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Development of risk indicators for losing navigational control of autonomous ships

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ABSTRACT

As autonomous ships become more viable, appropriate risk indicators are increasingly needed. In the existing literature, few works are related to developing such risk indicators. Existing indicators are general and not focused on a specific autonomous vessel, let alone an actual operating ship. To bridge this research gap, this article proposes a methodology for identifying risk indicators based on a Bayesian belief network (BBN). The methodology is applied to hazardous event "losing navigational control" of a trial-operating autonomous passenger ferry. The risk indicators developed cover technical equipment, remote supervisors' capacity, and environmental conditions. The probability of losing navigational control is calculated considering the states of the risk indicators, which contributes to risk monitoring of the system during operation. Further, strong wind, the state of battery health, end-to-end delay, and packet-loss rate have been identified as critical risk indicators. These should preferably be presented in a shore control center to human operators and provide a basis for decision support, and for defining operational procedures for safe takeover and shared autonomy. The findings can further improve practitioners' understanding, monitoring, analysis, and management of the risk of loss of navigational control of autonomous ships, which is crucial to prevent collisions.

1. Introduction

Risk analysis of autonomous ships is an increasingly popular research topic (e.g.,Zhou et al. (2020); Zhang et al. (2020)). One of the main tools for risk monitoring is risk and safety indicators. Researchers employ risk and safety indicators for various purposes, such as calculating the performance of a ship's hull and propeller (Oliveira et al., 2020), calculating real-time ship-conflict probability (Zhang et al., 2022b), and improving the safety of merchant's vessels (Gil et al., 2022).

Risk indicators (RIs) differ from safety indicators. The former are measurable variables of risk-influencing factors (RIFs) related to a risk model. This means that changes in the risk level and indicators should also be reflected in changes in a risk model (Øien et al., 2011). In contrast, the latter measures to what extent safety is present (Thieme and Utne, 2017).

Øien (2001) proposed a framework to establish organizational RIs. Later, Vinnem (2010) proposed RIs for major hazards on offshore installations, including major hazard precursor data and barrier performance data. Zhen et al. (2019) adopted a systematic risk-based approach to developing some major hazard RIs to monitor, measure, and predict the national risk levels in the offshore petroleum industry.

There exist limited research publications on the use of safety and risk indicators for autonomous ships. Thieme and Utne (2017) studied and applied safety indicators of autonomous marine systems to an autonomous underwater vehicle. Wróbel et al. (2021) performed a literature review on the use of leading safety indicators in Maritime Autonomous Surface Ships (MASS) and concluded that more research is needed not only to establish general indicators but also to explore the role of indicators within a specific system of an autonomous vessel. Zhang et al. (2022a) adopted a machine learning method incorporating safety indicators to evaluate the ship grounding risk.

Fan et al. (2020) conducted an extensive literature review of RIFs for MASS, covering human, ship, environmental, and technology factors during four operation phases. Li et al. (2021) proposed a concept named Rule-aware Time-varying Conflict Risk (R-TCR) for ship collision avoidance. These works can contribute to the development of risk indicators.

Furthermore, there is no literature about the RIs of losing navigational control of autonomous ships. Hence, to bridge this gap, this article proposes a methodology for identifying risk indicators based on a BBN.

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The application of the methodology is related to the loss of navigational control over an autonomous ship. The BBN presented in this article is further work and extension from Guo et al. (2021). The objective of the present article is to develop RIs connected to the BBN that can be updated during the operation of autonomous ships. Subsequently, it could be used by human supervisors in a shore control center as a risk-monitoring tool for any autonomous ships. The RIs can also provide useful information for developing operational limits and thresholds related to the safe takeover and shared control of the autonomous ship.

In the present work, the states of the RIs can be continuously monitored, thus giving early warnings of potential risks. Therefore, the RIs work as a proactive risk monitoring tool. The use of a BBN also makes it possible to quantify and trend the risk profile. The technical equipment components and layout are based on the pilot—namely, the autonomous all-electric passenger ferry named *MilliAmpere* developed by the Autoferry project[1] at the Norwegian University of Science and Technology (NTNU). In addition, there is a shore control center (SCC) with a remote supervisor monitoring the ferry (Veitch et al., 2021). RIs can provide useful information to the human supervisor about the current risk level in operation.

The autonomy level (AL) of this autonomous ferry is AL-4, which means "human in the loop: operator/supervisory—decisions and action are performed autonomously with human supervision" and that "high impact decisions are implemented in a way to allow human operators to intercede and over-ride them" (Lloyd's Register, 2016). For the *MilliAmpere* ferry, if the autonomous control system turns abnormal under supervision in the SCC, the remote supervisors can intervene and take control of the ferry.

The contributions and novelties of this work lie in the proposed methodology for the development of risk indicators from a BBN and the application to quantitative risk monitoring of an autonomous ferry. The results both estimate the probability of losing navigational control and reveal the most critical risk indicators. Even though the application in the article is focused on an autonomous passenger ferry, the methodology is expected to be useful for autonomous ships in general.

