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Risk assessment of collisions of an autonomous passenger ferry

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Abstract

Autonomous transportation is an increasingly popular concept and is gradually becoming a reality. This transformation also changes the way people travel. For example, the autonomous ferry is an emerging alternative for residents living in coastal areas. To evaluate the safety of an autonomous ferry, a thorough safety review is necessary. This paper makes an initial attempt by developing a model for performing a risk assessment of collisions between an autonomous ship with manned vessels and applying this to a specific ferry operating in a canal. The safety barriers to prevent a collision are identified, as well as the respective failure modes. A Bayesian belief network is employed to model the collision and to quantitively assess the collision risk of the autonomous ferry. Relevant data are collected to perform a quantitative risk analysis. By running the model, the likelihood of a collision is calculated. A sensitivity analysis is also performed to identify the most contributing causes.

Keywords

Risk assessment, Bayesian belief network, autonomous ships, collision

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Introduction

Influenced by the digitalization trend, a transformation of the transport industry toward autonomous transport has started. Autonomy can contribute to improved efficiency, reduced costs, and preventing human errors. This autonomy trend also applies to maritime transport. It is believed that the conventional vessels that transport passengers and goods across rivers, seas, or oceans may be remotely controlled and eventually fully autonomous.[1]

Autonomous passenger ferries have been proposed in recent years. In 2016, the Norwegian University of Science and Technology (NTNU) launched a research project named Autoferry, the major goal of which is to build the world's first autonomous urban passenger ferry that can be certified for passenger transportation.[2] This ferry is designed to be operating in the Trondheim canal in Norway with a capacity of 12 passengers.[2]

Attractive as the idea of autonomous ferries seems, there is a fundamental question that needs to be answered before approval and commissioning: Is it safe? Even though human-related errors may be reduced, which account for a significant number of marine traffic accidents, new safety issues related to, for example, the reliability of the technology and cybersecurity, arise.

To understand the risk associated with passenger transportation by autonomous ferries, a risk analysis must be performed. DNV GL[3] released a position paper, which briefly mentions the safety assurance of autonomous and remotely controlled ships. The Maritime Safety Committee (MSC) of the International Maritime Organization (IMO)[4] finalized the regulatory scoping exercise on Maritime Autonomous Surface Ships (MASS) in 2021. A Preliminary Hazard Analysis (PHA) of a prototype named *MilliAmpere* of the Autoferry concept has also been conducted.[5] In the PHA, five categories of hazard types and more than a hundred hazardous events were identified. Among the various potential hazards, the scenario "collision" is considered to be the most serious accident. This article aims to quantify the collision probability in the design phase between an autonomous ship with other crossing ships.

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A lot of literature covers probabilistic risk assessment of ship-ship collisions. For instance, Zhang et al.[6] proposed an approach for risk analysis of collisions based on AIS data. Hänninen and Kujala[7] presented a BBN where the factors were based on DNV[8] to assess the causation probability of a collision of large passenger ships affected by weather and human factors. These articles are concerned about traditional ships with crew onboard.

Recently, there has been an increasing number of publications on risk assessment of various aspects of autonomous ships, for example, Tam and Jones[9] on cyber-risk and Zhang et al.[10] on human errors.

Among the articles about systematic risk analysis of autonomous ships, Wrobel et al.[11]proposed a primary generic BBN by brainstorming to qualitatively assess the risk of collision, grounding, etc., of MASS. A system-theoretic model is developed to assess the safety of autonomous merchant vessels in Wróbel et al.[12] Fan et al.[13] proposed a framework to identify four categories of Risk influencing factors (RIFs) contributing to the navigational risk of MASS. Zhou et al.[14] employed System-Theoretic Process Analysis (STPA) to co-analyze the safety and security issues of autonomous ships. Chang et al.[15] use Failure Modes and Effects Analysis along with Evidence Reasoning and Rule-based Bayesian Networks to reduce the uncertainties in the risk assessment of MASS.

The ships discussed in all the above-mentioned literature refer to large ships navigating in open waters instead of canals. Also, most articles performed qualitative risk analysis while the quantitative risk analysis in the literature assumes a generic ship design, without considering the real number of equipment or backups, which could have considerable influence on the risk calculation and causal analysis as well. Further, the scope of the literature on risk analysis of MASS is general rather than focusing on specific scenarios such as groundings or collisions.

The objective of this paper is to propose a risk model that combines BBN with a traffic-based model proposed in Kristiansen[16] to include the impact of traffic on the collision risk of MASS. The autonomy level (AL) of the vessel is assumed to be AL-4, which means "Human in the loop: operator/supervisory – decisions and action are performed autonomously with human supervision. High impact decisions are implemented in a way to allow human operators to intercede and override them."[17] The risk model is based on the real used equipment of the prototype ferry model named *MilliAmpere*. The application is for a ferry, but the model considers the common components of the autonomy system of any autonomous ship, that is detection, decision, and propulsion system as well as remote supervision. The proposed model is applied to the autonomous ferry crossing a canal in Trondheim to show the likelihood of a collision between the ferry and a manned vessel.

The rest of this paper is organized as follows. The risk model for collisions is described in Section 2. Section 3 presents the application of the proposed model to the Autoferry case, including data collection for parameters in these models, estimation of collision probability by running the models, and sensitivity analysis that identifies the causes with the most significant influence on the occurrence of a collision. In Section 4, the results are briefly discussed. This is followed by Section 5, where conclusions are reached.

Methodology

A general model for impact accidents has been proposed by Kristiansen.[16] According to Kristiansen,[16] the probability of an accident is obtained by the probability of losing the vessel's navigational control multiplied by the impact probability. In the scenario of a collision between a vessel and other crossing vessels, the impact probability can be interpreted as the probability that the vessel enters the area where it is exposed to collision hazards with other crossing vessels.[16] It is shown in Kristiansen[16] as follows:

$$P_a = P_c \times P_i \tag{1}$$

Where:

P_a = The probability of an accident per passage.

