Real-time risk analysis model of autonomous passenger ferry
'Sundbåten' case study

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Abstract

"Necessity is the mother of all inventions" – this famous proverbial saying *(unknown author)* aptly suits the maritime shipping industry in the context of autonomous ships. Though shipping industry has had highly automated systems onboard specialised ships like DP vessels, fully autonomous shipping operations has eluded it for some time until recently.

The push towards increased innovation and testing of autonomous shipping has primarily begun due to the need for cutting operational costs, for increasing safety at sea, for increasing productivity and for reducing carbon-footprint to make shipping more sustainable to meet IMO's Greenhouse gas emission targets. It has also been ably supported by the enabling environment created by government policies worldwide, research institutions, shipping companies and ship classification societies.

In order to achieve fully autonomous shipping (or unmanned) operations, the ship besides replicating human senses of an onboard operator like vision, hearing and communicating – will also need to have the situational awareness and decision-making skill of humans especially expert seafarers with long experience.

Hence, a risk analysis method is required which can acquire the virtue of expert seafarers and provide accurate decision-making support to the ships autonomous system enabling it to take navigational decisions of its own without human-intervention.

The real-time risk analysis method looks promising in this regard. The objective of this thesis report is to establish a sound body of knowledge about real-time risk analysis, and to apply it to build a real-time risk analysis model for autonomous ships. For this purpose, the Sundbåten autonomous passenger ferry project which is currently under way is taken as a case-study. Here the mission is to develop a real-time risk model which is capable of warning the captain to take the ship's control when its autonomous system is incapable to do so. The real-time risk analysis model developed in this thesis is capable of identifying the critical risks from marine traffic analysis and expert judgements. The framework for risk model looks promising and its modular and flexible architecture makes it adaptable for a variety of ships & regions.

Keywords:

Autonomous ship, MASS, Systematic literature review, real-time risk analysis model, Bayesian network (BN), Rule-based Fuzzy network.

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List of Abbreviations

NMA	Norwegian Maritime Authority
MASS	Maritime Autonomous Surface Ships
DNV	Det Norske Veritas
MUNIN	Maritime Unmanned Navigation through Intelligence in Networks
RO	Research Objective
RQ	Research Question
MRC	Minimum Risk Condition
SLR / LR	Systematic Literature Review / Literature Review
SC	Scopus
WoS	Web of Science
SD	Science Direct
DOI	Digital Object Identifier
yrs	Years
nos.	Numbers
BN/ BBN	Bayesian Network / Bayesian Belief Network
THERP	Technique for Human Error Rate Prediction
ET / ETA	Event tree / Event tree analysis
STPA	Systems Theoretic Process Analysis
ER	Evidential Reasoning
DT	Decision Tree
DFM	Dynamic Flowgraph Method
FTA	Fault Tree Analysis
MCCMT	Markov Cell to Cell Mapping Technique

FAHP	Fuzzy Analytical Hierarchy Process
DBN	Dynamic Bayesian Network
FBN	Fuzzy BN
AUV	Autonomous Underwater Vehicle
LoA	Level of Autonomy
HAZID	Hazard Identification
FMEA	Failure Modes and Effects Analysis
RPN	Risk Priority Number
HRM	High Reliability management
MPC	Model Predictive Control
COLREGS	Convention on the International Regulations for Preventing Collisions at Sea
DRL	Deep Reinforcement Learning
SCC	Shore-based Control Centre
DP	Dynamic Positioning
RIF	Risk Influencing Factors
CPT	Conditional Probability Table
PHA	Preliminary Hazard Analysis
MTA	Marine Traffic Analysis
AIS	Automatic Identification System
NDA	Non-disclosure Agreement
CPA	Closest Point of Approach
IoT	Internet of Things

1 Introduction

1.1 The problem/challenge

Traditional risk analysis has been used until now which gives an average risk value which is suitable for design phase decision making (Thieme et al., 2021). Hence, it is also referred to as static risk analysis and is usually undertaken less frequently covering a longer life span which can be up to the entire lifecycle of the system (Mehdi et al., 2020). However, risk in real world during operation of the system is not stagnant, and varies with time or in other words is dynamic (Mehdi et al., 2020).

A hypothetical example of the above can be a ship sailing in rough weather with its risk value varying with time. The instantaneous risk at any moment of time may be higher than the traditional average risk, thereby under-estimating the risk. This under-estimated risk can very likely turn out to be a black-swan moment which was never considered in the design of the ship leading to its failure. Similarly, the same ship in calm weather would have an instantaneous risk which is lower than average risk value causing over-estimation of risk though not as dangerous as the previous case. Implementation of a real-time risk analysis on other hand gives a realistic risk figure at that particular instant of time which varies with time either increasing or decreasing or steady – in effect giving a true representation of the risk.

