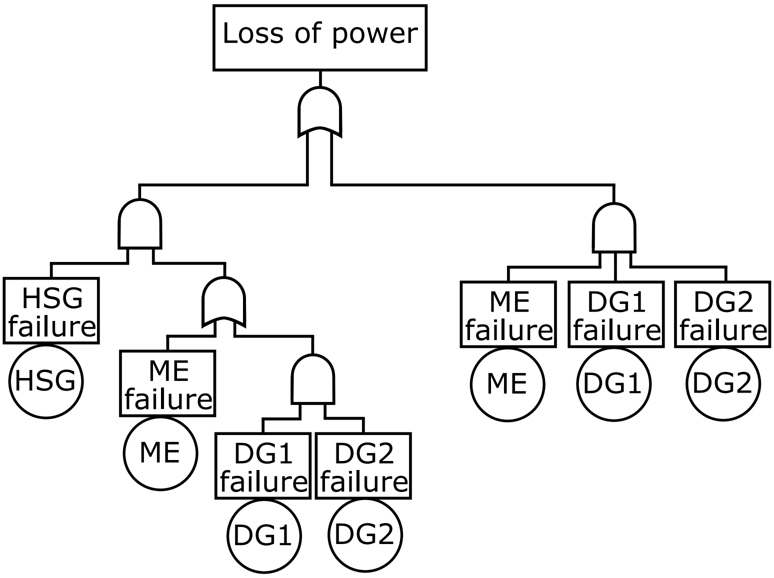

Figure 2. Fault tree showing a loss of power production for the autonomous ship

The information from the fault trees is used to construct the BBN so that specific components can be monitored in more detail. Each sub-system fault tree is represented by a node in the BBN to monitor the status of each sub-system. These components receive input from nodes in the BBN that describe the individual components.

Figure 2 shows that the machinery system can fail in two ways. If the ME, DG1, and DG2 fail, the ship loses power. It will also lose power if the HSG fails and either the ME or both DGs fail. If the HSG, ME, or both DGs fail, the ship loses redundancy in the power production system. It will, however, still have the necessary power for propulsion and navigation.

The propulsion system is analyzed in Figure 3. The propulsion system is considered to have failed if the MP or either of the two tunnel thrusters fails. The MP is critical since it provides forward thrust in both DP-mode and AP-mode. The tunnel thrusters are considered critical since they are necessary to control the ship if it enters the MRC. If the steering machinery fails, the ship can only operate in DP-mode and therefore loses redundancy.

Figure 4 shows the fault tree for the navigation and communication system. This system consists of the GNSS, which provides position and speed data, communication

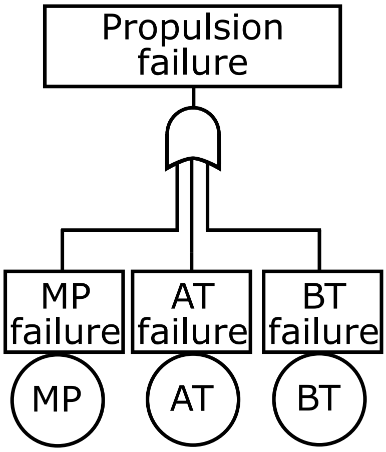

Figure 3. Fault tree showing a loss of propulsion for the autonomous ship

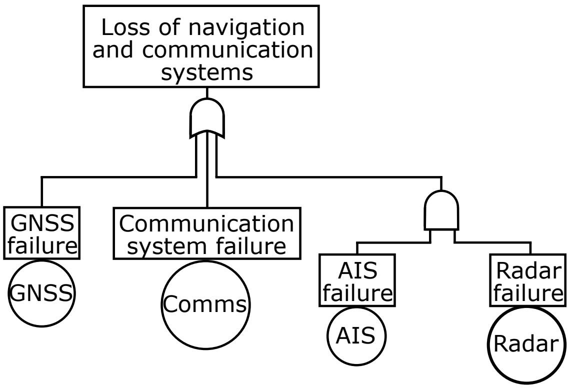

Figure 4. Fault tree showing a loss of navigation and communication systems onboard the autonomous ship

systems to send and receive information from the ROC, an AIS that obtains information about other vessels around the ship, and radar for sensing ships and other objects. The system is considered to have failed if the GNSS, communication systems, or both radar and AIS fail. GNSS is considered to be critical for obtaining the position and speed data that allow the ship to navigate. Communication is critical to maintaining the connection between the ship and the ROC. In this work, either AIS or radar is considered necessary to obtain information about other vessels around the ship. For an actual ship, this system should also include cameras and additional sensors to ensure sufficient situational awareness, as especially using only AIS can limit this. However, the fault tree and sensor package shown here is considered sufficient to show how such a system can work.

4.2. Step 2: Human STPA

The next step is focusing more specifically on the human supervisor, who is already included in the control structure (Figure 1) as a separate controller. In normal operation, the human supervisor is responsible for providing the plan(s) for the SRC to follow. When the autonomous ship is sailing, the human supervisor is in the ROC with a communication link to the ship. The human supervisor is responsible for following multiple ships at the same time and performing other tasks in the ROC. This means that the SRC must provide a notification in due time to allow the human supervisor to act. In this case study, the control system is not implemented with the ability to make new plans. The ship will therefore be operated at either LoA 3 or LoA 1.

The human supervisor can perform the following actions from the ROC:

- Notify other ships;
- Initiate and coordinate emergency actions, including contacting towing and rescue vessels;
- Take remote control of the ship;
- Hand over control to the autonomous system.

Table 6. HUCAs used to identify scenarios that can lead to hazardous events

HUCA	Description	Hazard(s)
HUCA-1	The human supervisor does not provide a notification to other ships.	H1
HUCA-2	The human supervisor is too late in notifying other ships.	H1
HUCA-3	The human supervisor does not initiate and organize emergency actions, including towing and rescue.	H1, H2, H3
HUCA-4	The human supervisor does not take remote control of the ship.	H1, H2, H3
HUCA-5	The human supervisor is too late in taking remote control of the ship.	H1, H2, H3
HUCA-6	The human supervisor takes remote control of the ship without the necessary understanding or time to safely control the ship.	H1, H2, H3
HUCA-7	The human supervisor hands over control to the autonomous ship when the autonomous system is unable to safely control the ship.	H1, H2, H3
HUCA-8	The human supervisor hands over control to the autonomous ship too early.	H1, H2, H3
HUCA-9	The human supervisor is too late in handing over control to the autonomous ship.	H1, H2, H3
HUCA-10	The human supervisor does not hand over control to the autonomous ship.	H1, H2, H3

Based on these actions, the ten unsafe human control actions (HUCAs) shown in Table 6 were identified. HUCAs are used to differentiate between unsafe control actions related to the computer-based control system and unsafe control actions related to the human supervisor. From the HUCAs, a total of 24 scenarios in which these actions can occur are identified; they are shown in Tables 7-8 .

This table includes both scenarios in which the control system fails to notify the human supervisor and scenarios in which the notifications are missed by the human supervisor. The rest of the paper focuses on the former scenarios since the aim is to design a control system that accounts for this possibility. Going into more detail on human factors, such as fatigue and boredom, is considered outside the scope of this work.

A challenge with integrating the human supervisor in the loop is providing enough time for intervention, i.e., to determine when it is necessary for the control system to notify the human supervisor. If the SRC is too late or does not provide a notification, the human supervisor will not be able to take the necessary action. However, if the SRC provides too many unnecessary notifications, the human supervisor may start neglecting these notifications. Over time, this can become a serious problem; the human supervisor may stop reacting to the notifications. The information given in the notifications can also affect the human supervisor's ability to react. Since the

Table 7. Scenarios in which a control action from the human supervisor can lead to a hazardous event

Scenario	Description	HUCA
Sc-1	The human supervisor is not notified when the ship loses power and therefore does not notify other ships that the ship has lost power and is drifting without control.	HUCA-1
Sc-2	The human supervisor misses a notification due to exhaustion or tiredness when the ship loses power and therefore does not notify other ships that the ship has lost power and is drifting without control.	HUCA-1
Sc-3	The human supervisor is not notified when the ship loses propulsion and therefore does not notify otherships that the ship has lost propulsion and is drifting without control.	HUCA-1
Sc-4	The human supervisor misses a notification due to exhaustion or tiredness when the ship loses propulsion and therefore does not notify other ships that the ship has lost propulsion and is drifting without control.	HUCA-1
Sc-5	The human supervisor is notified too late when the ship loses power and therefore notifies other ships too late that the ship has lost power and is drifting without control.	HUCA-2
Sc-6	The human supervisor is too late to recognize a notification due to exhaustion or tiredness when the ship loses power and therefore notifies other ships too late that the ship has lost power and is drifting without control.	HUCA-2
Sc-7	The human supervisor is notified too late when the ship loses propulsion and therefore notifies other ships too late that the ship has lost power and is drifting without control.	HUCA-2
Sc-8	The human supervisor is too late to recognize a notification due to exhaustion or tiredness when theship loses propulsion and therefore notifies other ships too late that the ship has lost propulsion and is drifting without control.	HUCA-2
Sc-9	The human supervisor is not notified when the ship loses power and therefore does not initiate or organize towing and rescue.	HUCA-3

autonomous ship is not monitored continuously, the human supervisor will most likely not have a full overview of the situation when they receive a notification. The SRC should therefore provide the human supervisor with the information they need to react in addition to the notification. The results from the H-STPA are used to set up up the SRC.