P_c = The probability of losing navigational control of the vessel per passage.

P_i = Impact probability.

Therefore, to derive the probability of an accident, two parts of the work need to be completed. The first part is calculating P_c, as presented in section 2.1. The second part is calculating P_i, as presented in the following section 2.2. The BBN model that is developed is related to P_c, while the calculation of P_i is in accordance with the model proposed by Kristiansen.[16]

Probability of losing navigational control of the vessel

In Kristiansen,[16] the probability of losing navigational control of the vessel per passage is obtained based on historical data from accidents. However, no data are available for autonomous ferries because it is a novel concept and has not operated in practice yet. To solve this challenge, a BBN model is developed to quantify the probability of losing navigational control. BBN is chosen because it is recommended by Thieme et al.[18] as a suitable tool for the risk assessment of autonomous vessels.

BBN is a directed acyclic graph made up of nodes and arcs, where the arcs represent conditional

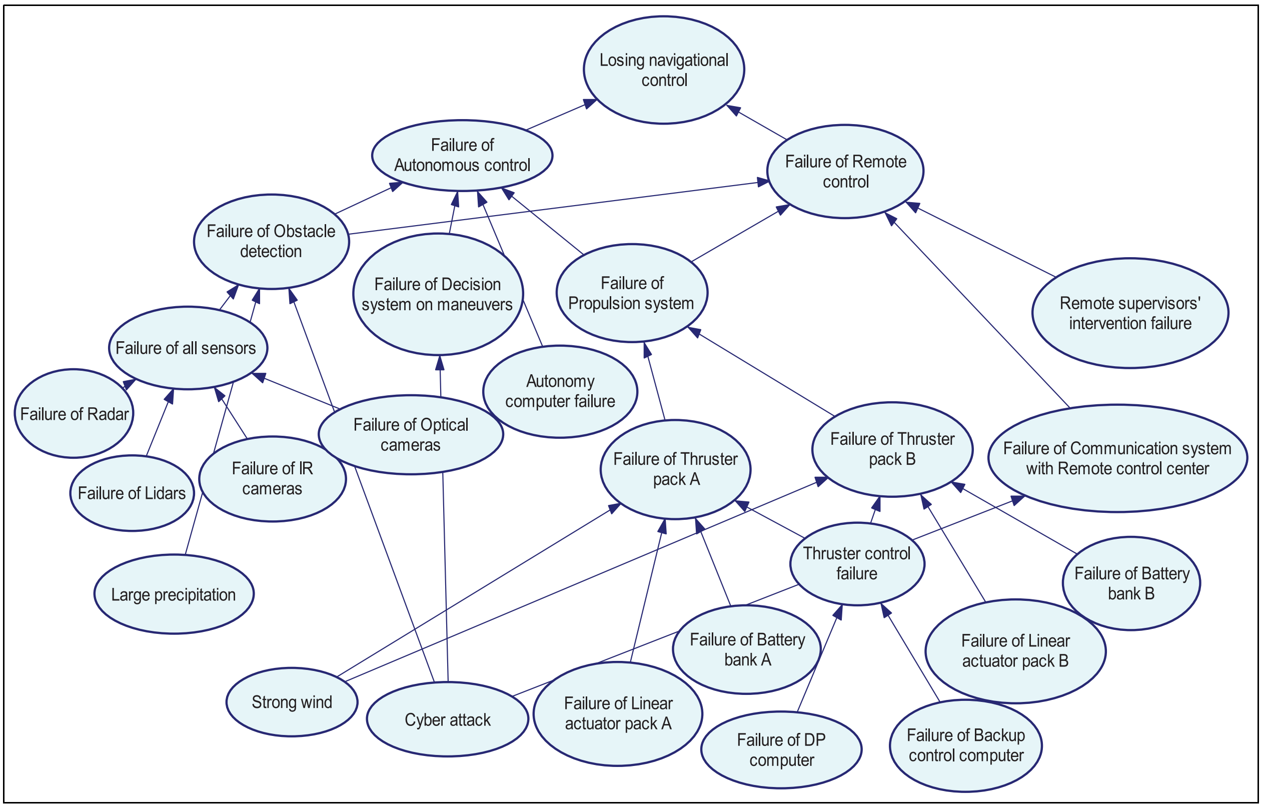

Figure 1. The BBN for losing navigational control over an autonomous ferry.

dependencies between nodes. The joint probability $P(U)$, where $U = \{A_1, \dots, A_n\}$ is calculated as:

$$P(U) = \prod_{i=1}^{n} P(A_i | P_a(A_i)) \quad (2)$$

Where $P_a(A_i)$ is the parent set of variable A_i and $P(A_i|P_a(A_i))$ refers to the probability of $P(A_i)$ given $P_a(A_i)$.[19]

The BBN is shown in Figure 1. It should be mentioned that many nodes of this BBN are inspired by or adapted from the position paper from DNV GL[3] and the PHA report.[5] The team that performed the PHA consists of more than 10 experts from various fields such as risk assessment, ship design, sensor fusion, cybernetics, etc.[5]

As the BBN shows, there are two barriers against the loss of navigational control – the autonomous control system and the remote control. Loss of control will only occur when both barriers fail.

First of all, the obstacle detection system, decision system on maneuvers, along with the electrical propulsion system constitute the autonomous ferry's control system. These subsystems must all function for the control system to work, that is, the detection system must accurately detect the obstacles, the decision system should subsequently decide on feasible actions, and the propulsion system needs to successfully implement these actions. Only if all of these are successful, the autonomous ferry operates normally.

The full sensor suite consists of one radar, two lidars, four IR cameras, and four optical cameras. This may vary from one ship to another, but in this case, it is based on the *Milliampere*.