The rest of this paper is organized as follows: the risk analysis model and the concepts of RIFs and RIs are discussed in Section 2. Section 3 presents the application of the proposed model to an autonomous ferry. In Section 4, the results are briefly discussed. Section 5 offers conclusions and implications.

2. The proposed methodology

This present article proposes a methodology to incorporate RIs in a BBN risk model and identify critical RIs. Fig. 1 shows the steps of the methodology.

2.1. Step 1: Develop the risk model (BBN)

The first step in developing a BBN model involves a causal analysis of the specific risks included in the scope of work. Preliminary hazard analysis (PHA) or similar types of risk analyses (see, e.g., Yang and Utne (2022)), and review of literature can contribute the development of BBN. The root nodes, intermediate nodes, the pivot node, and their logical relationships constitute the BBN, which is the foundation for identifying RI.

2.2. Step 2: Identify risk indicators

The next step entails identifying risk indicators, which requires introducing the concepts of RIFs and risk indicators. As defined by Øien (2001), an RIF is "an aspect (…) of a system or an activity that affects the risk level of this system or activity." An RI is defined as "a measurable/operation variable that can be used to describe the condition of a broader phenomenon or aspect of reality" (Øien, 2001).

RIs are used to measure RIFs. In the proposed BBN model, a root node is considered either an RIF or a direct RI. If the root nodes are RIFs, then the corresponding RIs need to be defined based on information from the literature, system knowledge and communications with experts. For example, precipitation is a risk factor and also a direct RI that is measurable. In contrast, the operation crew is an RIF, and some RIs cover the level of area-specific knowledge, the number of years of site-specific expertise, etc. (Haugen et al., 2012).

RIs are measurable and have different states. In the proposed methodology, the states of RIs are divided into to or three general categories. These categories are high, medium, and low and acceptable and unacceptable.

2.3. Step 3: Estimate pivot node probability

The third step involves estimating the probability of the pivot node. After identifying the RIs and their states, the prior probability distributions of the states should then be estimated according to available known data or expert opinions if data is unavailable. Subsequently, the pivot node probability can be calculated from the BBN. This provides a reference risk value.

2.4. Step 4: Identify critical risk indicators

The proposed method contributes to online risk monitoring by the supervisors in the remote-control center. Since numerous data sources exist, such as information from sensors, identifying which information to display on the remote-control screen so as not to overload supervisors remains a challenge in the design of remote-control centers (Veitch et al., 2021).

In step 4, the method identifies the critical RIs, i.e., what risk-related information should be prioritized for display on a remote-control center. To identify the most useful RIs, the evidence of the state of each RI is set, and the pivot node probability will then be updated. Specifically, the state of the worst performance of every RI is assumed. The resulting pivot probability with the most significant increase indicates the most useful RIs.

2.5. Step 5: Inference analysis

In this step, the inference analysis is conducted, which entails setting the state of the pivot node to be true and performing a backward probability updating analysis on the BBN. The updated probabilities of root nodes and RIs reveal the main causes of a top event, i.e., what led to the occurrence of the pivot node. This can also be used to determine intervals and thresholds of the RI, i.e., operational limits and when risk mitigation is needed from human operators involved in the risk monitoring.

3. Case study

The following section demonstrates an application of RI development to an autonomous ferry named *MilliAmpere* in the Autoferry project. The equipment included in the model was based on the setup of *MilliAmpere*. The autonomous ferry will operate in the Trondheim Canal, connecting two riverbanks. The AL of the ferry was assumed to be AL-4, as mentioned above.

3.1. Steps 1 and 2: Develop a risk model (BBN) and identify risk indicators

This risk model for losing navigational control over an autonomous ferry in Fig. 2 is based on the BBN model proposed by Guo et al. (2021), extended with RIs. Losing navigational control can only be caused by the

[1] https://www.ntnu.edu/autoferry.