4.3. Step 3: Building the online risk model

The UCAs and scenarios shown in Tables 4 and 5, respectively, form the basis of the risk model. The risk model uses the first four UCAs. Changing the route is considered separately based on how much space the ship needs to maneuver depending on the wind and current. The MRC is entered when the risk cost becomes too high. When this happens, however, updating the risk model is paused until the ship exits the MRC. The two last UCAs are therefore not specifically added to the risk model. This also means that only the 15 scenarios based on UCA1–UCA4 are used to identify high-level RIFs (H-RIFs).

To reduce the complexity of the risk model, the scenarios are grouped together into the six H-RIFs shown in Table 9. The H-RIFs are divided further into input nodes for the risk model, as shown in Table 10.

The risk model also has input nodes connected to the hazardous events and the consequences resulting from these events. The probability of collision/allision with another ship/obstacle depends on both the probability of violating the minimum separation distance and the ability of the other ship/obstacle to avoid the collision/allision. The consequences depend on different nodes and the hazardous event. If the ship collides/allides with another ship/obstacle, the damage to the ship depends on the size of the other ship/obstacle and the impact speed. If the ship grounds or has contact with the seabed, the consequences depend on the impact speed, the type of shore,

Table 8. Scenarios in which a control action from the human supervisor can lead to a hazardous event

Sc-10	The human supervisor misses a notification due to exhaustion or tiredness when the ship loses power and therefore does not initiate or organize towing and rescue.	HUCA-3
Sc-11	The human supervisor is not notified when the ship loses propulsion and therefore does not organize towing and rescue.	HUCA-3
Sc-12	The human supervisor misses a notification due to exhaustion or tiredness when the ship loses propulsion and therefore does not organize towing and rescue.	HUCA-3
Sc-13	The human supervisor is not notified that it is necessary to take remote control of the ship when the autonomous system is unable to control the ship.	HUCA-4
Sc-14	The human supervisor misses a notification due to exhaustion or tiredness that it is necessary to take remote control when the autonomous system is unable to control the ship.	HUCA-4
Sc-15	The human supervisor is notified too late that it is necessary to take remote control when the autonomous control system is unable to control the ship.	HUCA-5
Sc-16	The human supervisor is too late to recognize a notification due to exhaustion or tiredness that it is necessary to take remote control when the autonomous control system is unable to control the ship.	HUCA-5
Sc-17	The human supervisor takes remote control of the ship without the necessary situational awareness to safely control the ship.	HUCA-6
Sc-18	The human supervisor takes remote control of the ship while performing many other tasks in the ROC at the same time, which results in the unsafe control of the ship.	HUCA-6
Sc-19	The human supervisor receives incorrect information about the situation and therefore hands over control to the autonomous control system before it is safe to do so.	HUCA-7
Sc-20	The human supervisor has incorrect information about the system's autonomous capabilities and therefore hands over control to the control system before it is safe to do so.	HUCA-7
Sc-21	The human supervisor receives incorrect information about the situation and therefore hands over control to the autonomous control system when it is unsafe to do so.	HUCA-8
Sc-22	The human supervisor has incorrect information about the system's autonomous capabilities and therefore hands over control to the control system when it is unsafe to do so.	HUCA-8
Sc-23	The human supervisor must perform other tasks in the ROC before control is handed back to the autonomous system, which results in the unsafe control of the ship.	HUCA-9
SC-24	The human supervisor does not hand over control to the autonomous system while performing many other tasks in the ROC at the same time, which results in the unsafe control of the ship.	HUCA-10

and the seabed. Harm to humans depends on the number of people aboard the other ship/obstacle or the type of shore. Damage to other ships/obstacles depends on the impact speed and size of the other ship/obstacle. If the ship grounds or has contact with the seabed, the impact speed and type of shore affect the consequences. The conditional probability tables (CPTs) are built up based on data from Johansen and Utne (2022), DNVGL (2003), and Hassel et al. (2021) to obtain the likelihoods of the hazardous events shown in Figure 5.

The BBN is also used to monitor the machinery, propulsion, and navigation and communication systems based on the fault tree analysis with the nodes power status, propulsion status, and navigation status. This provides the SRC with the information it needs to assess whether the ship still has the necessary redundancy to continue sailing in a given situation. The power and propulsion systems have three states, ok, minimum, and failed, according to the fault tree analysis. Losing redundancy means that the node is set to minimum. The ship still has power and propulsion but will lose power and propulsion if another component fails. Each component, such as the ME and HSG, is modeled as either failed or working. The different navigation and communication systems are described using three states: poor, sufficient, and good. These systems are therefore only considered as failed or ok based on the fault tree

Table 9. High-level RIFs used in the case study with the relevant UCAs

H-RIF	Description	UCA(s)
H-RIF-1	Machinery health status	UCA-1
H-RIF-2	Estimation of necessary power	UCA-2
H-RIF-3	Propulsion system health status	UCA-3
H-RIF-4	Navigational situation	UCA-4
H-RIF-5	Situational awareness of the control system	UCA-2, UCA-4
H-RIF-6	Control system reliability	UCA-2, UCA-4

Table 10. Input nodes derived from the H-RIFs used to build the risk model

High-level RIF	Description	Input nodes
H-RIF-1	Machinery health status	ME state HSG state DG1 state DG2 state
H-RIF-2	Estimation of necessary power	PMS DP controller performance/accuracy AP controller performance/accuracy
H-RIF-3	Propulsion system health status	BT state AT state MP state ST state
H-RIF-4	Navigational situation	Traffic Obstacles Distance to closest grounding hazard Wind speed Wind direction Current Ship speed
H-RIF-5	Situational awareness of the control system	Wind speed Fog Rain Snow Cameras AIS Radar GNSS Communication system
H-RIF-6	Control system reliability	DP controller performance/accuracy AP controller performance/accuracy AIS Radar GNSS Communication system

analysis. In operation, the nodes describing power and propulsion are considered failed if the probability of losing power exceeds 0.3, and they are considered minimum if the probability of losing redundancy exceeds 0.3. The limit is set based on testing to find a balance between keeping the ship from stopping too often and also avoiding the situation in which the ship continues to sail when systems are not functioning.

The ENC module is used to find the presence and density of obstacles around the ship and the distance to the closest point the ship cannot safely navigate to. The module is set up such that anything shallower than 5 m is considered a shallow area that the ship must avoid in order to navigate safely. The obstacle density is based on the distance to the closest shallow point (i.e., areas with a water depth of less than 5 m) and on how much of the water around the ship is obstructed. The water depth of 5 m is the same as the maximum draft of the ship. Using this water depth is considered sufficient for assessing the proportion of obstructed water in this work. The ship must then avoid shallow areas with sufficient safety margins.

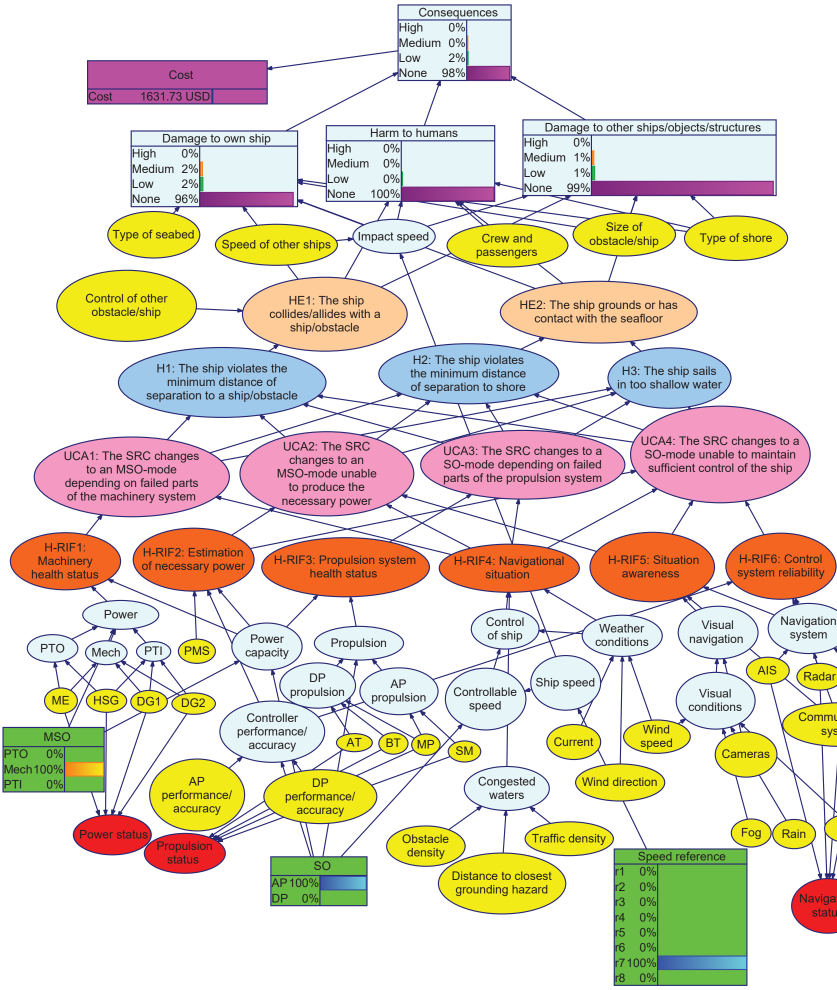

Figure 5. Online risk model BBN (adapted from Johansen and Utne (2022) and "Johansen et al. (2023) and extended) showing an example of the risk cost

The percentage of obstructed water is calculated by considering a disk with a radius of 1400 m and finding the portion of the disk with land and shallow water. The radius is set through testing to ensure that the disk gives a good picture of the sea area surrounding the ship, considering that the ship is 80 m long. The ENC module is checked every 30 seconds to provide updated measurements to the risk model. Testing shows that this provides a good balance between the computation time and updated data. This information is provided to the risk model through the nodes "Obstacles" and "Distance to closest grounding hazard."