Autonomy of autonomous systems is their ability to make decisions on their own to perform a certain task without external intervention (Thieme & Utne, 2017). According to *RSV 12-2020*, (2020) of the Norwegian Maritime Authority (NMA), there are five levels of autonomy for autonomous ships. Level 1 implies ships with autonomy limited to decision support only where humans are in manual command of the ship. Level 2 is for autonomous operation of vessel with continuous watch and operators onboard ready to take control of the ship when alerted by alarms. Level 3 is for periodically unmanned periods or days with the operators either in escort vessel or onboard in standby mode. Level 4 is unmanned operations with completely remote-controlled monitoring and operations from shore. Finally, level 5 is total autonomy with no operators neither onboard nor at remote shore control centers. These NMA levels of autonomy will be followed in this report.

Most autonomous systems of today require human or external intervention at certain times of their operation (Thieme & Utne, 2017). During those periods when they are externally controlled can be referred to as remote operated. Currently, autonomous or remote operated systems map & review risks after years of operation during which changes would have occurred in several domains like environmental, technical in much shorter intervals which have not been mapped or reviewed. Therefore, there is a need for capturing these risks at much shorter intervals (Thieme & Utne, 2017). Such an updated risk picture is possible to be achieved by real-time risk models. Hence, real-time risk analysis is a perfect match for autonomous and remote operated maritime systems.

1.2 Impact/ costs of the problem/ challenge

The biggest challenge to implementing Maritime Autonomous Surface Ships (MASS) is to gain the confidence of all stakeholders like the public, national / international authorities, regulatory bodies and the maritime industry. Utne et al., (2020, p. 1) has brilliantly summarized the gist of DNV's paper on remote controlled and autonomous ships which is a paper from a safety perspective considering its role as a classification society as: "It is essential to ensure that autonomous ships have the desired level of reliability, availability, maintainability and safety to be acceptable for widespread use at sea".

A concept of equivalent safety is recommended by DNV for autonomous ships, which implies that MASS should as a minimum have the same level of safety or better than that exhibited by traditional human operated ships against loss of human life, assets and environment (*DNV-CG-0264*, 2021, p.17).

The use of real-time risk analysis thus has the potential to help achieve this objective of equivalent safety by continuously observing the ship's & its environments variable parameters during her sea voyage and predicting the risk levels at that moment of time. A higher likelihood of achieving equivalent safety would greatly boost confidence of all stakeholders in the technology.

Assessing the real-time risk at a particular moment of time in autonomous vessels with traditional risk analysis methods is difficult to achieve since traditional methods rely on static average risk values, while the complex maritime systems are highly dynamic in nature with uncertainties which change with time (Thieme et al., 2021), (Chen et al., 2021). This uncertainty in estimating the real risk can increase the probability of loss of human lives in an autonomous ferry which has a high number of untrained people as passengers with no knowledge of the autonomous systems onboard the ship. The only assistance the vessel has is the onboard captain (on a supervisory role) and the remote operations center. But in order for either of them to react, they should be warned in advance by the autonomous system of the impending failure or an indecisive situation with sufficient reaction time.

Thus, the single biggest cost of a potentially uncontrollable / uncontrolled autonomous passenger ferry would be the loss of lives of passengers. Hence, the need to address this issue to achieve equivalent safety of autonomous passenger ferry.

Another aspect is that of total redundancy of ship machinery as proposed by MUNIN (Maritime Unmanned Navigation through Intelligence in Networks project funded by EU) for unmanned cargo ships to account for the lack of opportunity for conducting onboard maintenance during voyage (Eriksen et al., 2021). A higher redundancy entails higher costs for unmanned/autonomous ships. A real-time risk analysis model capable of monitoring the live condition of critical ship machinery would enable a realistic estimate of its robustness enabling predictive maintenance – in-effect minimizing or eliminating additional redundancy costs.

1.3 Goal of the thesis

The goal of the thesis is to explore and compile a sound body of knowledge for real-time risk analysis, and to apply it to improve predictability of autonomous maritime systems, thereby improving public-confidence in autonomous shipping technology.

The primary objectives of the research are thus two-fold as stated in Figure 1.

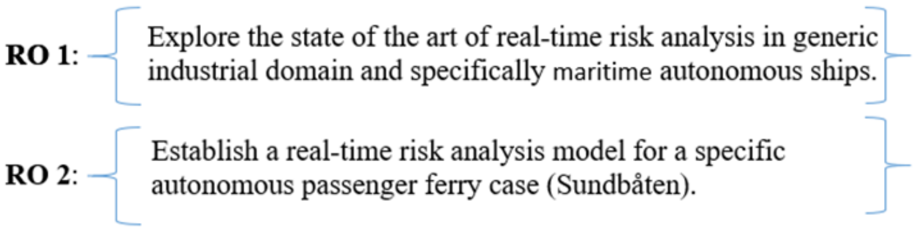


Figure 1 - Two-fold Primary research objectives (RO's)

The research objectives are pursued by research questions (RQ's) as stated in Figure 2.