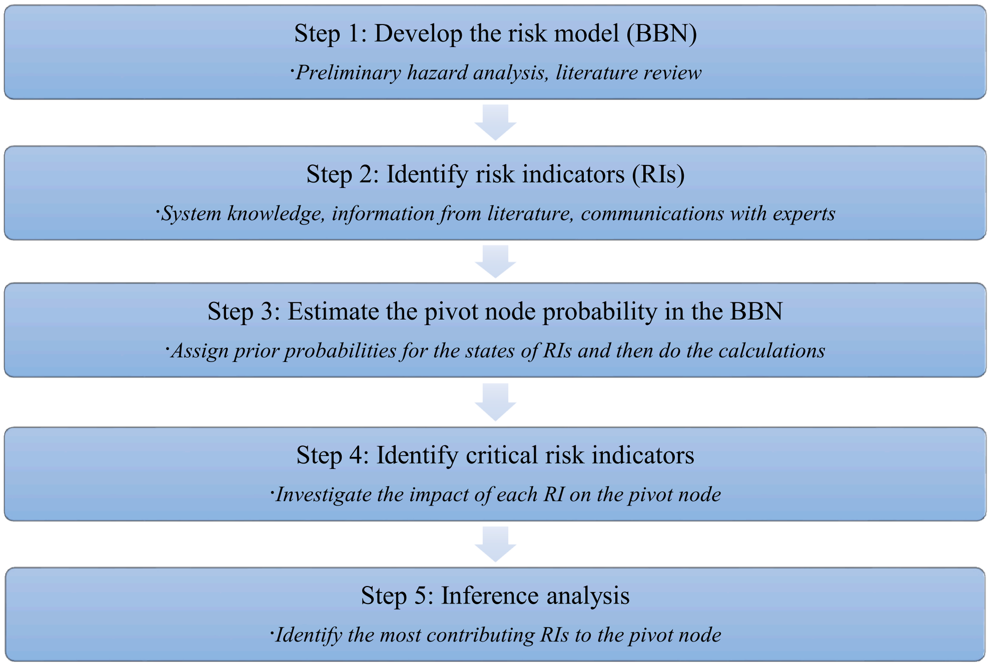

Fig. 1. The methodology for identifying risk indicators of a BBN.

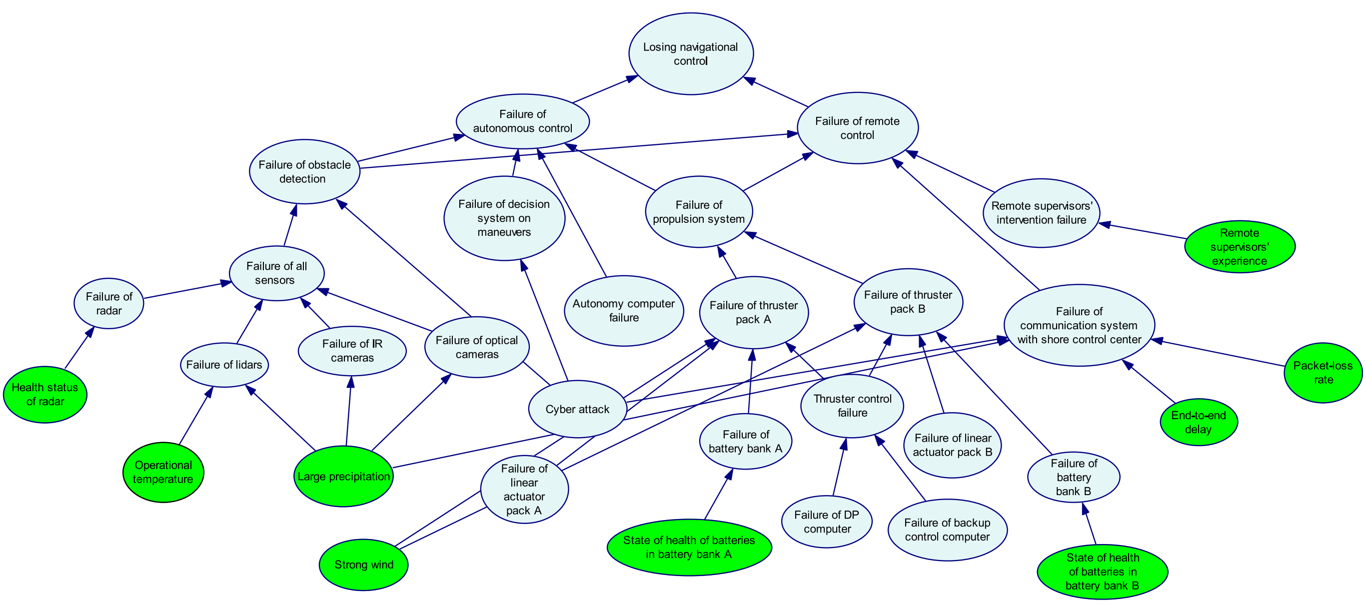

Fig. 2. The BBN model of losing navigational control of an autonomous ship with risk indicators (extended from Guo et al. (2021)).

simultaneous failures of both the autonomous and the remote-control, which both are affected by the state of the propulsion system.

Normally, the autonomous control system keeps the ferry on track. However, if the autonomous control turns abnormal under supervision, the remote supervisors can intervene and take control of the ferry to avoid losing navigational control. Therefore, both failures of autonomous and remote control will lead to the loss of losing navigational control of the autonomous ferry. The failure of the autonomous control is due to the failures of obstacle detection and the decision and propulsion systems. The failures of these systems are caused by the failures of sensors, batteries, thrusters, computers, etc., as represented by the parent nodes. The 'failure' here means the complete failures, e.g., the power is lost, or the obstacle detection fails, leading to the loss of navigational control. The failure of remote control can be caused by either the failure of communication system or human intervention failures.

The green nodes in the BBN represent the RIs developed in this article. The RIs are developed by searching the respective literature and communication with experts to find what affect the performance of the radar, lidar, batteries, etc. It should be clarified that in this case study, the RIs only refer to the measurement variables of the RIFs presented here, which mainly cover technical and environmental factors. The RIs concerned with the ship domain are out of the scope of this work.