4.4. Step 5: Building the SRC

The SRC is set up using two sub-steps: the first involves setting up the actual controller and testing it to identify operational limitations. The second part involves implementing notifications to the human supervisor based on the results from the H-STPA.

The SRC calculates the expected cost using Equation 1 for each set of decisions (MSO-mode, SO-mode, and speed reference). The cost is the sum of the fuel cost $F(d)$, risk cost $R(d)$, operation cost $O(d)$, and potential future loss $L(d)$, depending on the decisions d.

The fuel cost is calculated using a look-up table with the specific fuel consumption (SFC) for different MSO-modes, speeds, wind conditions, and current conditions. This is multiplied by the planned sailing distance and the fuel price, as shown in Equation 2. This provides a good approximation for the fuel consumption, despite not accounting for all variations due to changing angles for wind and current in different places along the route. Calculating for each specific part of the route would also take much longer time due to the increased complexity and need for more online simulations to estimate the fuel consumption. The following prices of LNG and diesel are taken from Ship & Bunker (2022): 1,326.50 USD/ton for LNG and 679.50 USD/ton for diesel. The price is therefore dependent on the MSO-mode, since this determines the type of fuel used:

$$F(d) = SFC(speed, wind, current, MSO) * distance * Price(MSO). \tag{2}$$

The risk cost is calculated from the risk model using Equation 3, which takes the probability of each consequence category from the STPA and multiplies it by the cost of the corresponding category. Severe consequences are given a cost of 4,550,640 USD, significant consequences have a cost of 455,064 USD, and minor consequences have a cost of 45,506.40 USD. These costs are estimated based on EfficienSea (2012), The Norwegian Agency for Public and Financial Management (2018), and IMO (2018):

$$\begin{aligned} R(d) = & Pr(severe)C_{severe} + Pr(significant)C_{significant} + Pr(minor)C_{minor} \\ & + Pr(none)C_{none}. \end{aligned} \tag{3}$$

The operation cost is calculated by taking the cost per hour, multiplying it by the planned sailing distance, and dividing the resulting value by the speed reference, as shown in Equation 4. This cost includes personnel costs in the ROC and maintenance, insurance, lubrication, spare-parts, and logistics costs. These costs are estimated to be 341.30 USD/ht, based on costs from similar ships and data from Stopford (2009):

$$O(d) = Cost_{operating} * distance/speed. \tag{4}$$

The potential future loss is calculated similarly using Equation 5, with the expected loss of income per hour set to 910.10 USD/h. This cost represents the potential income if the ship was free and could start the next trip or mission earlier and calculated similarly as the operation cost. This can also be considered as a penalty cost to balance the risk, fuel, and operation costs.

$$L(d) = Cost_{future\ loss} * distance/speed. \tag{5}$$

The SRC considers a constant planning horizon equal to the remaining sailing distance at the start of the mission, d_0, used to calculate both fuel cost, operation cost, and the potential future loss. The costs considered in the SRC are then the costs of sailing another distance d_0. For the case study, this is equal to around 57 km or 30 nautical miles. By using a constant distance to calculate the cost, the weights of the risk, fuel, operation, and potential future loss are kept constant. Without a constant distance, the SRC would put more relative weight on the risk when the distance is small. This would cause the ship to go slower and use more energy, the closer it gets to the final way-point.

To check a route, the SRC goes through all the way-points to determine if the ANS can follow it with sufficient margins. Between each way-point, a set of intermediate points is used to check that the margin is sufficient along the whole route. In this work, the margin is set based on how accurately the ANS can control the ship in different wind conditions.

As identified in the H-STPA, finding the right balance between providing and not providing notifications to the human supervisor has a significant effect on the overall performance. To achieve this, the human supervisor should only be notified when the SRC expects that it will be unable to control the ship in the future. However, these notifications should be made before the SRC loses control so that the human supervisor has time to react. The human supervisor should also be notified when components, or sub-systems, fail without warning. Based on this, the human supervisor is notified when it become necessary to perform any of the control actions described in subsection 4.2.

The SRC receives information from the risk model about the status of the machinery, propulsion, and navigation and communication systems, as described in subsection 4.3. If any of these sub-systems fail, the human supervisor is notified that the ship is unable to continue. There is little the human supervisor can do in these situations, except for notifying nearby ships and the relevant authorities. The risk model is also used to assess redundancy in the machinery and propulsion system. If the autonomous ship loses redundancy in these systems, the human supervisor is notified, and the ship will enter the MRC. The ship will also enter the MRC if the risk cost becomes too high, e.g., due to changes in the environment or weather. In this case study, the cost limit for the SRC to enter the MRC is set at 5,119.47 USD, which is very low compared to the costs associated with the different consequences. However, testing shows that the risk cost very rarely exceeds this value, and this only occurs when the ship is unable to continue to sail safely. This is discussed further in subsection 5.2.1.

When the ship enters the MRC, it will try to maintain its current position until the human supervisor has checked the situation and decided how to proceed. In the MRC, the autonomous ship uses the DP-controller to maintain its position. The MSO-mode is chosen by checking the risk model to find out which mode has the lowest risk cost. If the ship is unable to change the active route, the human supervisor is sent a notification that explains why the route should be changed and why the SRC was unable to change the actively selected route.

4.5. Step 7: Testing and verification of the control system

The SRC should be tested to check that it can control the ship in a safe and efficient manner before implementation and/or during updates/modifications. Setting up test scenarios starts with the different UCAs and HUCAs identified in the STPA and H-STPA. These are used as the basis for formulating high-level safety constraints and scenarios in which these constraints can be violated.

The STPA scenarios are mainly related to selecting an MSO-mode that is unable to produce the necessary power, a mismatch between the speed reference and SO-mode, using propulsion parts that have failed, or the speed being higher than it should be in confined or narrow areas. The scenarios describing insufficient power production are either caused by failures or due to the total load on the machinery system. Problems with setting the speed reference can involve setting it too low to use the rudder to steer the ship or setting it too high to use the tunnel thrusters. Scenarios identified in the H-STPA focus mostly on when the human supervisor is or should be notified. The H-STPA also identified scenarios in which the human supervisor has an insufficient understanding of the situation (mainly scenarios 17–24). Verification objectives are formulated based on the STPA and H-STPA scenarios; they are shown in Table 11.

Table 11. Verification objectives based on the STPA and H-STPA

Verification objective	Description
VO-1	Verify that the SRC handles machinery failures by either changing the MSO-mode or entering the MRC-mode.
VO-2	Verify that the SRC selects a safe combination of the SO-mode and speed reference.
VO-3	Verify that the SRC enters the MRC with sufficient time and functionality for the ship to maintain its current position.
VO-4	Verify that the human supervisor is notified in the intended situations and avoid unnecessary notifications.
VO-5	Verify that the SRC provides notifications with the necessary information to allow the human supervisor to react to the situation.
VO-6	Verify that the SRC checks the route and, when necessary, either changes it or notifies the human supervisor that it is unable to change the route.

The proposed control system is tested against the six verification objectives by simulating the ship and allowing random changes in the system and environment. The SRC must handle these changes, regardless of the timing and location of these changes. The simulator is based on the equations from Fossen (2011) with simplified dynamics and machinery models. The DP and autopilot controllers are PID controllers included as part of the simulator.

5. Results and discussion

5.1. Results

To demonstrate the proposed methodology, the SRC is tested using the verification objectives on a route close to Brønnøysund in a number of simulations with varying wind and current conditions, as well as random failures in the machinery and propulsion system. The wind speed is from 0–21 m/s from north, east, south, and west. The initial wind speed is increased by 0.5 m/s after each simulation, resulting in a total of 176 simulations to check. The wind is given an initial speed, with a 1×10^{-4} probability of changing at each time step during the simulation. The current is between 0 and 0.1 m/s. The current is given a random initial speed and direction that is then kept constant for the remaining time. Both the wind and current conditions are based on historical data from Norwegian Meteorological Institute (2021) and Barentswatch (2022) for the area considered, but they are assumed to be the same over the whole area.

The ship is simulated with random failures occurring in the machinery and propulsion system that the SRC must handle correctly. The ship has an original route passing through Brønnøysund (the yellow route in Figure 6) and an alternative route going around Brønnøysund (the white route in Figure 6). The alternative route provides more space for the ship to maneuver but is slightly longer.