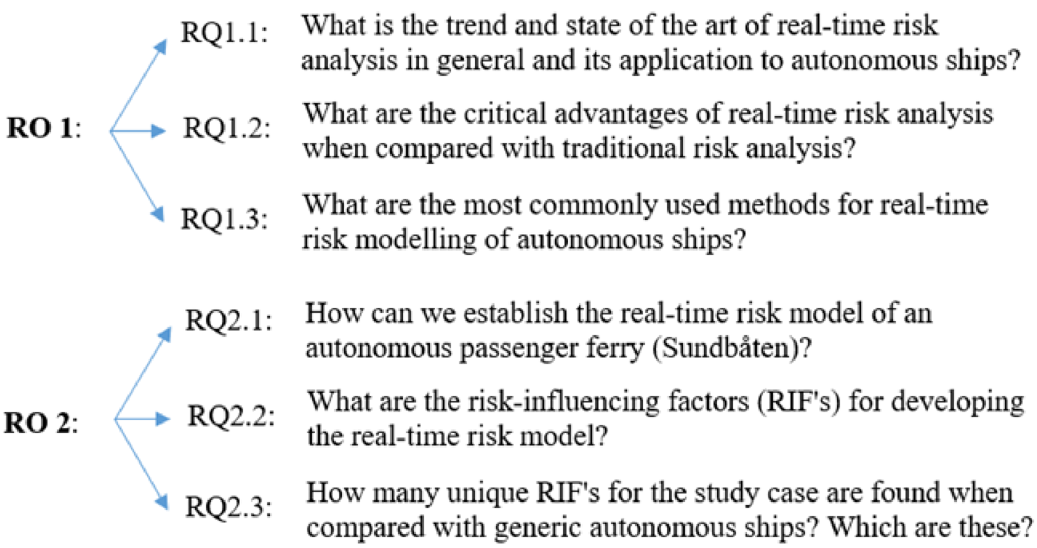


Figure 2 – Six (6) Research questions based on the research objectives

The two research objectives are pursued in two-steps namely: conducting a literature review for real-time risk analysis for a autonomy level-4 Maritime Autonomous Surface Ship (MASS) project named “KASS (Korean Autonomous Surface Ship” – an autonomous container ship of Korea currently under development; and secondly establishing a real-time risk analysis model for a autonomy level-2 *(ultimate goal is autonomy level 3)* autonomous passenger ferry named “Snøgg” (Sundbåten) to be operated in Kristiansund, Norway which is also being developed currently (Figure 3). The scope of the former is to find what is a real-time risk analysis and why is it required, and to perform an exploratory search of the various theories, methods with an overview of the state of art of the technology in academia. While the scope of the latter is to develop a real-time risk analysis model which will warn the on-board captain to take physical control of the ship from the autonomous system referred to as MRC (Minimum risk condition). MRC is a fail-safe state that the autonomous ship should enter into so as to minimize the adverse consequences to life, environment and property whenever its self-driving system is out of order or fails to work as intended (*DNV-CG-0264*, 2021, p. 18).