The detailed introduction of various RIs appears in the following subsections.

3.1.1. *Risk indicators for valve-regulated lead-acid batteries*

The state of health (SOH) of valve-regulated lead-acid (VRLA) batteries is defined as the ratio between the theoretical maximum amount of charge of the aged batteries and that of new batteries. The SOH reflects the times of discharging and charging of the batteries when they still supply adequate power (Shahriari and Farrokhi, 2013). As shown by Shahriari and Farrokhi (2013), SOH can be dynamically estimated based on a fuzzy system by measuring three indicators: the state of charge (SOC), the battery power (Q), and the open-circuit voltage (VOC) while the battery is discharging or charging.

In applications, these three indicators can be continuously measured to calculate the SOH of batteries based on the method proposed by Shahriari and Farrokhi (2013). The SOH can be classified into three categories: high, medium, and low. Technical experts in the autonomous ship group decide if the current SOH of VRLA batteries is acceptable for the safe operation of the ship.

3.1.2. Risk indicators for communication systems

As exhibited by Zormatai and Kargathara (2018), packet-loss rate and end-to-end delay are two measurements of a 4G wireless network. These two RIs can also be applied to a 5G communication network. As Yasar and Zola (2022) put it, 'a packet means a basic unit of data that is grouped together and transferred over a computer network.' Packet-loss rate is thus the ratio of lost data to the total transmitted data (Zormatai and Kargathara, 2018). End-to-end delay is the time a packet takes to travel across a network from the source to the destination (Zormatai and Kargathara, 2018). It is the sum of the transmission, propagation, processing, and queuing delays (Zormatai and Kargathara, 2018). The lower packet-loss rate and end-to-end delay are, the more reliable the communication system is.

The packet-loss rate can be classified into two categories: acceptable (the packet-loss rate is lower than the threshold rate, e.g., 20% (this value is an initial assumption and should be later adjusted) such that remote supervisors receive adequate data from sensors to manipulate maneuvers of the autonomous ship) and unacceptable (the packet-loss rate is higher than the threshold rate such that remote supervisors do not receive enough data to manipulate maneuvers).

The end-to-end delay can also be classified into the same two categories. An acceptable delay is smaller than the threshold delay—e.g., 0.1 s (this value is an initial assumption and should be later adjusted)—such that remote supervisors have adequate time to manipulate maneuvers of the autonomous ship, and an unacceptable delay is higher than the threshold delay such that remote supervisors do not have enough time to manipulate maneuvers.

3.1.3. Risk indicators for radar

Gao and Chu (2017) identified that the health of radar antennas can be evaluated by the radar-detection range and antenna side-lobe level. A faulty radar TR module will lead to a decrease in these two characteristics. Therefore, the radar-detection range and antenna side-lobe level were chosen as RIs for radar.

Gao and Chu (2017) adopted the D-S evidence theory to fuse the decrease trend of side-lobe level and detection range to conclude whether the radar health status is normal, minor, approaching, deterioration, and serious. This article simplifies the health states of radar by classifying them as high, medium, and low.

3.1.4. Risk indicators for lidar

The ferry has integrated light detection and ranging (lidar) to facilitate autonomous navigation. The literature regarding reliability analysis of lidar is limited. Among the few relevant works, Strasser et al. (2020) introduced a novel SOH-monitoring system focusing on the operation temperature for lidar. Strasser et al. (2020) emphasized that the failure in-time (FIT) rate of semi-conductors such as lidar is highly relevant to the operation temperature. By measuring the current temperature of the lidar with a temperature sensor and comparing it with a histogram temperature profile, the estimated FIT rate can be derived. Therefore, the operation temperature was selected as an RI for lidar. This risk indicator is categorized as acceptable and unacceptable.

3.1.5. Risk indicator for remote supervisors' intervention

There are many factors that could impact the remote supervisors, e.g., the machine-human interface, machine-style movements of the ship, reliability of MASS, and visibility constraints Yoshida et al. (2021). However, these are not fully covered in this paper as it is an extensive topic. This should be subject, however, to further analysis in a separate study. However, since the scope of this work mainly focuses on the risk associated with the autonomous system, the risks concerning RCC and the remote supervisors are not fully covered. Therefore, only the remote supervisors' experience in supervising or operating autonomous ships remotely is chosen as a RI for remote supervisors' intervention. According to Thieme (2014), the experience can be categorized into three states low, medium, and high, with probabilities of 0.667, 0.250, and 0.083 respectively.

3.1.6. Risk indicators for environmental conditions

The precipitation per hour and the instantaneous wind speed (gusts' speed) comprise the RIs for environmental conditions. Large precipitation (more than 7.6 mm/h) can influence the performances of cameras, lidars, and the communication system. Wind speed is classified into acceptable if lower than or equal to 10 m/s and unacceptable if more than 10 m/s, according to the operation limit of the small autonomous ferry.