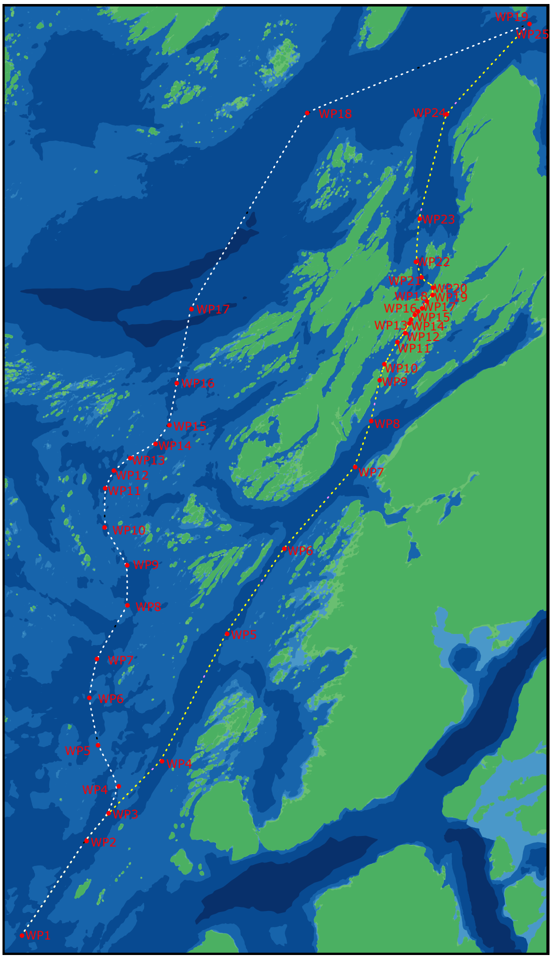

Figure 6. Map of the two routes sailed by the ship. The main route followed in simulation 1 is shown in yellow, and the alternative route followed in simulation 2 is shown in white.

The simulator is based on a simplified ship model without waves but with the wind and current affecting the ship. Failures are introduced using a random function in Python; there is a 1×10^{-5} probability of losing either power or propulsion, and losing redundancy, at each time step in the simulation. This is an artificially high probability to ensure that failures occur in order to test the controller. The wind is given an initial speed, which may both increase and decrease. The wind has a 1×10^{-4} probability of changing at each time step. The current is given a random initial speed and direction that is then kept constant for the remaining simulation time. The six verification objectives must be satisfied in each simulation for the SRC to pass the test.

Out of the 176 simulations, the SRC enters the MRC in 28 simulations, and the ship has a critical failure in three of these 28 simulations. The route is changed in 95 cases because of the current, wind, or a combination of both. The SRC manages to control the ship in a safe and efficient manner from start to finish by selecting the best MSO-mode, SO-mode, speed reference, and route according to the conditions. If any systems fail or the conditions exceed the operational limits of the autonomous ship, the SRC enters the MRC with sufficient time to stop and maintain its position. The human supervisor is then able to check the situation and decide how to proceed. Overall, the results show that the control system satisfies the verification objectives, but it is slightly conservative for the current setup. The following subsections show how the SRC works in some of the simulations.

5.1.1. Simulation 1: Calm wind and current without any machinery problems

The first simulation has a wind speed between 0 and 2 m/s and a current speed of 0.07 m/s. The ship has no problems with the machinery and there is thus no need to change the route while the ship is underway. The ship starts with a speed of 7 m/s, as shown in Figure 8. This speed is reduced to 3 m/s after around 85 minutes because the route passes through a narrow strait. The route then passes through a more open area for a short while, and thus the speed is increased back to 7 m/s. As the autonomous ship enters the harbor area of Brønnøysund after around 95 minutes, the speed is reduced to around 3 m/s to account for speed limitations when sailing close to land. The ship keeps this speed through the harbor and increases the speed back to 7 m/s when it exits the harbor after around 115 minutes. The costs estimated

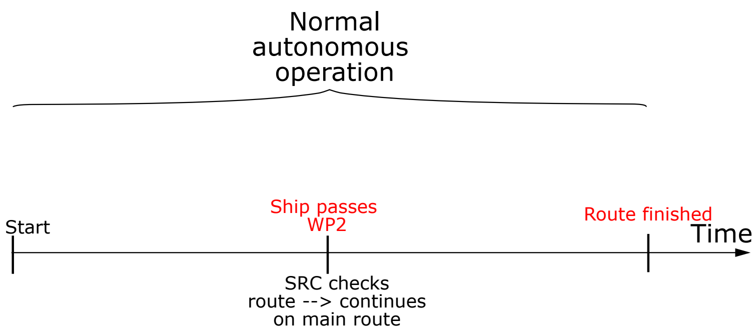

Figure 7. Timeline of the first simulation showing when the route is checked and the SRC decides how to proceed

by the SRC are shown in Figure 9. As long as the decisions d (MSO-mode, SO-mode, speed reference) and conditions stay the same, the fuel cost, operation costs, and potential future loss stay constant since they are calculated as the assumed cost of continuing to sail for a distance equal to d_0, as described in subsection 4.4. When the ship enters the narrower parts of the route after 85 minutes, the risk cost starts to increase since the obstacle density increases and the distance to the closest grounding

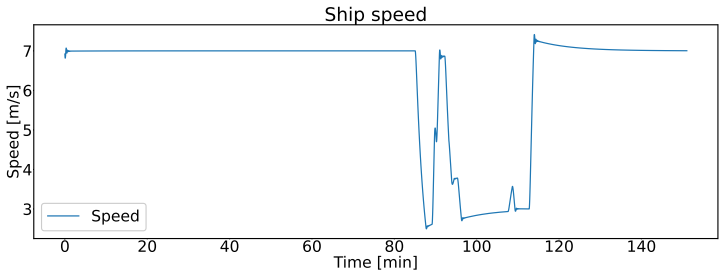

Figure 8. Ship speed in simulation 1

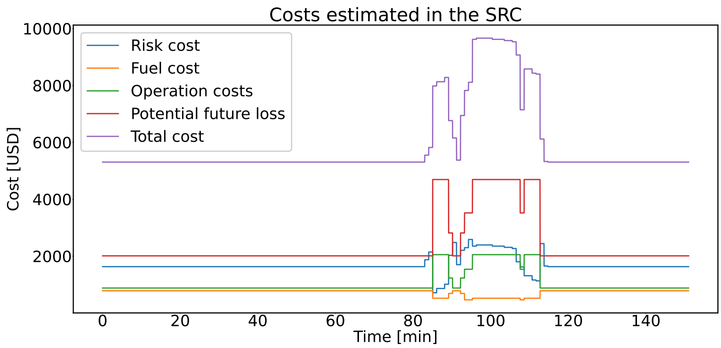

Figure 9. Cost in simulation 1 (d_0 = distance of the full route)

hazard decreases. After a short period of around five minutes, the risk cost is high enough for the SRC to lower the speed reference from 7 m/s down to 3 m/s. The ship will then use significantly more time to sail another distance d_0, which increases the operation costs and potential future losses. The fuel cost is reduced slightly since the ship uses less fuel and switches to PTI, which is cheaper with respect to fuel costs.

The SRC changes the MSO-mode from Mech to PTI when it sails at a lower speed since the ship then needs less power. Operating in PTI also reduces the fuel cost slightly. The ship uses the autopilot for the whole simulation. The ship takes 150 minutes to sail the whole route and sails 57.7 km.

5.1.2. Simulation 2: Strong breeze without machinery problems

In the second simulation, the ship is sailing in wind with a speed between 10 and 11 m/s. The route is first checked at WP2, where the SRC decides to follow the longer route (white route in Figure 6), where there are fewer obstacles to maneuver around and more space. The two routes split at WP3, where the ship then follows the white route. On the alternative route, the distance to the closest grounding hazard and the obstacle density do not change enough to affect the risk cost. Combined with the constant planning horizon, this means that the costs stay constant throughout the whole simulation, as shown in Figure 11. Since the risk cost stays constant, the

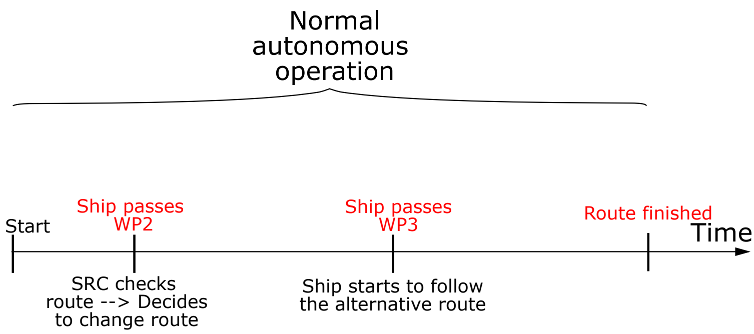

Figure 10. Timeline of the second simulation showing when the route is checked and when the ship starts to follow the alternative route

MSO-mode, SO-mode, and speed stay constant.