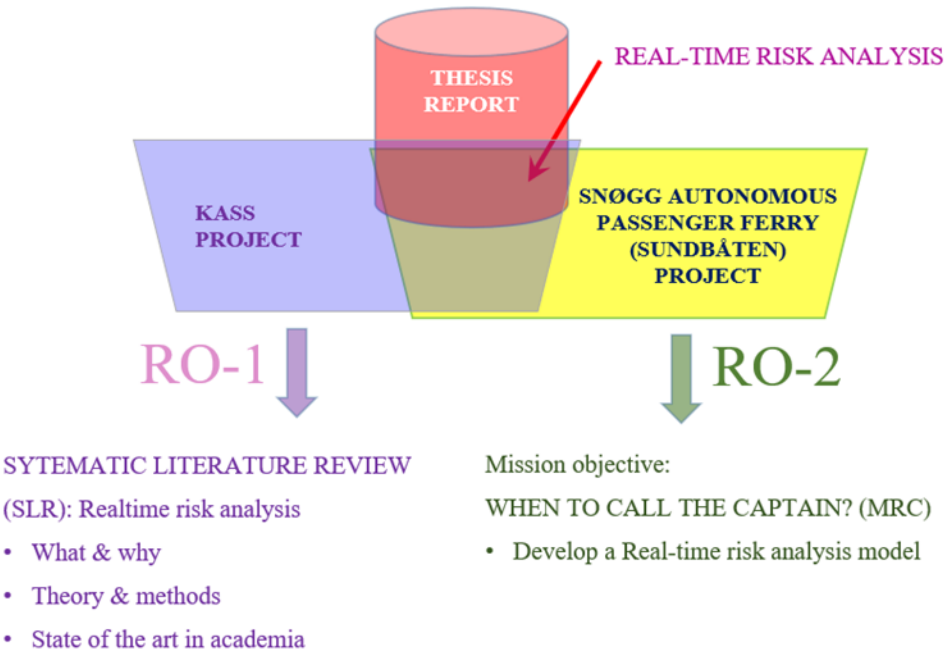


Figure 3 - Schematic view of thesis goal

2 Literature review

2.1 *Goals for the review*

The literature review is performed using inductive research method for gathering information about real-time risk analysis (LR-I) and maritime autonomous ships (LR-II) (Figure 4). The inductive research analysis consists of exploring peer-reviewed scientific journals to gain a better understanding of the two subjects.

The goal of LR-I is to find various ways of establishing a real time risk analysis model, comparing, contrasting and short-listing one or more methods to design and implement the real-time risk analysis model.

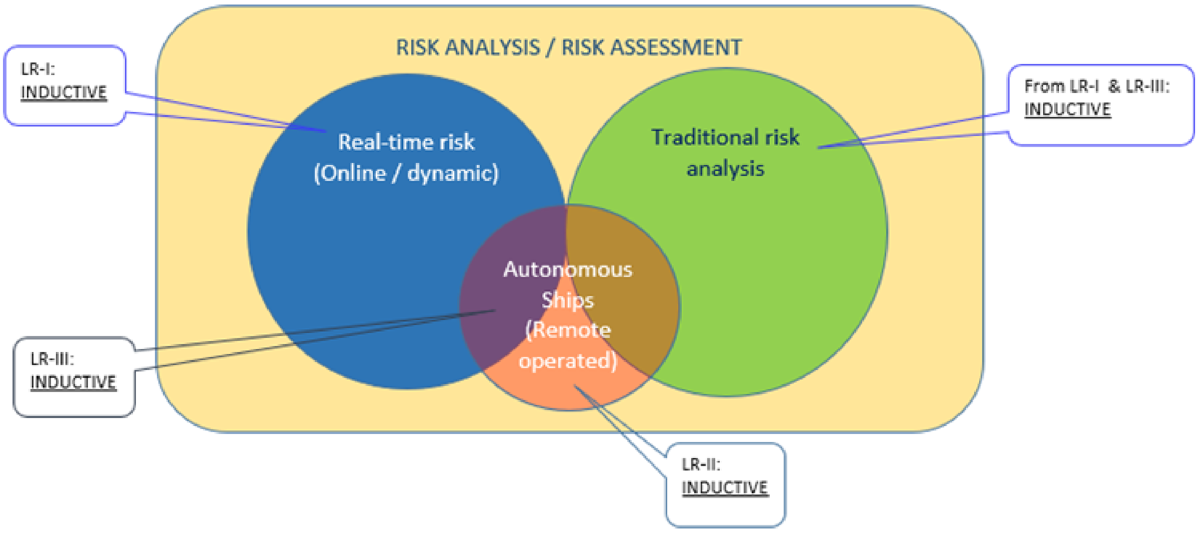


Figure 4 - Concept map showing goals for the literature review

The objective of LR-II is to search for existing knowledge base for maritime autonomous ships to understand how they function, what are their biggest challenges and get an insight into existing solutions as well as unsolved challenges which need to be addressed.

A third inductive research (LR-III) is done at the intersecting region of LR-I and LR-II, and its goal is to find information about real-time risk analysis methods as applied to autonomous ships. LR-III holds the key to finalise a suitable real-time risk model concept which would enable the autonomous system to take a decision regarding when to alert the onboard captain/ remote operations center to take control of the ship as part of MRC.

2.2 Method for finding and selecting literature

A systematic literature review for each of LR-I, LR-II and LR-III has been performed using the two databases: Scopus (SC) and Web of Science (WoS). A third database of Science Direct (SD) was planned to be used, however it does not give the number of citations for each journal article when list of journals is exported – hence this database has been excluded since it didn't give the possibility to apply the same inclusion/exclusion parameters as were used for SC and WoS databases. However, since LR-III yielded the least results in both SC and WoS, only LR-III was searched in SD database which also yielded equally low results.

Scopus (SC) has been selected as the starting point for the literature review, followed by Web of Science (WoS), and lastly Science Direct (SD) for the LR-III literature review.

The following steps have been followed:

Step 1:

Keywords for the search were identified: "online risk analysis", "dynamic risk analysis" and "real-time risk analysis".