3.2. Step 3: Estimate pivot-node probability

In this case, the pivot node is losing navigational control. Before each autonomous ship's departure, a risk assessment should be conducted using RIs to determine the level of risk inherent in allowing the ship to sail. The risk indicators with the respective initial probability distributions are presented in Table 1. These prior probabilities are obtained from expert judgment based on knowledge from and interactions with participants in the Autoferry project, the literature, and the meteorological data. Taking the state SOH VRLA batteries as an example, the prior probability distributions of high SOH, medium SOH, and low SOH are first assumed to be 0.990, 0.009, and 0.001 respectively. These numbers are based on the belief that the SOH of the batteries onboard the newly operated autonomous ferry is most probably high, less likely to be medium, and unlikely to be low. Those prior probability numbers

Table 1
Initial probability distributions of risk indicators for an autonomous ferry.

Risk Indicator	Prior Probability Distributions of States of the Risk Indicators (Per Passage)			Source
	High (Acceptable/ No)	Medium	Low (Unacceptable/ Yes)	
State of health	0.990	0.009	0.001	Expert judgment
Packet-loss rate	0.999		0.001	Expert judgment
End-to-end delay	0.999		0.001	Expert judgment
Health status of radar combining radar-detective range and antenna side-lobe level	0.990	0.009	0.001	Expert judgment
Operation temperature	0.999		0.001	Expert judgment
Remote supervisor's experience	0.667	0.250	0.083	Thieme and Utne (2017)
Wind	0.9998		0.0002	Yr (2020)
Large precipitation	0.9999		0.0001	Yr (2020)

Table 2
CPT for failure of radar (based on Zrnic et al. (2007) and expert judgment).

Health Status of Radar	High	Medium	Low
Fail	1.96e-05	0.196	0.784
Work	0.99998	0.804	0.216

Table 3
CPT for failure of lidar (based on manufacture data and expert judgment).

Large Precipitation	Yes		No	
Operation Temperature	Normal	Abnormal	Normal	Abnormal
Fail	0.0625	0.5	6.25e-14	0.25
Work	0.9375	0.5	0.9999	0.75

Table 4
CPT for battery pack (based on Adams et al. (2004) and expert judgment).

State of Health	Low	Medium	High
Fail	0.8	0.2	2e-07
Work	0.2	0.8	0.9999998

can be updated if more information on the batteries (e.g., precursors, i. e., the actual low SOH occurrence per 1000 passages) is available.

Once the initial probability distributions of RIs are established, the quantification of conditional probability tables (CPT) should be done to reflect the influence of RIs on RIFs (in the BBN). The CPTs are quantified based on manufacture data, the literature, the preliminary hazard analysis workshop, and expert judgment. These can afterwards be updated as soon as the autonomous ferry is operating, and more precursors occur and are recorded. The CPTs are shown in Tables 2–7. For example, Table 2 shows that, if the RI health status of radar is in medium or low states, then the failure probability of the radar increases from 1.96e-5, as in the high state, to 0.196 and to 0.784, respectively.

3.3. Step 4: Identify critical risk indicators

By setting the state of the RI health status of radar as low and then updating the BBN, the radar's failure probability becomes 0.39, which is a substantial increase. However, since other sensors have very low probabilities of failure and are unaffected by radar, the failure probability of obstacle detection has not changed much. As a result, the probability of losing navigational control of the autonomous ferry remains unchanged at 4.6e-5. Similarly, if the state of the RI operation temperature of lidar is abnormal, the resulting probability of losing navigational control remains unchanged at 4.6e-5. To conclude, these two RIs—health status of radar and operation temperature of lidar—have little influence on the risk of losing navigational control of the autonomous ferry. The reason is that any of the four types of sensors—radar, lidar, optical camera, and IR camera—can provide sufficient information for obstacle detection. Therefore, one single failure of any sensor will not directly lead to the failure of obstacle detection or the loss of navigational control, so the probability of losing navigational control is largely unaffected by the states of the indicators for radar or lidar. Consequently, these two indicators are not prioritized in the risk monitoring.

By setting large precipitation to present ('yes'), the probability of losing navigational control of the autonomous ferry slightly increases, from 4.6e-5 to 4.9e-5. This is due to large precipitation not only increasing the failure probabilities of lidar and IR and optical cameras but, more importantly, impairing the communication system with the SCC. The communication system's increased failure probability increases the failure probability of remote control from 0.24 to 0.27. Consequently, the probability of losing navigational control also increases.

Table 5
CPT for the communication system (based on the preliminary hazard analysis workshop and expert judgment).

Cyber Attack	Yes								No							
Large Precipitation	Yes				No				Yes				No			
End-to-End Delay	Acceptable		Unacceptable		Acceptable		Unacceptable		Acceptable		Unacceptable		Acceptable		Unacceptable	
Packet-Loss Rate	Acceptable	Unacceptable	Acceptable	Unacceptable	Acceptable	Unacceptable	Acceptable	Unacceptable	Acceptable	Unacceptable	Acceptable	Unacceptable	Acceptable	Unacceptable	Acceptable	Unacceptable
Fail	1	1	1	1	1	1	1	1	0.034	1	1	1	3.4e-5	1	1	1
Work	0	0	0	0	0	0	0	0	0.966	0	0	0	0.99997	0	0	0

Table 6
CPT for remote supervisors' intervention (based on Williams (2015) and expert judgment).