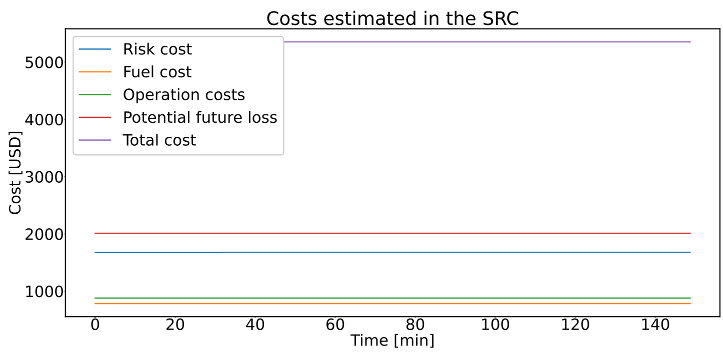

Figure 11. Cost in simulation 2 (d_0 = distance of the full route)

5.1.3. Simulation 3: Wind increases after the ship passes the alternative route

The third simulation shows the autonomous ship in winds with a speed of 6.5 m/s. The ship starts with a speed of 7 m/s, similar to the first simulation. The SRC first checks the route after passing WP2 in Figure 12. At that point, the SRC determines that it should follow the original route because the conditions are not too bad. As the ship continues, the wind starts to increase from the original speed of 6.5 m/s up to 8.5 m/s. At that point, the SRC reevaluates the route and determines that it would be best to be on the alternative route since it might encounter problems if it continues. However, the ship has passed the point where the two routes split, WP3, and turning around is not a possible decision for the current implementation of the SRC. Instead, the SRC enters the MRC-mode, starts slowing the ship down, and notifies the human supervisor about the situation. At this point, the SRC stops updating the cost since it stays in the MRC-mode until the human supervisor has decided how to proceed. In this case, the ship stops and the simulation is stopped without showing what the human supervisor decides to do, as shown in Figure 13. Since the SRC enters the

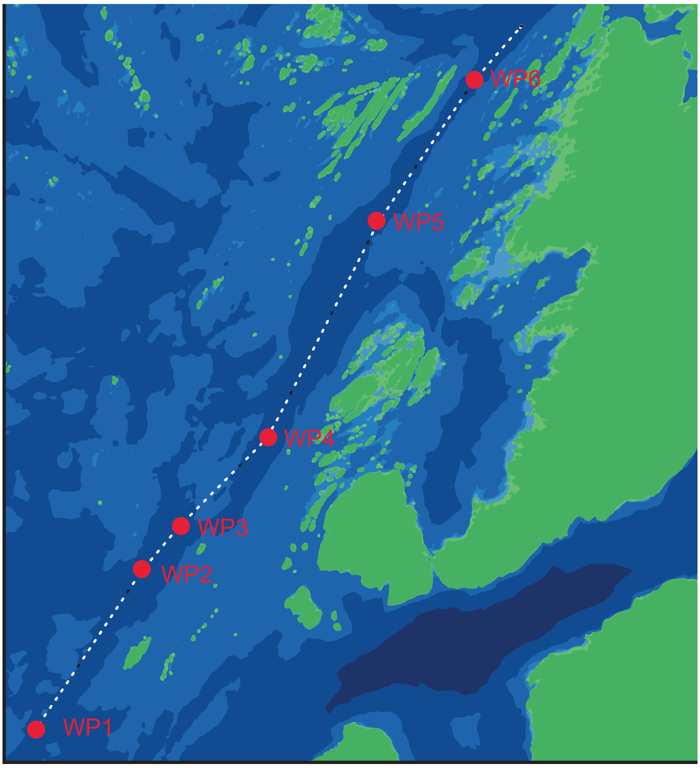

Figure 12. Map of simulation 3

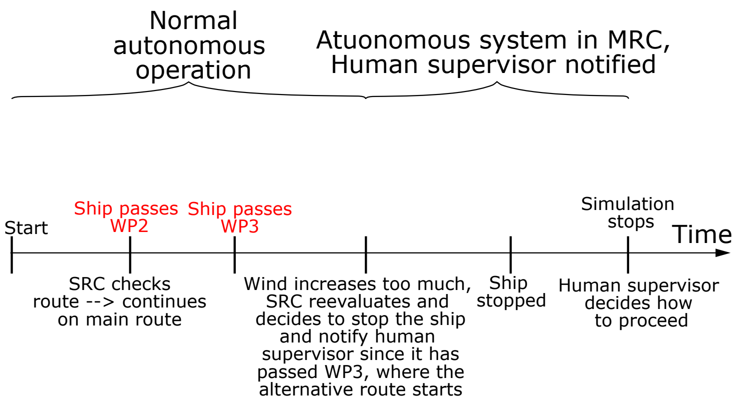

Figure 13. Timeline of the third simulation showing when the autonomous control system controls the ship and when the human supervisor is notified

MRC-mode because of the potential future situation, the costs shown in Figure 14 are constant.

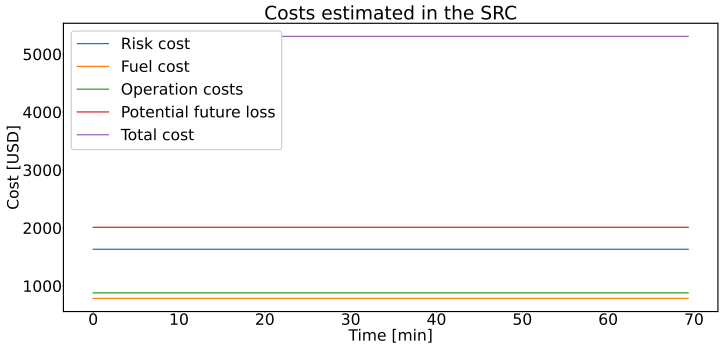

Figure 14. Cost in simulation 3 (d_0 = distance of the full route)

5.1.4. *Simulation 4: Ship loses redundancy in power production*

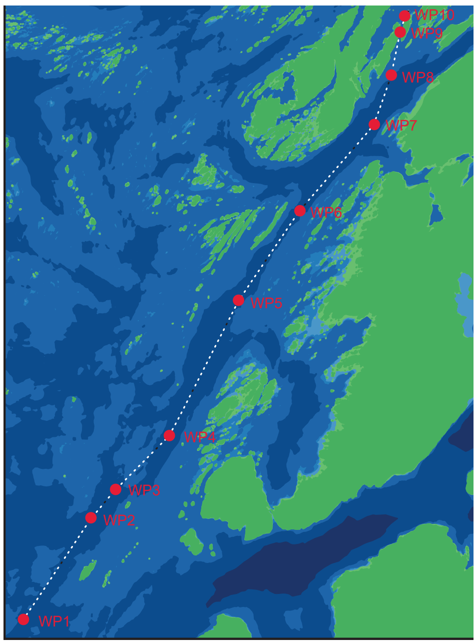

Figure 15. Map of simulation 4

The fourth simulation shows how the SRC handles losing redundancy in the machinery system. The ship is sailing in calm weather with a wind speed of 2 m/s and a current speed of 0.07 m/s. The ship starts with a speed of 7 m/s, similar to the previous simulations. The ship passes WP3, where the SRC checks the route and decides to continue as planned. As the ship reaches WP9, the risk cost increases, as shown in Figure 17, at around 85 minutes. The SRC then starts reducing the speed reference to maintain sufficient control. At the same time, as the ship is slowing down, the SRC recognizes that the main engine has problems. It then decides to switch the MSO-mode to PTI to avoid using the main engine. At the same time, the SRC decides to enter the MRC-mode and notifies the human supervisor since the fault tree showed that this main engine problem results in a loss of redundancy. While the human supervisor is notified, the ship stops and maintains its position. The simulation is stopped after the ship has stopped, without showing the decision made by the human supervisor.

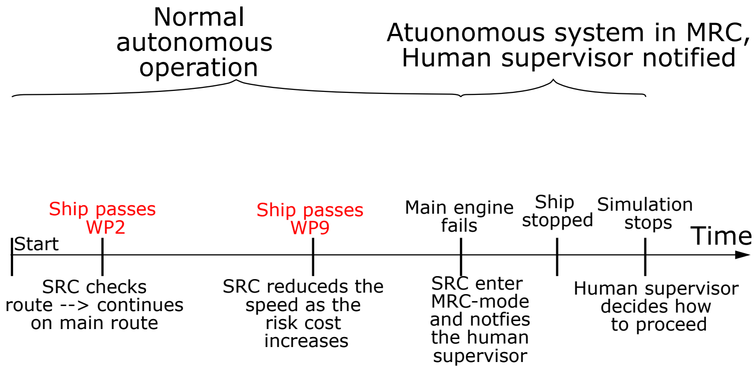

Figure 16. Timeline of the fourth simulation showing when the autonomous system controls the ship and when the human supervisor is notified

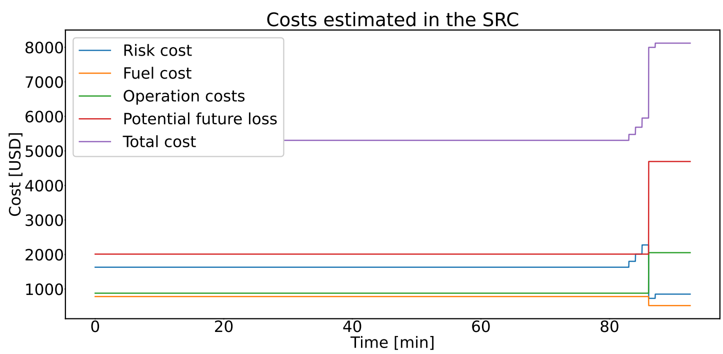

Figure 17. Cost in simulation 4 (d_0 = distance of the full route)

5.2. Discussion

5.2.1. Risk-based control of autonomous ships

The control system proposed in this paper uses a BBN online risk model to assess the situation as the ship is sailing. The output from the risk model is a risk cost. This describes the expected cost related to potential hazardous events, given the current conditions and ship state. The risk model considers a constant time horizon equal to the initial estimated time needed to finish the route. The same time horizon is used to estimate fuel and operation costs. These estimates also assume constant conditions and a constant ship state. This approach provides a cost function that the SRC can use to assess the risk and reward of operating the ship, even if the reward is represented by the cost of operating the ship, i.e., fuel and operation costs. The proposed control system can therefore find a trade-off between reducing risk and minimizing operation costs, since there will always be some risk related to autonomous ship operation. As shown in the case study, this enables the SRC to control the ship, similarly to how humans control conventional ships.