The remote control is another safety barrier besides the autonomous control. The supervisor in the onshore control room can take control of the ferry when needed. The BBN shows that the failure of remote control can be caused by either failure of the communication system, obstacle detection system, propulsion system, or remote supervisors' failures in intervention. It is noted that the remote control will also rely on the same obstacle detection and propulsion systems, as the autonomous control.

Looking further down in Figure 1, the detailed causes that lead to the failures of the safety barriers are presented, including environmental hazards, cyber attacks, reliability of technical components, human errors, and so on. Notably, the propulsion system is composed of two thruster packs (diagonally distributed thrusters), Thruster pack A and Thruster pack B. The function of either thruster pack can make the propulsion system operate normally. In other words, only

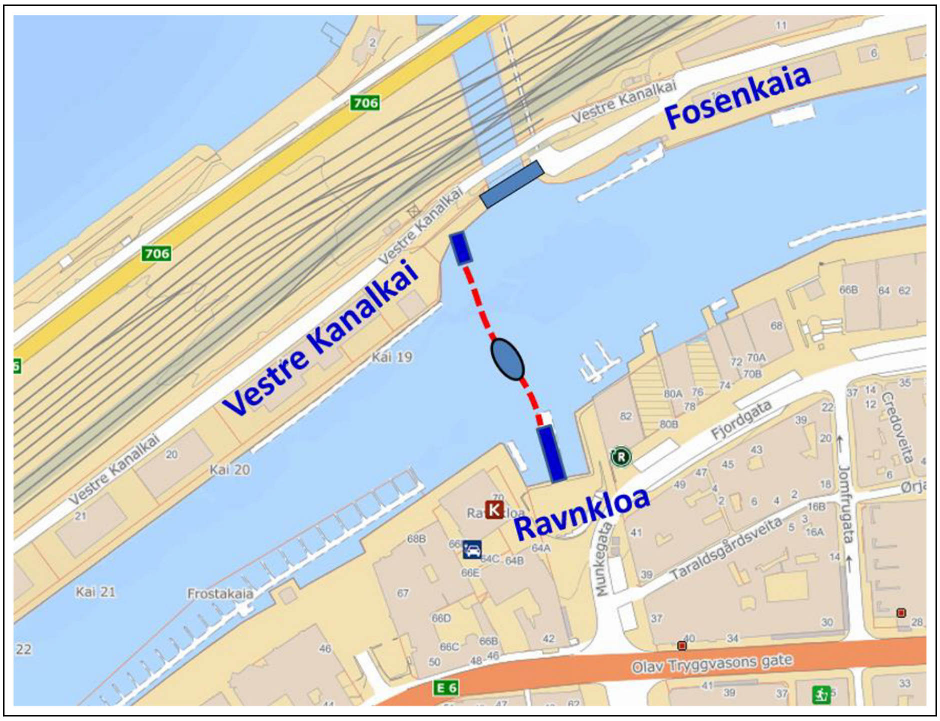

Figure 2. The designed operation course of the autonomous ferry in Trondheim.

when two thruster packs fail at the same time will lead to the failure of the propulsion system. Similarly, there are backup linear actuators and battery banks.

Calculation of the impact probability

When the autonomous ferry is transferring passengers in the canal, other vessels are also occasionally crossing the passage of the ferry. As a result, collisions could occur. According to Kristiansen,[16] for the scenario of a crossing collision, the expected collision frequency F_i per passage can be calculated using the below equation:

$$F_i = (B_1 + L_2)\frac{N_{m1}}{\nu_2} + (L_1 + B_2)\frac{N_{m1}}{\nu_1} \tag{3}$$

where

B_1 = Beam of crossing ship (m)
L_1 = Length of crossing ship (m)
ν_1 = Speed of crossing ships (knots)
B_2 = Mean beam of the subject ship (m)
L_2 = Mean length of the subject ship (m)
ν_2 = Mean speed of subject ship (knots)
$N_{\mathrm{m}1}$ = arrival frequency of crossing ships (ship/unit of time)

It should be stated that the P_i in equation (1) can be viewed as equal to F_i when F_i is low. For instance, if the calculated F_i is 0.01 per passage of the ship, in other words, one collision is expected when the ship crosses the canal a hundred times, then the probability that a collision will occur per passage of the ship is 0.01.

Application

The following section presents the application of the model, with the various data needed to conduct a quantitative risk assessment of collision between the prototype autonomous ferry named *MilliAmpere* in the Autoferry project and other crossing vessels in the Trondheim canal. It should be stressed that the autonomous ferry has not operated in the canal yet but is supposed to run during the summertime in Trondheim. Thus, this application is a risk assessment at the design stage.

Operation of the ferry

The autonomous ferry will operate in the Trondheim canal, connecting Ravnkloa and Vestre Kanalkai, as shown in Figure 2. The beam and length of the ferry are 3.5 and 8.45 m, respectively. The mean speed is 3 knots (approximately 1.5 m/s).

It is assumed that the autonomous ferry will operate from 8 am to 6 pm every day in the summer season. The frequency of crossings is assumed to be every 10 min, meaning the ferry will depart from either side every 20 min. The duration of each transfer, including loading passengers, crossing the canal, docking, and unloading passengers, will be approximately 1.5 min. Based on

Table 1. Weather data based on data recorded in June 2019.[20]

Month	Duration of precipitation $\geqslant 7.6$ mm/h	Duration of strong wind (gusts' speed $\geqslant 10$ m/s)
June	1 h	2 h

these assumptions, the total number of transfers of the autonomous ferry in the summer month of June is 1800, and June is used in further analysis.

Traffic data

Other traffic in the canal plays an important role when assessing collision risk. In general, the busier the canal is (the more boats, canoes, paddles, kayaks, etc.), the higher the risk will be. Thus, to gather knowledge and data of the traffic in the area of the canal where the autonomous ferry will operate, simple observation and counting of the crossing traffic have been performed.