Remote Supervisors' Experience	High	Medium	Low
Fail	0.16	0.32	0.64
Work	0.84	0.68	0.36

Table 7
Updated probability of health status of radar (inference analysis).

High	0.990
Medium	0.009
Low	0.001

The results are substantial after setting evidence that there is strong wind. The failure probability of the propulsion system goes to 0.03. The failure probability of autonomous control and the probability of losing navigational control both jump to 0.03, around 500 times greater than before.

Weather clearly affects the probability of losing navigational control, and therefore, especially wind speed, should be monitored closely by the SCC.

Assuming that the SOH of the battery is low, the probability of losing navigational control rises from 4.6e-5 to 2.2e-4, around 4.8 times larger than before. Therefore, the SOH of the battery is a vital indicator and should be prioritized in the SCC's monitoring.

By setting either the state of the end-to-end delay or packet-loss rate as low, the probability of losing navigation control of the autonomous ferry both rises from 4.6e-5 to 1.2e-4, a more than double increase. Consequently, the SCC should emphasize both RIs in their monitoring.

Finally, setting the remote supervisors' experience to low, the probability of the node losing navigational control rises from 4.6e-5 to 8.6e-5, an 87% increase.

3.4. Step 5: Inference analysis

This section relays the inference analysis wherein the state of the node losing navigational control is set as 'yes.' In the GeNIe software, the probabilities of the intermediate and root nodes are updated automatically. Fig. 3 shows the results. Different RI colors reflect to what extent the updated probabilities of states that lead to the loss of navigational control (low, unacceptable, etc.) deviate from the original probabilities. Red, orange, yellow, and green mean extreme, large, medium, and small deviations, respectively. Specifically, red means the updated probabilities have an increase of more than 100 times, orange a double increase or more, yellow a 50%–90% increase, and green ones an increase of less than 1%.

It should be clarified that, due to the limited presentation of numbers in the bar chart, many nodes appear as 0% in some states. This does not mean the occurrence probabilities are 0 but that they are smaller than 0.005. Such small probabilities and some key RIs are summarized in Tables 7–12.

Table 8
Updated probability of large precipitation.

Yes	8.8e-5
No	0.9999

Table 9
Updated probability of strong wind.

Strong	0.10
Not Strong	0.90

Table 10
Updated probability of state of health of batteries.