The current SRC uses the risk model to obtain a "picture" of the current risk level and make decisions based on this picture. As shown in the case study, this results in a good performance, and the ship is controlled in an efficient and safe manner. However, computer-based controllers can also use simulations to predict the future state of the ship. This enables the controller to predict how decisions affect the ship before actually making them. This concept is already used in model predictive control (MPC): the controller can simulate the system and compute the optimum control inputs to drive the system towards the intended state. A similar approach could enable an SRC to plan multiple steps ahead, instead of just making decisions based on the current situation, which is done in the current paper.

The proposed control system enters the MRC if the risk cost becomes too high, if the power, propulsion, or navigation and communication systems fail or lose redundancy, or if the conditions worsen and cause the ship to be unable to follow the planned route with sufficient margins. As described in subsection 4.4, the cost limit is set to the low value of 5,119.47 USD; this value is especially low compared to the costs estimated for the different consequences. However, the current cost limit ensured that the SRC entered the MRC when the ship was unable to continue safely while also limiting the number of times it could have continued sailing. The current limit is therefore considered suitable for the current controller, but it should be assessed further in future work. Assessing the MRC in more detail is also considered outside the scope of this paper. For the purpose of showing how the proposed control system works, it is deemed sufficient that the ship stops and maintains position. However, there might be cases where this is not the best way due to traffic and other conditions. Considering other ways to reduce the risk should therefore be considered in further work.

Deciding whether the power, propulsion, or navigation and communication systems have failed or do not have sufficient redundancy is done based on the fault tree analysis and the modeling of these systems in the online risk model. The nodes representing the power and propulsion systems calculate the probabilities that the systems have failed or do not have sufficient redundancy. The node representing the navigation and communication system only calculates the probability that the system has failed since these sub-systems are not modeled as binary systems. The threshold for when the systems are considered to have failed or to be without sufficient redundancy is set to 0.3 based on testing, similar to the cost limits. The controller works well with the current models and thresholds; it operates with sufficient safety margins. However, the fault tree analysis, models, and thresholds should be assessed in more detail in future work.

5.2.2. Human supervisors in the operation of autonomous ships

The human element is often overlooked or briefly mentioned as part of the technical development of the control of autonomous ships. However, since the operation of most ships under development and testing today still involves humans, this should still be accounted for when new control systems are designed. Situations in which responsibilities shift from the autonomous system to the human supervisor (shared control) are especially important to consider. This paper focuses on UCAs in which the human supervisor fails to react sufficiently that are caused by the poor design of the control system. Other important risk factors, such as the experience level of the human supervisor, human reliability, reaction time, and human-machine interactions, are not considered here to limit the scope of the paper, but they should be studied in future work.

In this paper, the ship can enter the MRC-mode when the SRC recognizes that the ship performance may imply risks that are too high. This happens if the risk cost is too high, if any of the systems analyzed with the fault tree analysis fails or loses redundancy, or if the ship is unable to follow the planned route. When it is in the MRC-mode, the ship stops and uses the DP-controller to maintain its position while the human supervisor is notified. In this way, the ship is in a safe and stable situation while the human supervisor has time to assess and make a good decision about how to continue. The work in this paper is therefore the first step towards developing a control system that actively supports the human supervisor. The control system should be further improved by assessing which pieces of information should be provided to the human supervisor in different situations. By offering better and more relevant risk-based information through efficient human-machine interfaces (HMIs), the safety of the systems and operations should improve. This is left as an important topic for future research.

Another challenge with existing control systems is that humans are sometimes notified so often that over time, it can become routine to cancel alarms without reacting further. Discussing this in detail is considered outside the scope of this paper, but the SRC is designed to avoid unnecessary notifications by allowing the autonomous control system to make more decisions without human input, such as changing routes, SO-modes, and MSO-modes; the system only notifies the human supervisor when it is unable to control the ship with the proper safety and efficiency margins. Setting these limits is still a potential challenge and a topic that should be addressed in more detail in future work, but the proposed SRC is a step in the right direction.

5.2.3. Testing and simulation setup

The proposed methodology is tested by simulating an autonomous cargo ship controlled by the SRC. The simulator is based on the models from Fossen (2011), but with some important simplifications. These simplifications make it easier to set up and run simulations, but they can also affect the accuracy. Not including wave forces is one such simplification. Wave forces are usually estimated using hydrodynamic programs in which 3D models of the ship are tested. However, the data necessary to make such models are not available for the considered ship. This affects both disturbances from waves and also waves made by the ship, which add damping.

Another simplification is related to the machinery and propulsion system. The machinery models provide the fuel consumption and power output but include no dynamics. The time necessary to change loads or start/stop parts of the machinery is therefore neglected. For the propulsion system, some simple dynamics are included by adding a slight time delay to the thrusters. The reduction in thrust from the tunnel thrusters at high speeds and the lack of force from the rudder at low speeds are, however, not included. As with wave forces, it is difficult to make an accurate model of these effects for the simulator. Therefore, the risk model is adjusted such that using the tunnel thrusters at high speeds and the rudder at low speeds increases the risk cost.

Including wind and current in the simulation also means some simplifications. Both wind and current will depend on the terrain around the ship when sailing close to shore and will change both speed and direction. However, the simulations done as part of this work assumes that wind and current are unaffected of the topography both over and under water. For the purpose of testing the proposed control system, this is deemed good enough. The testing include a limited number of simulations, 176 to be specific. This is done by selecting a combination of wind directions and wind speeds such that the ship is tested with wind from 4 different directions for each 0.5 m/s speed. The current is given a random direction and speed for each simulation. This mean that not all combinations of wind and current are tested. To ensure that all potential combination were tested, both wind and current would have to be varied in a systematic manner resulting in many more simulations. However, since the proposed control system is tested in a reasonable number of different combinations, it is deemed sufficient to show how it works and that it can handle a wide range of conditions.

Accuracy in the control system, especially for the motion controllers, affects the results. The motion controllers, i.e., the DP and autopilot controllers, are included in the simulator. The DP controller is a proportional integral derivative (PID) controller. The autopilot uses a PID controller for the heading and a PI for the speed. These have a base tuning that offers sufficient control of the ship to test the methodology and the SRC. However, since the SRC is a separate controller, both the DP and autopilot can be changed to more advanced and improved controllers later. Testing the SRC with more advanced motion controllers is left as an interesting topic for future research. Failures in the DP system and autopilot controllers, such as losing the position while in MRC mode, are also considered to be outside the main scope of this paper, and therefore they are left for future work.

The GNSS accuracy will affect the ship and its ability to navigate safely. The accuracy of GNSS has improved significantly over the last few years, but it is still assumed to be +/- 5 m. This can be improved using differential GNSS, but it can also be reduced by the environment around the ship. Sailing in narrow fjords with high mountains, where the satellite signal can be blocked and reflected by the mountains, can reduce the position accuracy. This uncertainty in the position data is something that future control systems for autonomous ships should account for. However, for the purpose of testing the methodology and the SRC, the accuracy is assumed to be sufficient for navigation in the case study. Investigating how to best account for this variation in the position accuracy is left for future research.

The proposed control system is tested using a set of verification objectives. These objectives are used to check that it can control the ship in a safe and efficient manner. However, the current verification objectives only consider high-level functionalities. This is deemed sufficient in this paper to verify the control system and show that the methodology works. However, further work should include more detailed verification objectives.

5.2.4. Uncertainty and sensitivity in the online risk model and SRC

The online risk model is used to assess the current situation and state of the ship to improve the decision-making capabilities of the control system. The SRC combines the risk cost, estimated using the online risk model, with fuel and operation costs to find the best way to sail the ship. Using a BBN is a good way to model different RIFs, especially when the exact relationship between all risk factors is not known. However, this also means that the model contains uncertainty. The structure of the BBN, states in the different nodes, and CPTs all contribute to uncertainty in the BBN.