On 12th June 2019, Wednesday from 15:15 to 18:30, there were in total 34 crossing boats observed. On 15th June 2019, Saturday from 12:15 to 14:15, there were 58 crossings, which means that this was a much more crowded day than Wednesday.

Based on the observed data, the approximate number of all kinds of boats that cross the course of the autonomous ferry for a weekday in June 2019 from 8 am to 6 pm can be estimated as

$$\frac{34}{3.25h} \times 10h = 104.62 \tag{4}$$

It should be clarified that this is a simplified estimation of the actual traffic based on the assumption that the traffic is constantly distributed over the day. If time allowed, the observation of the traffic in the full day should have been carried out. Likewise, the estimated number of boats on a Saturday or Sunday in June 2019 from 8 am to 6 pm is

$$\frac{58}{2h} \times 10h = 290 \tag{5}$$

There are 20 weekdays and 10 weekend days in June 2019. Thus, the estimated number of total crossing boats in the canal in June is as follows.

$$20 \times 104.62 + 10 \times 290 = 4992.31 \approx 4992 \tag{6}$$

Weather data

Data for harsh weather – large precipitation ($\geqslant 7.6$ mm/h) and strong wind (Gusts' speed $\geqslant$ 10m/s) – during the operation period of the autonomous ferry in June 2019 in Trondheim are retrieved from Yr[20] and shown in Table 1. These data are the inputs to the harsh weather nodes in the BBN that affect the probability of losing control of the ferry. The limit for the large precipitation ($\geqslant 7.6$ mm/h) is based on the categories of rain intensity.[21] However, the actual precipitation limit should be verified against the design limit of the sensors onboard the ferry. The limit for strong wind (Gusts' speed $\geqslant$ 10 m/s) is chosen based on the design of the ferry. It should be clarified that the fog or darkness are not considered as influencing factors in our case because, in the practice of the operation of the autonomous ferry in urban water channels, the fog rarely can be so dense that the visibility is too limited for the ferry to operate in such a short distance, that is crossing a channel. Also, the ferry is designed to operate in the daytime of the summer season, therefore the darkness is not taken into account.

Failure probabilities

One of the key challenges when performing a quantitative risk assessment is the availability of failure data. Little or no specific data for autonomous ships are available. In this paper, a variety of data sources have been searched. Where we have not been able to find data from literature, expert opinion from the PHA workshop[5] has been used. In general, it is considered that this gives conservative estimates. All the occurrence probabilities for the nodes in the BBN are summarized in Table 2.

It should be stressed that the estimated probabilities are quantified in terms of per passage of the autonomous ferry. It should also be mentioned that some data sources do not completely correspond to the components. The data source for IR camera, for instance, refers to the failure frequency of IR cameras used for fire detection, rather than that detect objects on water. Better data sources may be available in future work, but the current data are used as a basis for the first step of a quantitative risk assessment.

Conditional probability tables

The next step is to quantify the conditional probability tables (CPT). This is based on the PHA workshop. One of the CPTs is presented in Table 3. This table shows how large precipitation could disturb the successful detection of the obstacles around the autonomous ferry. The effect is represented by the CPT.

Impact probability

The expected collision frequency is calculated based on equation (3). In our case, the beam of a crossing vessel is averaged to be 8.5 ft (2.59 m) while the length is 26 ft (7.92 m). The speed of crossing vessels is 4 knots. Further, the arrival frequency of crossing vessels, based on the observation, is $\frac{4992\ \textit{crossing vessels in June}}{30\ \textit{days} \times 10\ \textit{hours of operation per day}} = 16.64 \textit{vessels/hour}$. With the data for the autonomous ferry, as presented in

Table 2. Failure probabilities of the nodes in the BBN.

Item	No. of failures	Failure frequency (per hour)	Failure frequency (per passage)	Note	Source
Linear actuator	560 per 10^9 h	5.60E-07	1.40E-08		Beurden-Amkreutz[22]
Thruster	1 per 8 years	3.42E-05	8.56E-07		From manufacturer
Radar	1 per 1275 h	7.84E-04	1.96E-05	Radar for weather observations	Zrnic et al.[23]
Lidar	1 per 10^9 h	1.00E-05	2.50E-07		From manufacturer
Large precipitation ($\geqslant$7.6 mm/h)	1 h over 300 h	3.33E-03	8.33E-05		Yr[20]
Strong wind (gusts' speed $\geqslant$ 10m/s)	2 h over 300 h	6.67E-03	1.67E-04		Yr[20]
Autonomy computer	2 per 10^6 h	2.00E-06	5.00E-08	Data for control logic unit	OREDA[24]
Cyber attack	1 per 1 year	2.28E-04	6.85E-06		PHA
DP computer	2 per 10^6 h	2.00E-06	5.00E-08	Data for control logic unit	OREDA[24]
Backup control computer	2 per 10^6 h	2.00E-06	5.00E-08	Data for control logic unit	OREDA[24]
Battery bank	1 per 125,000 h	8.00E-06	2.00E-07		Adams et al.[25]
Communication system with the remote-control center	5 per 1 year	1.37E-03	3.42E-05		PHA
IR camera	1800 per 10^9 h	1.80E-06	4.50E-08	IR camera for fire detection	Beurden-Amkreutz[26]
Optical cameras	1 per 100 years	2.28E-06	6.85E-08		PHA
Probability of failures in obstacle detection by sensors			1.00E-05		Wilthil et al.[27]
Failure probability of decision system on maneuvers to avoid collisions			1.00E-04		PHA
Human errors in the remote operator's intervention			0.16	Type C – difficult task	Williams[28]

Table 3. The CPT for obstacle detection by sensors.

Large precipitation	Yes				No			
Cyber attack	Yes		No		Yes		No	
All sensors	Fail	Work	Fail	Work	Fail	Work	Fail	Work
Obstacle detection failure	1	1	1	0.001	1	1	1	0.00001
Obstacle detection success	0	0	0	0.999	0	0	0	0.99999

section 3.1, the expected collision frequency per passage of the autonomous ferry, F_i, is calculated to be 0.06. As stated in section 2.2, the impact probability P_i is almost equal to F_i, which is 0.06.