Step 2:

A quick search was performed to get a feel of the type of results obtained, and to include any new keywords discovered in the search.

Step 3:

More levels are added or removed to the search query by use of Boolean operators AND, OR, ANDNOT *{NOT}* and also the proximity operator W/n *{NEAR/xx}* depending on the relevance of results obtained. SC *{WoS}*

Step 4:

The final combination of search query which gives search results that are more or less relevant to the research topic is selected. A unique identification code is assigned to the final search query as "SCxxx" for Scopus results; "WoS_xxx" for Web of Science results and "SD_xxx" for Science Direct results, for traceability *(Final search queries are enclosed in Appendix A).*

Step 5:

The saved results of journal articles is exported to Microsoft Excel for further data processing & data analysis.

Step 6:

The imported journal list inside MS Excel are further trimmed by use of inclusion and exclusion parameters by use of “filters” within MS Excel for filtering number of citations and filtering published year.

Step 7:

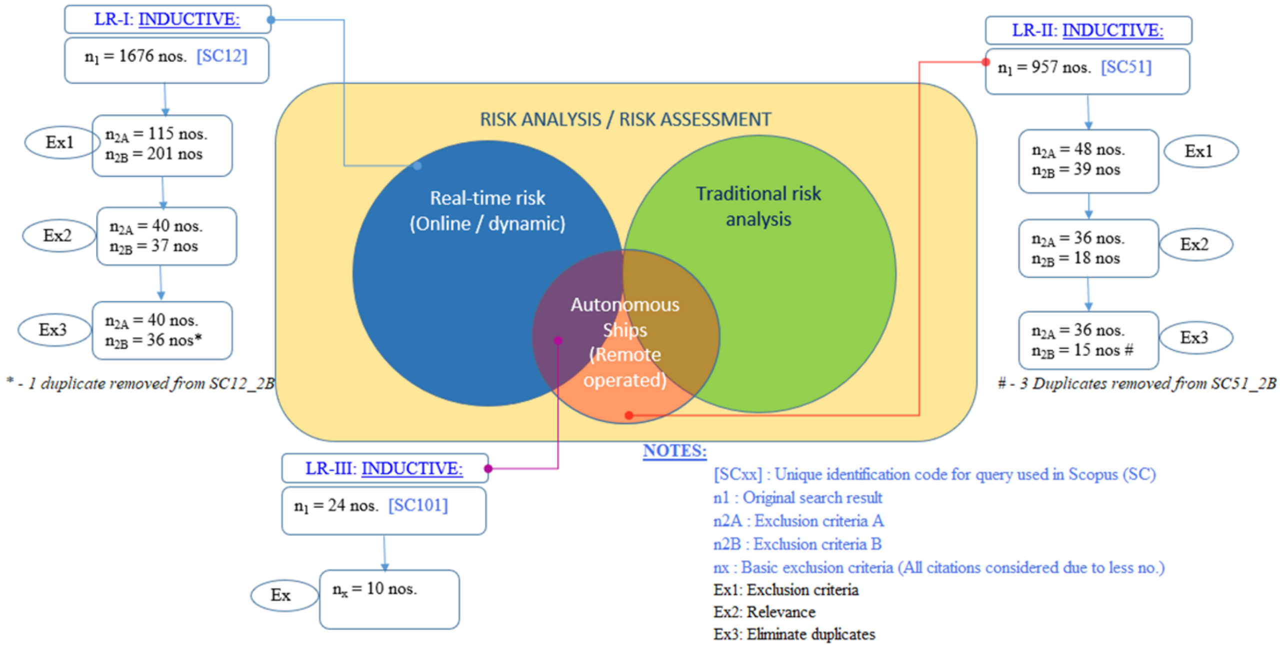
For search queries which resulted in considerable results in range of multiple of 100’s (eg. SC12 /WoS_02; SC51 /WoS_51) were further narrowed down by use of three levels of exclusions: Ex1: for exclusion based on exclusion criteria’s A & B, followed by Ex2: exclusion based on relevance of articles to the subject of interest, and finally Ex3: for exclusion by elimination of duplicate articles (between search queries LR-I/II/II or between databases).

For search queries which resulted in fewer results less than 50 (eg. SC101 /WoS_101), only two levels of exclusions have been used: Ex2: exclusion based on relevance of articles to the subject of interest, and finally Ex3: for exclusion by elimination of duplicate articles (between search queries LR-I/II/II or between databases).

The relevance of articles is mainly found by reading the article title and abstract. If this was inconclusive, only then the complete research article has been read to find if it is relevant or not.

Step 8:

The final shortlisted articles are then added to Zotero using the magic wand tool of adding items by identifier (DOI). This enabled all articles to be filed in one location, and duplicate items if any were found and merged into single article.