The structure of the BBN is based on the STPA results, which describe the different RIFs. The STPA offers a good foundation for the BBN structure based on the different UCAs, scenarios, and hazardous events. Even though this reduces the model uncertainty, the STPA is a qualitative method for identifying hazards, and it provides less data for assigning states and building CPTs. These are therefore mostly based on the literature and expert judgement. The STPA provides some information that can be used to assign states for the different nodes and to determine what information is necessary in the risk model. In the case study, the nodes with the most uncertainty are the RIFs and UCAs; the main challenge is deciding how much each should affect the risk cost. The effect of the different RIFs is assessed by conducting a sensitivity

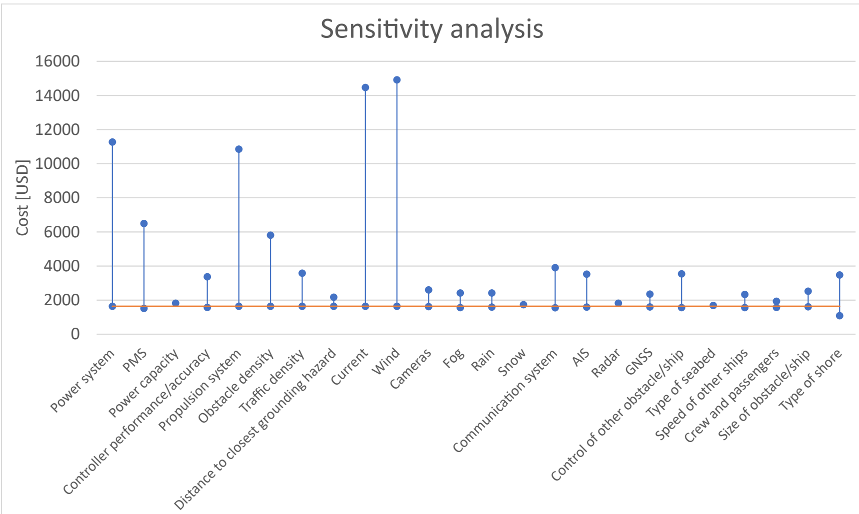

Figure 18. Sensitivity analysis showing the risk cost from the BBN with the nodes in the best and worst conditions

analysis on the BBN risk model to see how the risk cost is affected by the different nodes in the best and worst conditions. The results, shown in Figure 18, illustrate that the sensitivity varies significantly. The two RIFs that have the largest effect are the current and wind, followed by the power system, propulsion system, and PMS. Other important nodes impacting the risk cost are the obstacle density, traffic density, and navigation and communication systems. All these nodes can obtain good information from sources such as Norwegian Meteorological Institute (2021), Barentswatch (2022), Norwegian Mapping Authority (2021), and Marine Traffic (2021). The effect of failed machinery and propulsion systems is also thoroughly discussed in the STPA. However, the sensitivity analysis indicates that the system may be tuned more towards handling these nodes or factors, and it may potentially be neglecting other factors, such as visibility. Testing this idea is left as an interesting and important topic for future research.

The balance between the different terms in the cost function is also a source of uncertainty that affects decision-making. To reduce the uncertainty, the fuel cost and operation costs are based on simulation testing and historical data for similar ships, respectively. This helps reduce the uncertainty but may still affect the overall results. Basing the risk cost on the risk model, with the associated uncertainty, together with the potential future loss estimated based on the cost of hiring similar ships, will also add uncertainty to the total cost. Based on the performance over a wide range of conditions, however, the balance is assumed to be sufficient to test the proposed control system and show how the proposed control system functions. Reducing the uncertainty as improved data become available should be the subject of future work. This could be accomplished through model testing or running the proposed control system as a support system on an actual ship to see how its decisions compare to the decisions made by the crew.

6. Conclusion

The objective of this paper was to develop a methodology for building a risk-based control system for autonomous ships, designed with the ability to involve a human supervisor when potential operational challenges arise. The methodology uses an STPA as the basis for building an online risk model and for setting up the SRC, including the human supervisor. The BBN-based risk model is used to assess the current state of the autonomous ship and environment to obtain an estimation of the current risk. This is represented as a risk cost, describing the expected cost from potential consequences, given the current situation. The risk cost is combined with the cost of fuel, other operating costs, and potential future losses caused by the ship taking a longer amount of time to complete the current voyage. The SRC is then able to configure the ship according to the lowest total cost.

Since humans are still expected to be involved in the operation of autonomous ships, the proposed control system is designed with this factor in mind. The result is an autonomous control system capable of operating the ship in a safe and efficient manner, with the ability to assess its performance and determine whether it has the necessary control of the ship to continue safely on its voyage. If not, it will notify the human operator while transitioning to a minimum risk condition (MRC) to reduce the risk level and thereby reduce the probability of a hazardous event. By analyzing the human responsibilities with an H-STPA, the SRC can be designed to make it safer and easier for the human supervisor to decide how the ship should continue. While the human supervisor uses time to react and decide how to proceed, the SRC is designed to keep the ship in an MRC to reduce the occurrence of hazardous events and serious accidents. In this way, both the autonomous control system and the human supervisor contribute to operating the ship safely and efficiently.

The proposed methodology and control system is tested in a case study involving an autonomous cargo ship sailing along the Norwegian coast. The human supervisor is in an ROC with a remote connection to the ship. The resulting control system is tested using a set of verification objectives based on the STPA and H-STPA. The shared control between the autonomous control system and the human supervisor enables the ship to pass the test for a wide range of conditions and situations, including calm winds, a strong breeze, machinery failures, and changing conditions that force the SRC to reevaluate decisions.

This study is the first step towards designing risk-based control systems that include the human supervisor in the loop. Future work includes improving the control system and the human-machine interface, as well as putting more of an emphasis on human reliability aspects and contingency situations. The current risk controller is designed to make decisions to gradually reduce the risk cost. However, if the risk cost is above a certain limit, the controller will go straight into the MRC-mode. Future work should determine if the controller can reduce the risk further before entering the MRC-mode, without compromising safety. This could enable the ship to continue sailing in more situations. A path planner capable of planning new routes while the ship is sailing would also improve the control system and make it capable of operating more autonomously.

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128		Nonlinear Finite Element Models for Use in Design of Aluminium Structures Exposed to Fire. (Dr.Ing. Thesis)
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MTA-99-131	Tveiten, Bård Wathne, MK	Fatigue Assessment of Welded Aluminium Ship Details. (Dr.Ing. Thesis)
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		(Dr.Ing. Thesis)
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IMT-6-2018	Bård Stovner	Aided Intertial Navigation of Underwater Vehicles
IMT-7-2018	Erlend Liavåg Grotle	Thermodynamic Response Enhanced by Sloshing in Marine LNG Fuel Tanks
IMT-8-2018	Børge Rokseth	Safety and Verification of Advanced Maritime Vessels
IMT-9-2018	Jan Vidar Ulveseter	Advances in Semi-Empirical Time Domain Modelling of Vortex-Induced Vibrations
IMT-10-2018	Chenyu Luan	Design and analysis for a steel braceless semi-submersible hull for supporting a 5-MW horizontal axis wind turbine
IMT-11-2018	Carl Fredrik Rehn	Ship Design under Uncertainty
IMT-12-2018	Øyvind Ødegård	Towards Autonomous Operations and Systems in Marine Archaeology
IMT-13-2018	Stein Melvær Nornes	Guidance and Control of Marine Robotics for Ocean Mapping and Monitoring
IMT-14-2018	Petter Norgren	Autonomous Underwater Vehicles in Arctic Marine Operations: Arctic marine research and ice monitoring
IMT-15-2018	Minjoo Choi	Modular Adaptable Ship Design for Handling Uncertainty in the Future Operating Context
MT-16-2018	Ole Alexander Eidsvik	Dynamics of Remotely Operated Underwater Vehicle Systems
IMT-17-2018	Mahdi Ghane	Fault Diagnosis of Floating Wind Turbine Drivetrain- Methodologies and Applications
IMT-18-2018	Christoph Alexander Thieme	Risk Analysis and Modelling of Autonomous Marine Systems
IMT-19-2018	Yugao Shen	Operational limits for floating-collar fish farms in waves and current, without and with well-boat presence
IMT-20-2018	Tianjiao Dai	Investigations of Shear Interaction and Stresses in Flexible Pipes and Umbilicals
IMT-21-2018	Sigurd Solheim Pettersen	Resilience by Latent Capabilities in Marine Systems
IMT-22-2018	Thomas Sauder	Fidelity of Cyber-physical Empirical Methods. Application to the Active Truncation of Slender Marine Structures
IMT-23-2018	Jan-Tore Horn	Statistical and Modelling Uncertainties in the Design of Offshore Wind Turbines

IMT-24-2018	Anna Swider	Data Mining Methods for the Analysis of Power Systems of Vessels
IMT-1-2019	Zhao He	Hydrodynamic study of a moored fish farming cage with fish influence
IMT-2-2019	Isar Ghamari	Numerical and Experimental Study on the Ship Parametric Roll Resonance and the Effect of Anti-Roll Tank
IMT-3-2019	Håkon Strandenes	Turbulent Flow Simulations at Higher Reynolds Numbers
IMT-4-2019	Siri Mariane Holen	Safety in Norwegian Fish Farming – Concepts and Methods for Improvement
IMT-5-2019	Ping Fu	Reliability Analysis of Wake-Induced Riser Collision
IMT-6-2019	Vladimir Krivopolianskii	Experimental Investigation of Injection and Combustion Processes in Marine Gas Engines using Constant Volume Rig
IMT-7-2019	Anna Maria Kozlowska	Hydrodynamic Loads on Marine Propellers Subject to Ventilation and out of Water Condition.
IMT-8-2019	Hans-Martin Heyn	Motion Sensing on Vessels Operating in Sea Ice: A Local Ice Monitoring System for Transit and Stationkeeping Operations under the Influence of Sea Ice
IMT-9-2019|	Stefan Vilsen	Method for Real-Time Hybrid Model Testing of Ocean Structures – Case on Slender Marine Systems
IMT-10-2019	Finn-Christian W. Hanssen	Non-Linear Wave-Body Interaction in Severe Waves
IMT-11-2019	Trygve Olav Fossum	Adaptive Sampling for Marine Robotics
IMT-12-2019	Jørgen Bremnes Nielsen	Modeling and Simulation for Design Evaluation
IMT-13-2019	Yuna Zhao	Numerical modelling and dyncamic analysis of offshore wind turbine blade installation
IMT-14-2019	Daniela Myland	Experimental and Theoretical Investigations on the Ship Resistance in Level Ice
IMT-15-2019	Zhengru Ren	Advanced control algorithms to support automated offshore wind turbine installation
IMT-16-2019	Drazen Polic	Ice-propeller impact analysis using an inverse propulsion machinery simulation approach
IMT-17-2019	Endre Sandvik	Sea passage scenario simulation for ship system performance evaluation