Running the BBN model

The BBN can now be run with the input data provided. The model is implemented in the software GeNIe 2.3 developed by Bayes Fusion LLC (https://www.bayesfusion.com/). The probability results for some key nodes are retrieved and summarized in Table 4.

The collision frequency can subsequently be derived by multiplying the probability of losing navigational control (per passage) with the number of passages of the autonomous ferry and the impact probability per passage, which are from section 3.3. The results for June 2019 at the Trondheim canal are as follows:

Table 4. The occurrence probabilities for the accident scenarios for June 2019 at the Trondheim canal.

Node	Probability (per passage)
Failure of autonomous control	1.2×10^{-4}
Failure of remote control	0.16
Losing navigational control	3.8×10^{-5}

- Number of passages of the ferry 1800
- Impact probability per passage 0.06
- Probability of losing navigational control per passage 3.8×10^{-5}

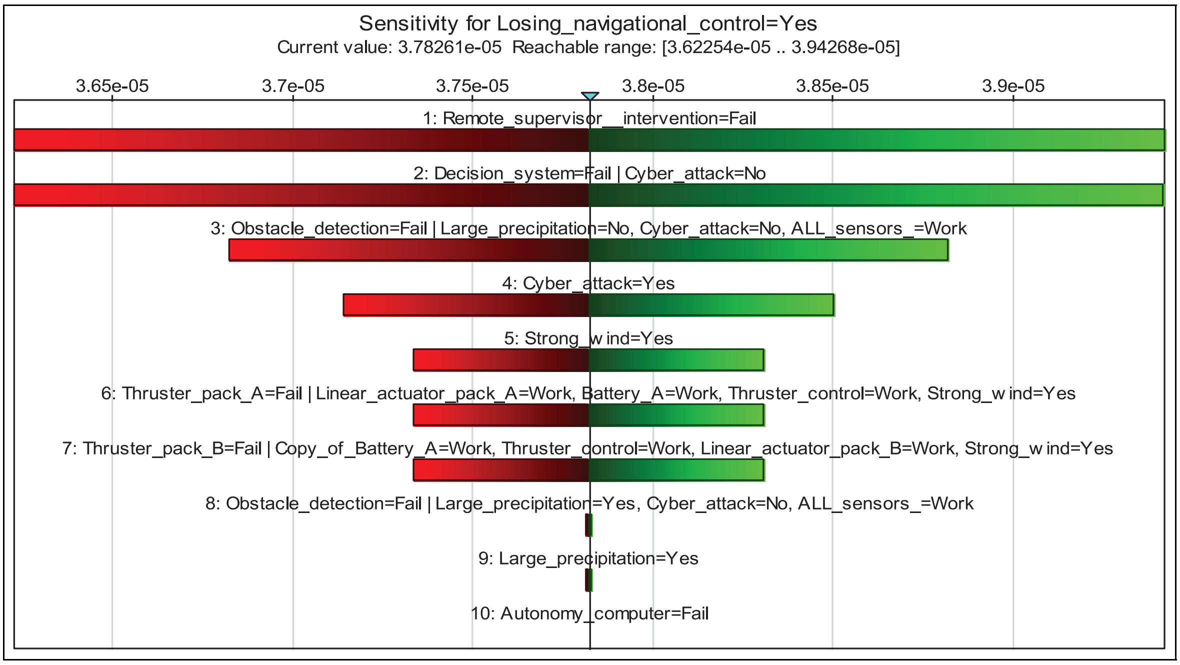

Figure 3. Sensitivity tornado diagram for losing navigational control.

- Probability of collision per passage 2.2×10^{-6}
- Collision frequency per month 0.0041

Sensitivity analysis

The sensitivity analysis is aimed at identifying the factors that contribute the most to the probability of losing control and accordingly to propose risk reduction measures. A sensitivity analysis also indicates where more effort should be put on data collection. If a factor contributes very little to the losing navigational control probability, reducing the uncertainty will have little impact on the uncertainty in the total result and is therefore of limited value.

Figure 3 presents the results for the sensitivity analysis with losing navigational control as the target. The analysis is performed in GeNIe 2.3. As can be seen in Figure 3, the result is most sensitive to the Failure of the Remote supervisor's intervention. At the same time, the probability applied for this node (0.16) is uncertain because it is a generic failure probability number referring to a complex task requiring a high level of comprehension and skill.[28] Therefore, another sensitivity tornado diagram is generated conditioned that the failure probability of the remote supervisor's intervention drops to 0.09. The results are shown in Figure 4.

It must be stressed that a very low value of 1.0×10^{-5} has been applied for the obstacle detection system. This is also an uncertain value and depends on whether many so-called "false alarms" can be accepted. If the probability of successfully detecting obstacles is high, there will also be many false alarms, meaning that the ferry stops when it does not have to. To study the effect of the failure conditional probabilities of obstacle detection system, another sensitivity tornado is generated by increasing the conditional probabilities by a factor of 10, from 1.0×10^{-5} under large precipitation and 1.0×10^{-3} without large precipitation to 1.0×10^{-4} with large precipitation and 1.0×10^{-2} without large precipitation per passage, respectively. The results are shown in Figure 5.

Discussion

Discussion of the results

As can be seen from Section 3.7, the probability of a collision between the autonomous ferry with crossing vessels is about 2.2×10^{-6} per passage. Specifically speaking, the probability of losing navigational control of the autonomous ferry is 3.8×10^{-5} per passage. Compared to the historical probability of losing navigational control for manned ships of 2.0×10^{-4} per passage,[16] the autonomous ferry seems to have a lower collision risk. The probability that the autonomous control system fails is 1.2×10^{-4} per passage. This indicates the reliable capability of collision avoidance for an autonomous ferry.