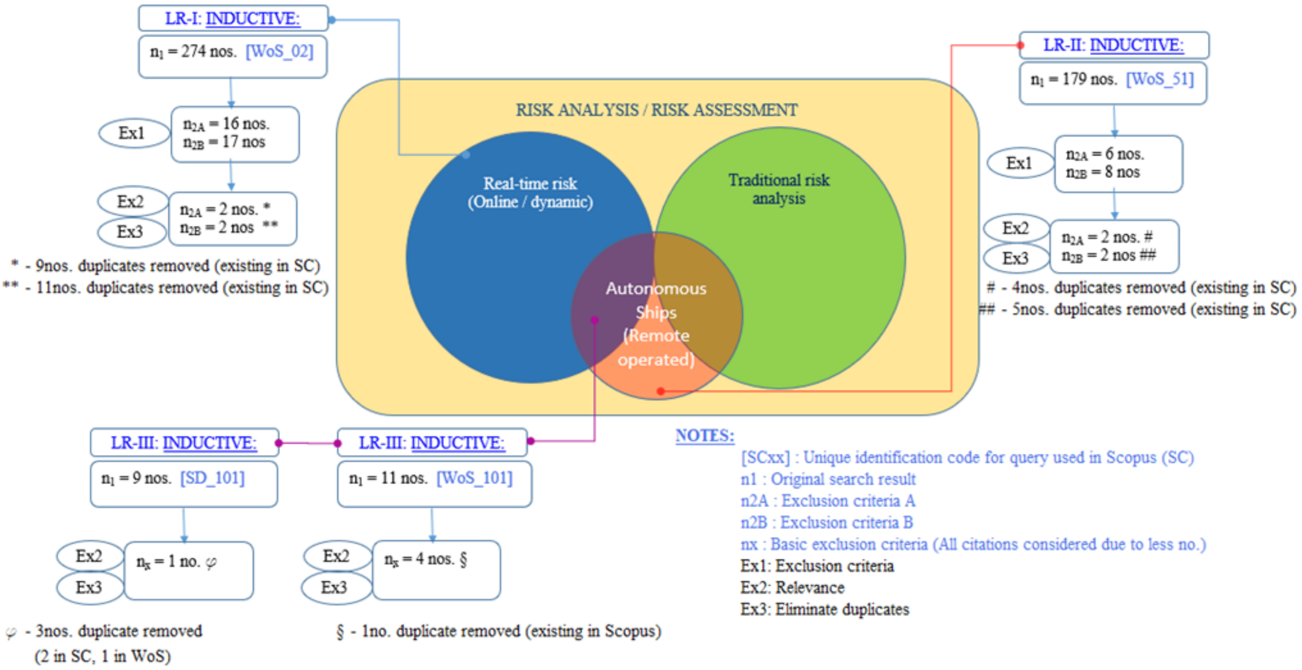


Scopus

	INCLUSIONS:	EXCLUSIONS:
(A)	**>= 50 citations* All years**	**< 50 citations***
	English	Non-English
	Journal articles (Peer-reviewed)	Non-journal articles (Non-Peer-reviewed)
	Engineering, decision sciences, multi-discipline, chemical engineering, energy	All other disciplines
	Non-medical journals	Medical journals (Medical/Medicine/Diabetes/Biomedical)
(B)	**>=25 & < 50 citations* Last 4yrs #**	**< 25 citations***
	English	Non-English
	Journal articles (Peer-reviewed)	Non-journal articles (Non-Peer-reviewed)
	Engineering, decision sciences, multi-discipline, chemical engineering, energy	All other disciplines
	Non-medical journals	Medical journals (Medical/Medicine/Diabetes/Biomedical)

Note: * - Filtering of citations done using MS Excel
- Intention was to find journal articles with fewer citations for latest 3yrs, however due to fewer results, last 4 yrs. considered)

Figure 5 - Search stages & results for Scopus (SC) database



WoS

	INCLUSIONS:	EXCLUSIONS:
A)	**>= 50 citations***	**< 50 citations***
	English	Non-English
	Journal articles (Peer-reviewed)	Non-journal articles (Non-Peer-reviewed)
	Engineering or Operations Research Management Science or Transportation or Automation Control Systems or Construction Building Technology or Nuclear Science Technology or Instruments Instrumentation or Robotics or Metallurgy Metallurgical Engineering (Research Areas)	All other disciplines
	Non-medical journals	Medical journals (Medical/Medicine/Diabetes/Biomedical)
B)	**>=25 & < 50 citations***	**< 25 citations***
	English	Non-English
	Journal articles (Peer-reviewed)	Non-journal articles (Non-Peer-reviewed)
	Engineering or Operations Research Management Science or Transportation or Automation Control Systems or Construction Building Technology or Nuclear Science Technology or Instruments Instrumentation or Robotics or Metallurgy Metallurgical Engineering (Research Areas)	All other disciplines
	Non-medical journals	Medical journals (Medical/Medicine/Diabetes/Biomedical)