High	0.86
Medium	0.10
Low	0.04

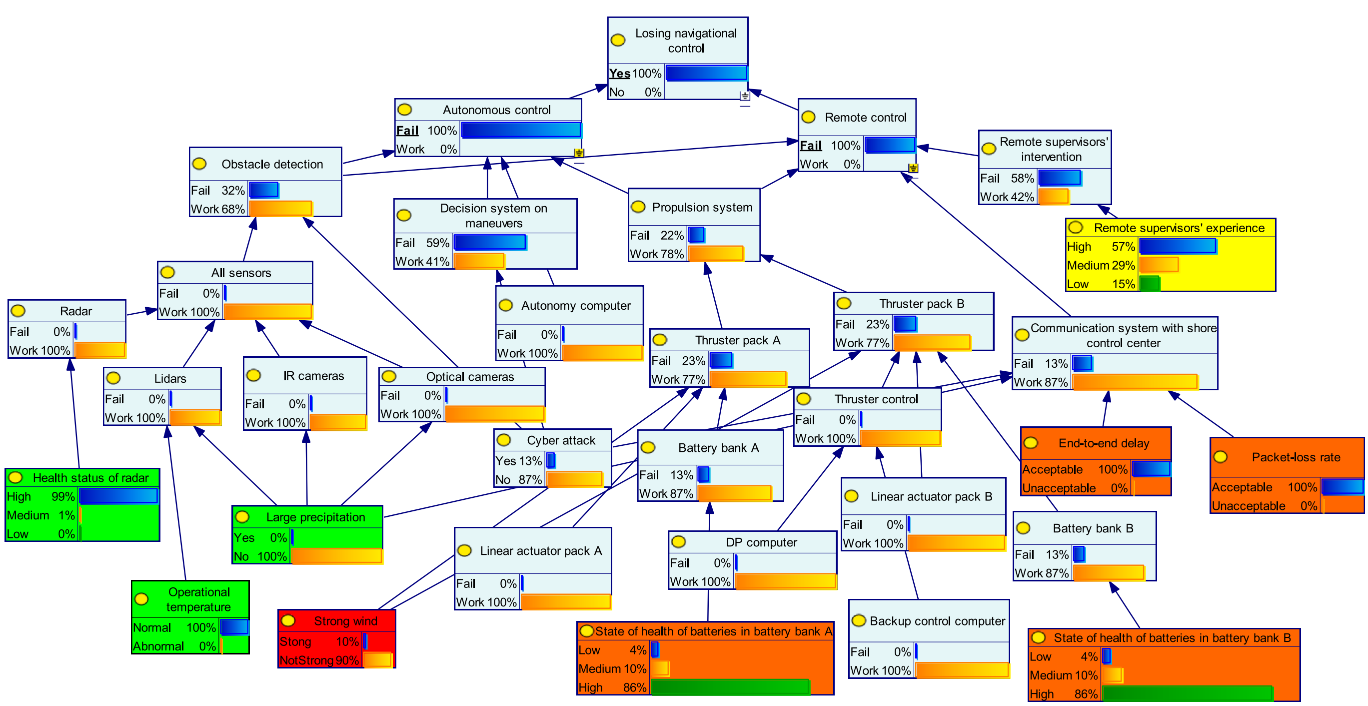

Fig. 3. Inference analysis of losing navigational control.

Table 11
Updated probability of end-to-end delay.

Acceptable	0.998
Unacceptable	0.002

Table 12
Updated probability of remote supervisors' experience.

High	0.566
Medium	0.288
Low	0.146

4. Discussions

4.1. Probability of losing navigational control while monitoring risk indicators

By applying the initial probability distributions of RIs for an autonomous ferry in Table 1 to the nodes in the BBN, the occurrence probabilities of failure of autonomous control, failure of remote control, and losing navigational control are obtained. These numbers, along with the respective probabilities from Guo et al. (2021) in which no RIs are considered, are compared with and presented in Table 13. The failure probability of autonomous control while considering RIs is similar to that without RIs. Also, the probability of losing navigational control is close to but slightly larger than the corresponding result from Guo et al. (2021).

This is because, in this article, the performance of safety barriers (RIFs) is not considered perfect as the manufacturers, or the literature would suggest. In contrast, RIs have been used, which affect the probabilities of RIFs, as the conditional probability tables show. For example, in Guo et al. (2021), the failure probability of radar is 1.96e-5. But, in this article, considering the possibilities of different states of RIFs, as represented by RIs, the failure probability of radar is 2.57e-3, approximately 131 times as large. This will lead to the increased failure probabilities of RIFs and subsequently increases the failure probability of autonomous control and eventually the probability of losing navigational control.

4.2. Critical risk indicators and inference analysis

As demonstrated in the findings in section 3.3, the strong wind, SOH of batteries, end-to-end delay, and packet-loss rate are useful RIs for the loss of navigational control of the autonomous ferry.

The inference analysis results shown in Fig. 3 and Table 7–Table 12 indicate that strong wind is the RI with the highest contribution to losing navigational control. SOH of batteries, end-to-end delay, and packet-loss rate are also all large contributors, with more than double increase in occurrence probabilities for each. Remote supervisors' experience is a medium contributing RI, with a 50%–90% increase. In contrast, health status of radar, operation temperature of lidar, and large precipitation show minimal changes. These findings reinforce those from Section 3.3, cross-confirming which RIs should be prioritized in risk monitoring.

Table 13
Comparison of the occurrence probabilities for the accident scenarios for June 2019 at the Trondheim Canal with and without risk indicators.

Node	Probability per passage (considering risk indicators with prior probabilities of states)	Probability per passage (without risk indicators)
Failure of autonomous control	$1.3•10^{-4}$	$1.2•10^{-4}$
Failure of remote control	0.24	0.16
Losing navigational control	$5.3•10^{-5}$	$3.8•10^{-5}$

The results from the inference analysis also potentially show thresholds of the RI, i.e., the difference in their probabilities when the pivot node is set to true (losing navigational control is set to "yes") and untrue (losing navigational control is set to "no"). Such information may be used to determine the operational limits of the autonomous ferry, and when risk mitigation and/or the human operator in the SCC needs to take over control. The current BBN has a limited number of states and nodes, but further work should explore the model, its states and CPTs, and how inference analysis could contribute to decision support for the operators.

4.3. Sensitivity analysis

Since there are uncertainties associated with the prior probabilities of the risk indicators, a sensitivity analysis is performed in GeNIe. As Fig. 4 shows, the state of health of batteries in battery bank A or B being high are both the most sensitive nodes. A 10% decrease in the probability of either node both increases the probability of losing navigational control from 5.3e-5 to 1.2e-4 about a 127% increase. Such significant change indicates that the uncertainties associated with the prior probabilities of these two risk indicators should be paid more attention to than other indicators.

4.4. Advantages of deriving risk indicators from a BBN

In traditional BBNs, the failure of one unit of a system is usually represented by one single node with one single probability number. This representation does not incorporate the changes in the nodes' conditions over time. This article overcomes this limitation by identifying RIs of the RIFs in a BBN to achieve more effective risk monitoring of the performance.