Section 3.7 also shows that for the autonomous ferry operating in a summer month like June 2019 in the Trondheim canal, the estimated collision frequency is 0.0041. If it is assumed that the autonomous ferry operates 6 months each year, the result corresponds to about 0.024 collisions per year. However, this result is conservative because the actual number of collisions could be lower considering that other vessels can also perform evasive maneuvers while encountering the out-of-control autonomous ferry. For instance, assuming that the probability of failed evasive maneuvers attempts by

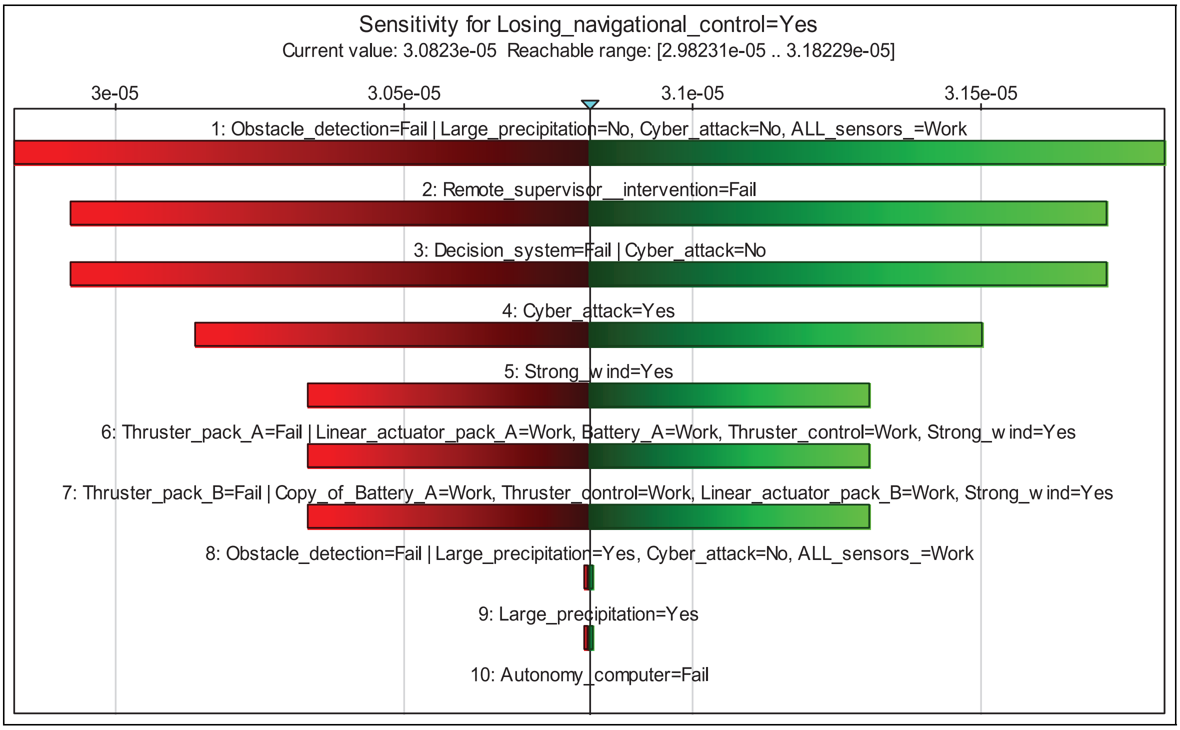

Figure 4. Sensitivity tornado diagram for losing navigational control while the failure probability of the remote supervisor's intervention is 0.09.

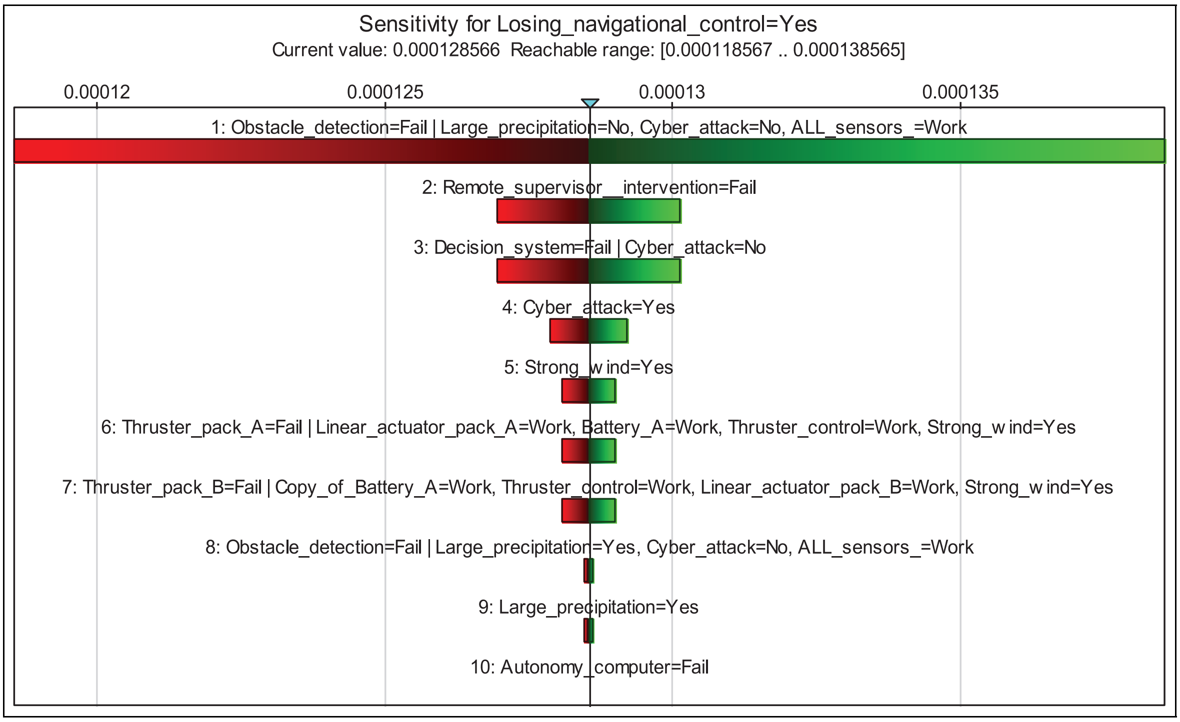

Figure 5. Sensitivity tornado diagram for losing navigational control while the failure probability of obstacle detection system increases by nine times.

the crossing vessels is 0.1, then the collision frequency of autonomous ferry drops to 0.0024, or one collision every 400 years.