Note: * - Filtering of citations done using MS Excel

- Intention was to find journal articles with fewer citations for latest 3yrs, however due to fewer results, last 4 yrs considered)

Figure 6 - Search stages & results for Web of Science (WoS) database & Science Direct (SD)*
** - Science Direct database used only for LR-III*

2.3 *Reviewed literature*

It is found that LR-I (Real-time/ online/ dynamic risk) and LR-II (autonomous ship) queries returned with significant number of results which is further filtered down to a manageable number by use of inclusion / exclusion parameters. However, significantly lower results is obtained for LR-III (Real-time risk analysis of autonomous ships), indicating that real-time risk analysis applied to autonomous ships is a field of new-interest with very little data available. This is also visible in Figure 7, the search results for LR-III in all three databases: SC, WoS and SD show a year's range of only 2018 to 2021/22 indicating a recent interest in this field of study.

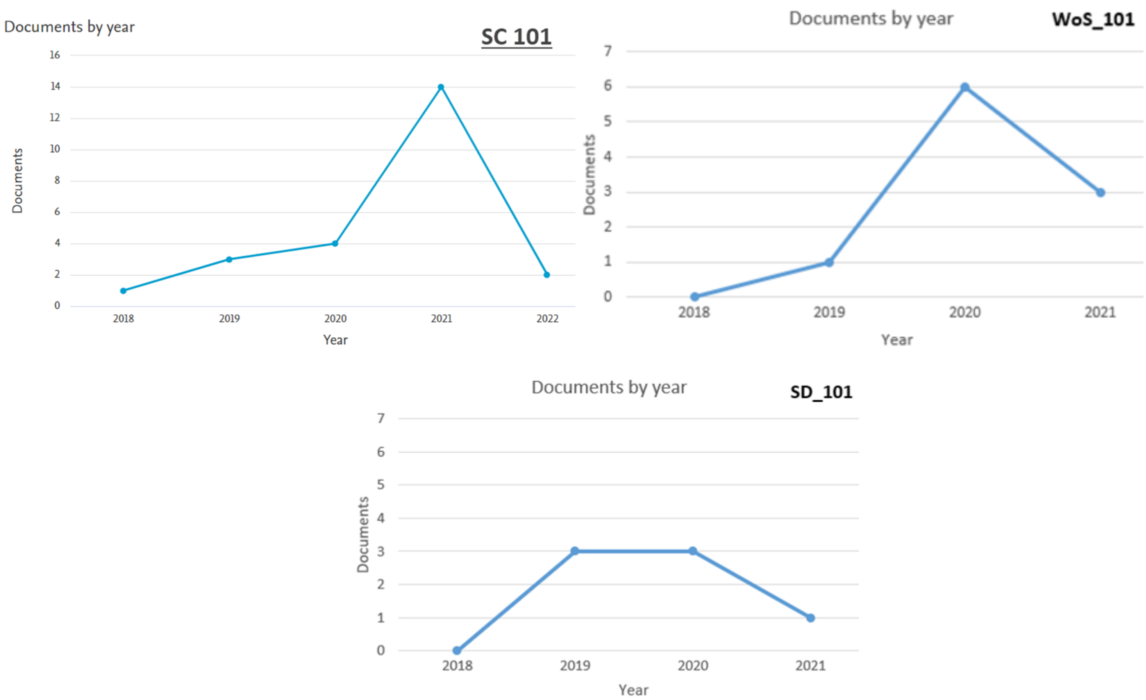


Figure 7 - LR-III (SC 101: top left) no. of articles distribution (source: Scopus query chart); LR-III (WoS_101: top right) no. of articles distribution (created in MS Excel); LR-III (SD_101: bottom) no. of articles distribution (created in MS Excel)

Considering that the primary area of focus of the report is that of real-time risk analysis of maritime autonomous ships – the LR-III journal articles have been thoroughly reviewed. This was also manageable due to the relatively finite number of results returned for LR-III (15 articles) across all three database searches. The results from LR-I (real-time/ online/ dynamic risk analysis: 80 articles) and LR-II (autonomous ships: 55 articles) partly satisfied the focus area and were considerably larger in number. Hence, a quantitative data analysis of the list of journal articles for LR-I and LR-II is performed using MS Excel to have an overview of the underlying themes and trends which were then selectively explored by reading those journal articles only.