4.5. Limitations

At first, only the most relevant RIs were integrated in the BBN model, meaning one or two indicators for each RIF. Besides, uncertainties exist in the probabilities of the RIs. The probabilities are adopted from the literature or expert judgement, which has not been validated since the RIs have not been practically applied to the autonomous ferry yet.

A trial period of the autonomous passenger ferry *MilliAmpere 2* across the canal in Trondheim was performed from 21 September until mid-October 2022 (Haugen, 2022). Noticeably, a safety supervisor was onboard the *MilliAmpere* 2 in case of unexpected circumstances during this trial period. *MilliAmpere 2* may operate regularly from next summer. Therefore, more data can become available to validate this work.

Last but not least, when introducing the RIs for the remote supervisors' intervention failure, only remote supervisors' experience is considered. Other factors, such as the machine-human interface, should be further investigated in the future work.

5. Conclusions

In this paper, a method of deriving risk indicators from a BBN risk model is proposed. It is applied to identifying RIs of an autonomous ferry, which an SCC can use to monitor the ferry's operation. The measurement and monitoring of the states of risk indicators provide a tool for proactive performance monitoring of the autonomous ship. Some key conclusions are listed as follows:

- Risk monitoring of an autonomous ferry is facilitated using risk indicators in the BBN by applying the proposed methodology. The risk indicators can contribute to information which may be used as a

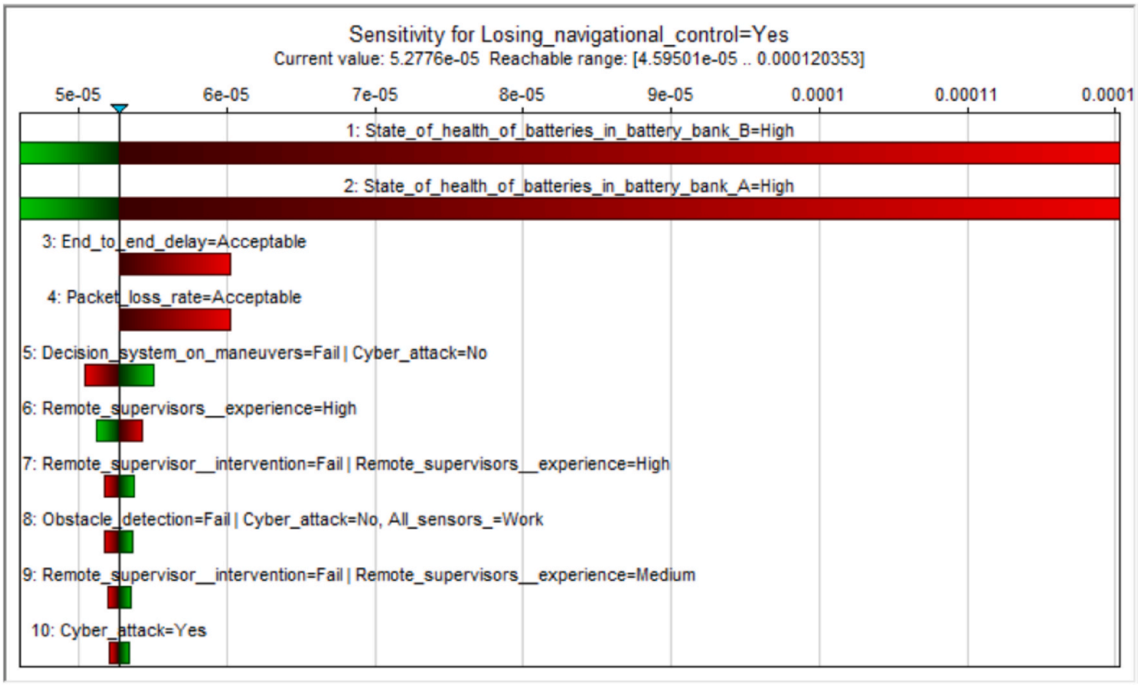

Fig. 4. Sensitivity tornado diagram for losing navigational control.

basis for developing operational procedures for the safe takeover of the human operator.

- The most significant risk indicators have been identified: strong wind, batteries' SOH, end-to-end delay, and packet-loss rate. These risk indicators influence the risk level most during the operation of the autonomous ferry and should be closely monitored. The inference analysis may contribute to identifying the operational limits and thresholds for risk mitigation is necessary to perform, and/or when the human operator in the SCC should take over control. More work, however, is necessary to explore this aspect of the BBN, in particular with respect to its states and CPTs.
- The limitations of this work are related to the non-measurable RIFs and human-related risk indicators which have not been included due to the scope of this research. Furthermore, there is lack of empirical measurements of the input data for the risk indicators because the ferry has not yet been regularly operated. Therefore, the probability numbers, and inference analysis have yet to be validated. This can be solved in future work, particularly by testing the model and collecting sensor and experience data on the real ferry when it becomes in service.

CRediT authorship contribution statement

Chuanqi Guo: Conceptualization, Methodology, Software, Investigation, Writing – original draft. **Ingrid Bouwer Utne:** Methodology, 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.

Data availability

Data will be made available on request.

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