From Figure 3, it is interesting to note that the failures of remote supervisor's intervention and decision system are almost equally the most contributing factors to the loss of navigational control. Apart from these two, failure of obstacle detection and cyber attack also make significant contributions to causing a collision. Thus, to improve the reliability of the remote operation, to improve the successful obstacle detection rate, and to enhance cyber security could be effective measures to reduce the risk of losing navigational control.

Figure 4 shows that the remote supervisor's intervention becomes the second most sensitive node when the failure probability decreases to 0.09. Further, the probability of losing navigational control is only about 20% smaller than the original probability, indicating it is not as much affected by the failure probability of the remote supervisor's intervention.

Figure 5 shows that the probability of losing navigational control is about 3.4 times larger than the original probability when the probability of obstacle detection failures is increased by a factor of 10. This shows that the failure probability of obstacle detection system can affect the occurrence of losing navigational control of the autonomous ferry to a large extent.

The strengths and weaknesses of the model

The strengths of the proposed model are as followings: Instead of using a generic value for the probability of losing vessel navigation control, this work develops a BBN to calculate the specific probability. The BBN covers the whole process of the autonomous control system – detection, decision, and action – to avoid potential collisions. Even though the detailed technical units in the BBN, for instance, the kinds and number of sensors, the configuration of thrusters, etc. are based on the design of the autonomous ferry in the Autoferry project, the BBN can still be easily adapted to another autonomous ship design.

The weaknesses of the model lie in the following aspects: First, the developed BBN may have not captured all the possible causes that lead to a collision. Also, certain nodes in the BBN are not fully developed but assigned probability numbers instead. For instance, one reason why BBN often is preferred as a method for modeling is that it is well suited for including human and organizational factors. In this case, the only non-technical node is "Remote supervisor's intervention." The reason for this is of course that the system primarily is autonomous, not relying on any human intervention. The remote supervisor node could have been expanded further and there will also be human involvement in the design and maintenance of the systems that could have been included. However, finding data for such nodes would have been difficult and at this stage, we consider the applied level of detail to be sufficient.

Uncertainties of the data

Data for the failure modes, weather conditions, remote control are collected where possible. The traffic in the canal during 2 days is observed and recorded, providing practical data while obtaining the impact probability. However, there are also uncertainties in the failure frequency data and CPTs, especially in those data based on expert opinion in the PHA. The uncertainty associated with the autonomous system is primarily related to the software that interprets the signals from the sensors and decides whether there is an object that needs to be acted upon. This can be further studied by investigating the mechanisms of such software. Lastly, a longer period of observation, for example 1 month, of the traffic in the canal will be more useful.

Fortunately, not all uncertainties in data will necessarily substantially affect the result. By conducting a sensitivity analysis, failure of decision system, failure of obstacle detection, and cyber-attack are among the top nodes that influence the resulting losing navigation control probability the most. In contrast, the uncertainties of other nodes, for example large precipitation, only have little impact on the probability of losing navigational control. Thus, the uncertainties of data for the topmost sensitive nodes could be carefully investigated, for example by fault tree analysis for these nodes, in future work to reduce the uncertainties and consequently improve the conciseness of the model.

Further, considering that the presented BBN in our article can be extended and revised when we have experimental data of the autonomous ferry, a structured uncertainty assessment, such as the work by Pitchforth and Mengersen,[29] can be followed in future research.

Conclusions

In this paper, a generic model is developed for risk assessment of autonomous ship−manned vessel(s) collisions. This model is further populated with data to perform a specific quantitative probabilistic estimation of the collision for the future autonomous ferry in Trondheim, Norway. The data is based on literature and two PHA workshops with experts, which build a realistic and theoretically convincing foundation of this work. Results from the case study reveal that the collision of an autonomous ferry with other boats is rather unlikely to occur. This justifies the robustness and applicability of the proposed model. This model can be modified and adapted to other autonomous ships based on their specific configurations.

In the future, this work can be improved by identifying more causes of a collision, both from literature and by communication with experts in the field of autonomous ships, modeling the failure mechanisms of the critical causes in the BBN, and reducing the uncertainties of the most sensitive nodes. These are also the key directions for the authors' ongoing research.