IMT-18-2019	Loup Suja-Thauvin	Response of Monopile Wind Turbines to Higher Order Wave Loads
IMT-19-2019	Emil Smilden	Structural control of offshore wind turbines – Increasing the role of control design in offshore wind farm development
IMT-20-2019	Aleksandar-Sasa Milakovic	On equivalent ice thickness and machine learning in ship ice transit simulations
IMT-1-2020	Amrit Shankar Verma	Modelling, Analysis and Response-based Operability Assessment of Offshore Wind Turbine Blade Installation with Emphasis on Impact Damages
IMT-2-2020	Bent Oddvar Arnesen Haugaløkken	Autonomous Technology for Inspection, Maintenance and Repair Operations in the Norwegian Aquaculture
IMT-3-2020	Seongpil Cho	Model-based fault detection and diagnosis of a blade pitch system in floating wind turbines
IMT-4-2020	Jose Jorge Garcia Agis	Effectiveness in Decision-Making in Ship Design under Uncertainty
IMT-5-2020	Thomas H. Viuff	Uncertainty Assessment of Wave-and Current-induced Global Response of Floating Bridges
IMT-6-2020	Fredrik Mentzoni	Hydrodynamic Loads on Complex Structures in the Wave Zone
IMT-7-2020	Senthuran Ravinthrakumar	Numerical and Experimental Studies of Resonant Flow in Moonpools in Operational Conditions
IMT-8-2020	Stian Skaalvik Sandøy	Acoustic-based Probabilistic Localization and Mapping using Unmanned Underwater Vehicles for Aquaculture Operations
IMT-9-2020	Kun Xu	Design and Analysis of Mooring System for Semi-submersible Floating Wind Turbine in Shallow Water
IMT-10-2020	Jianxun Zhu	Cavity Flows and Wake Behind an Elliptic Cylinder Translating Above the Wall
IMT-11-2020	Sandra Hogenboom	Decision-making within Dynamic Positioning Operations in the Offshore Industry – A Human Factors based Approach
IMT-12-2020	Woongshik Nam	Structural Resistance of Ship and Offshore Structures Exposed to the Risk of Brittle Failure
IMT-13-2020	Svenn Are Tutturen Værnø	Transient Performance in Dynamic Positioning of Ships: Investigation of Residual Load Models and Control Methods for Effective Compensation
IMT-14-2020	Mohd Atif Siddiqui	Experimental and Numerical Hydrodynamic Analysis of a Damaged Ship in Waves
IMT-15-2020	John Marius Hegseth	Efficient Modelling and Design Optimization of Large Floating Wind Turbines

IMT-16-2020	Asle Natskår	Reliability-based Assessment of Marine Operations with Emphasis on Sea Transport on Barges
IMT-17-2020	Shi Deng	Experimental and Numerical Study of Hydrodynamic Responses of a Twin-Tube Submerged Floating Tunnel Considering Vortex-Induced Vibration
IMT-18-2020	Jone Torsvik	Dynamic Analysis in Design and Operation of Large Floating Offshore Wind Turbine Drivetrains
IMT-1-2021	Ali Ebrahimi	Handling Complexity to Improve Ship Design Competitiveness
IMT-2-2021	Davide Proserpio	Isogeometric Phase-Field Methods for Modeling Fracture in Shell Structures
IMT-3-2021	Cai Tian	Numerical Studies of Viscous Flow Around Step Cylinders
IMT-4-2021	Farid Khazaeli Moghadam	Vibration-based Condition Monitoring of Large Offshore Wind Turbines in a Digital Twin Perspective
IMT-5-2021	Shuaishuai Wang	Design and Dynamic Analysis of a 10-MW Medium-Speed Drivetrain in Offshore Wind Turbines
IMT-6-2021	Sadi Tavakoli	Ship Propulsion Dynamics and Emissions
IMT-7-2021	Haoran Li	Nonlinear wave loads, and resulting global response statistics of a semi-submersible wind turbine platform with heave plates
IMT-8-2021	Einar Skiftestad Ueland	Load Control for Real-Time Hybrid Model Testing using Cable-Driven Parallel Robots
IMT-9-2021	Mengning Wu	Uncertainty of machine learning-based methods for wave forecast and its effect on installation of offshore wind turbines
IMT-10-2021	Xu Han	Onboard Tuning and Uncertainty Estimation of Vessel Seakeeping Model Parameters
IMT-01-2022	Ingunn Marie Holmen	Safety in Exposed Aquacultrue Operations
IMT-02-2022	Prateek Gupta	Ship Performance Monitoring using In-service Measurements and Big Data Analysis Methods
IMT-03-2022	Sangwoo Kim	Non-linear time domain analysis of deepwater riser vortex-induced vibrations
IMT-04-2022	Jarle Vinje Kramer	Hydrodynamic Aspects of Sail-Assisted Merchant Vessels
IMT-05-2022	Øyvind Rabliås	Numerical and Expermental Studies of Maneuvering in Regular and Irregular Waves

IMT-06-2022	Pramod Ghimire	Simulation-Based Ship Hybrid Power System Conspet Studies and Performance Analyses
IMT-07-2022	Carlos Eduardo Silva de Souza	Structural modelling, coupled dynamics, and design of large floating wind turbines
IMT-08-2022	Lorenzo Balestra	Design of hybrid fuel cell & battery systems for maritime vessels
IMT-09-2022	Sharmin Sultana	Process safety and risk management using system perspectives – A contribution to the chemical process and petroleum industry
IMT-10-2022	Øystein Sture	Autonomous Exploration for Marine Minerals
IMT-11-2022	Tiantian Zhu	Information and Decision-making for Major Accident Prevention – A concept of information-based strategies for accident prevention
IMT-12-2022	Siamak Karimi	Shore-to-Ship Charging Systems for Battery-Electric Ships
IMT-01-2023	Huili Xu	Fish-inspired Propulsion Study: Numerical Hydrodynamics of Rigid/Flexible/Morphing Foils and Observations on Real Fish
IMT-02-2023	Chana Sinsabvarodom	Probabilistic Modelling of Ice-drift and Ice Loading on Fixed and Floating Offshore Structures
IMT-03-2023	Martin Skaldebø	Intelligent low-cost solutions for underwater intervention using computer vision and machine learning
IMT-04-2023	Hans Tobias Slette	Vessel operations in exposed aquaculture – Achieving safe and efficient operation of vessel fleets in fish farm systems experiencing challenging metocean conditions
IMT-05-2023	Ruochen Yang	Methods and models for analyzing and controlling the safety in operations of autonomous marine systems
IMT-06-2023	Tobias Rye Torben	Formal Approaches to Design and Verification of Safe Control Systems for Autonomous Vessels
IMT-07-2023	YoungRong Kim	Modeling Operational Performance for the Global Fleet & Application of an Energy Saving Measure
IMT-08-2023	Henrik Schmidt-Didlaukies	Modeling and Hybrid Feedback Control of Underwater Vehicles
IMT-09-2023	Ehsan Esmailian	Optimal Ship Design for Operating in Real Sea States
IMT-10-2023	Astrid Vamråk Solheim	Exploring the performance of conceptual offshore production systems for deep-sea mining
IMT-11-2023	Benjamin Lagemann	Conceptual design of low-emission ships

IMT-12-2023	Erling Neerland Lone	Fatigue reliability of offshore Mooring chains under influence of mean load and corrosion
IMT-13-2023	Kamyar Malekibagherabadi	Simulator Approach to Concept Analysis and Optimization of Marine Power Plants
IMT-14-2023	Håvard Snefjellås Løvås	Optical Techniques for Hyperspectral Imaging of the Seafloor
IMT-15-2023	Stian Høegh Sørum	Uncertainties in the Design of Monopile Offshore Wind Turbines
IMT-16-2023	Nathalie Ramos	Mechanical and thermal simulations of 3D printed structures and the 3D printing process
IMT-17-2023	Daeseong Park	Model-Based Design of Marine Hybrid Power Systems
IMT-18-2023	Chuanqi Guo	Analysis and modeling of risk of an autonomous ferry for safer design and operation
IMT-01-2024	Dennis David Langer	Hyperspectral Push-broom Systems: Operations, Software Development, and Spatial Resolution
IMT-02-2024	Jens Einar Bremnes	Safe Autonomy in Marine Robotics
IMT-03-2024	George Katsikogiannis	Estimation of Long-Term Fatigue and Extreme Responses of Large-Diameter Monopiles for Offshore Wind Turbines
IMT-04-2024	Alexandre Cardaillac	Towards autonomous underwater navigation and perception for end-to-end ship hull inspection
IMT-05-2024	Tale Egeberg Aasland	Numerical studies of viscous flow around straight and curved tandem cylinders
IMT-06-2024	Felix Mehlan	Digital Twins for Fault Prognosis in Offshore Wind Turbine Drivetrains
IMT-07-2024	Thomas Johansen	Risk-Based Control of Autonomous Surface Ships