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References

1. Kretschmann L, RødsethØ, TjoraÅ, et al. *Maritime unmanned navigation through intelligence in networks–qualitative assessment*. MUNIN project report, 2015 Hamburg, Germany: Fraunhofer CML.
2. Havdal G, Heggelund CT, Larssen CH, et al. *Design of a small autonomous passenger ferry*. NTNU. Trondheim, Norway, 2017.
3. DNV GL. Remote-controlled and autonomous ships. Position Paper DNV GL Høvik, Norway, 2018.
4. IMO. Meeting summaries of Maritime Safety Committee, 103rd session (MSC 103), https://www.imo.org/en/MediaCentre/MeetingSummaries/Pages/MSC-103rd-session.aspx (2021, Accessed 17 August 2021).
5. Thieme CA, Guo C, Utne IB, et al. *Final report of the preliminary hazard analysis of the MilliAmpere ferry*. 2019.
6. Zhang W, Kopca C, Tang J, et al. A systematic approach for collision risk analysis based on AIS data. *J Navig* 2017; 70: 1117–1132.
7. Hänninen M and Kujala P. The effects of causation probability on the ship collision statistics in the Gulf of Finland. In: Weintrit A (ed.) *Marine navigation and safety of sea transportation*. London: Taylor and Francis, 2009, pp.267–272.
8. Det Norske Veritas. *Formal aafety assessment – large passenger ships, ANNEX II*. 2003. Høvik, Norway: DNV.
9. Tam K and Jones K. Cyber-risk assessment for autonomous ships. In: *2018 international conference on cyber security and protection of digital services (cyber security)*, Glasgow, 11–12 June 2018, pp.1–8. New York, NY: IEEE.
10. Zhang M, Zhang D, Yao H, et al. A probabilistic model of human error assessment for autonomous cargo ships focusing on human–autonomy collaboration. *Saf Sci* 2020; 130: 104838.
11. Wrobel K, Krata P, Montewka J, et al. Towards the development of a risk model for unmanned vessels design and operations. *TransNav Int J Mar Navig Saf Sea Transp* 2016; 10: 267–274.
12. Wróbel K, Montewka J and Kujala P. Towards the development of a system-theoretic model for safety assessment of autonomous merchant vessels. *Reliab Eng Syst Saf* 2018; 178: 209–224. Article.
13. Fan C, Wróbel K, Montewka J, et al. A framework to identify factors influencing navigational risk for maritime autonomous surface ships. *Ocean Eng* 2020; 202: 107188.
14. Zhou X-Y, Liu Z-J, Wang F-W, et al. A system-theoretic approach to safety and security co-analysis of autonomous ships. *Ocean Eng* 2021; 222: 108569.
15. Chang C-H, Kontovas C, Yu Q, et al. Risk assessment of the operations of maritime autonomous surface ships. *Reliab Eng Syst Saf* 2021; 207: 107324.
16. Kristiansen S. *Maritime transportation : safety management and risk analysis*. Amsterdam, The Netherlands: Elsevier/Butterworth-Heinemann, 2005.
17. Register Lloyd's. *Cyber-enabled ships-ShipRight procedure–autonomous ships*. Southampton: LR, 2016.
18. Thieme CA, Utne IB and Haugen S. Assessing ship risk model applicability to marine autonomous surface ships. *Ocean Eng* 2018; 165: 140–154.
19. Nielsen TD and Verner Jensen F. *Bayesian networks and decision graphs*. 2nd ed. New York, NY: Springer, 2007.
20. Yr. Weather statistics for Trondheim in june 2019, https://www.yr.No/en/statistics/graph/5-68010/Norway/Tr%C3%B8ndelag/Trondheim/H%C3%B8vringen (2020, Accessed 17 August 2021).
21. Glossary of Meteorology. Categories of rainfall intensity, https://web.archive.org/web/20100725142506/http://ams-glossary.allenpress.com/glossary/search?id=rain1 (2010, Accessed 18 August 2021).
22. Beurden-Amkreutz R. *Safety equipment reliability handbook: vol. 3: final elements*. 3rd ed. Sellersville, PA: exida, 2007.
23. Zrnic DS, Kimpel JF, Forsyth DE, et al. Agile-beam phased array radar for weather observations. *Bull Am Meteorol Soc* 2007; 88: 1753–1766.
24. OREDA. *Offshore reliability data volume 1 topside equipment*. Trondheim, Norway: OREDA Participants, 2009.
25. Adams WA, Blair JD, Bullock KR, et al. Cost/benefit analyses of a new battery pack management technique for telecommunication applications: future directions with fuel cell/battery systems. In: *INTELEC 2004 26th annual international telecommunications energy conference*, Chicago, IL, 19–23 September 2004, pp.73–82. New York, NY: IEEE.
26. Beurden-Amkreutz R. *Safety equipment reliability handbook: vol. 1: sensors*. 3rd ed. Sellersville, PA: Exida, 2007.
27. Wilthil EF, Brekke E and Asplin OB. Track initiation for maritime radar tracking with and without prior information. In: *2018 21st international conference on information fusion (FUSION)*, Cambridge, 10–13 July 2018, pp.1–8. New York, NY: IEEE.

28. Williams JC. Heart—a proposed method for achieving high reliability in process operation by means of human factors engineering technology. *Saf Reliab* 2015; 35: 5–25.

29. Pitchforth J and Mengersen K. A proposed validation framework for expert elicited Bayesian networks. *Expert Syst Appl* 2013; 40: 162–167.

Appendix

Table A1. The CPT for the thruster pack.

Linear actuator pack	Fail								Work							
Battery bank	Fail				Work				Fail				Work			
Thruster control	Fail		Work		Fail		Work		Fail		Work		Fail		Work	
Strong wind	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Thruster pack fails	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.171	1.71e-06
Thruster pack works	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.829	0.999998

Table A2. The CPT for all sensors.

Radar	Fail								Work							
Lidars	Fail				Work				Fail				Work			
IR cameras	Fail		Work		Fail		Work		Fail		Work		Fail		Work	
Optical cameras	Fail	Work	Fail	Work	Fail	Work	Fail	Work	Fail	Work	Fail	Work	Fail	Work	Fail	Work
All sensors fail	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Not all sensors fail	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

Table A3. The CPTs for decision system on maneuvers and communication system with the remote control center.

Cyber attack	Yes	No	Cyber attack	Yes	No
Decision system fails	1	0.0001	Communication system fails	1	3.42e-05
Decision system works	0	0.9999	Communication system works	0	0.99997

Table A4. The CPTs for the thruster control and the propulsion system.

DP computer	Fail		Work		Thruster pack A	Fail		Work	
Backup control computer	Fail	Work	Fail	Work	Thruster pack B	Fail	Work	Fail	Work
Thruster control fails	1	0	0	0	Propulsion system fails	1	0	0	0
Thruster control works	0	1	1	1	Propulsion system works	0	1	1	1