2.3.1 *Real-time risk analysis of autonomous ships (LR-III)*

SR. NO.	AUTHORS	Title	Year	RISK ANALYSIS METHOD	DOMAIN	PURPOSE	SIGNIFICANCE	RISK MODEL
1	Zhang M., Zhang D., Yao H., Zhang K.	A probabilistic model of human error assessment for autonomous cargo ships focusing on human–autonomy collaboration	2020	BN + Fuzzy + THERP + ET (Event tree)	Human error + autonomous ship autonomy	Human error assessment for level 3 autonomous cargo ship	Input to risk model	**Y**
2	Xue J., Van Gelder P.H.A.J.M., Reniers G., Papadimitriou E., Wu C.	Multi-attribute decision-making method for prioritizing maritime traffic safety influencing factors of autonomous ships' manoeuvring decisions using grey and fuzzy theories	2019	GRA + Fuzzy theory	Autonomous ship manoeuvring decisions	Prioritising of risk influencing factors which affect decision making of autonomous ship during manoeuvring	Input to risk model	**Y**
3	Utne I.B., Rokseth B., Sørensen A.J., Vinnem J.E.	Towards supervisory risk control of autonomous ships	2020	STPA + BBN	"Supervisory risk control" of autonomous ships	Embedding risk model into the supervisory layer of autonomous ship's control system, such that the autonomous system itself can perform risk management	**Framework for risk model**	**Y**
4	Thieme, CA; Rokseth, B; Utne, IB	Risk-informed control systems for improved operational performance and decision-making	2021	ALL METHODS DISCUSSED	Exploratory review of risk analysis & how to incorporate into control system of autonomous systems (Cybernetics)	Literature review & framework for algorithm/ risk model	**Framework for risk model**	**Y**

SR. NO.	AUTHORS	Title	Year	RISK ANALYSIS METHOD	DOMAIN	PURPOSE	SIGNIFICANCE	RISK MODEL
5	Yu Q., Teixeira Â.P., Liu K., Rong H., Guedes Soares C.	An integrated dynamic ship risk model based on Bayesian Networks and Evidential Reasoning	2021	Static risk (from Ship risk profile inspection data) + Dynamic risk (from AIS data showing traffic flow) combined using BN & validated by (ER) evidential reasoning. Bayesian search algorithm is used to extract static ship risk profile from ship risk profile inspection data.	Ship manoeuvring risks	Ship manoeuvring risks	Input to risk model	**Y**
6	Sahin B., Soylu A.	Multi-Layer, Multi-Segment Iterative Optimization for Maritime Supply Chain Operations in a Dynamic Fuzzy Environment	2020	FAHP (Fuzzy Analytic Hierarchy process) as multi-criteria decision making technique + Dijkstra algorithm (for minimising cost & risk, maximising performance)	Decision making algorithm for maritime supply chain (applicable to various other areas including autonomous ship manoeuvring)	Decision making algorithm for maritime supply chain (applicable to various other areas including autonomous ship manoeuvring)	Input to risk model	**Y**
7	Li Z., Hu S., Gao G., Xi Y., Fu S., Yao C.	Risk Reasoning from Factor Correlation of Maritime Traffic under Arctic Sea Ice Status Association with a Bayesian Belief Network	2021	BN based on DA effect (Dynamic association effect) for ship in arctic sea	Ship-ice collision risk	Ship-ice collision risk which is continuously updated	Input to risk model	**Y**

Figure 8 - List of LR-III articles (with real-time risk model presented)

Out of the total 15 articles found for LR-III, a limited number of research articles (seven) are found presenting a real-time risk analysis model or its framework as applied to autonomous ships (Figure 8). The predominant subject of interest is that of ship maneuvering (Xue et al., 2019), (Yu et al., 2021) and collision avoidance (Li et al., 2020). Additionally, there is a study on human errors on autonomous cargo ship from point of view of interaction between autonomy and persons with focus on the remote shore control centre (SCC) (Zhang et al., 2020). Utne et al. (2020) goes one-step further and presents how a real-time risk analysis model can be built and how it can be embedded into the ships control system – such that the two work in tandem enabling an intelligent autonomous system which can itself perform risk analysis that will trigger decision-making on its own such that the mission goal is achieved without human interference. Similarly, Thieme et al. (2021) presents a similar view-point of linking the ships control system to the real-time risk model albeit with a generic overview of a ships control architecture, with possible interfaces to the risk analysis model, supplemented with a toolbox of risk analysis methods and tools leaving its choice to the reader based on their evaluation of the most relevant approach. Thus, Thieme et al. (2021) and Utne et al. (2020) have been considered as a good starting point for the purpose of building the real-time risk analysis model to meet the mission goal of alerting the onboard captain when MRC is about to be breached for the Sundbåten case study.

The predominant causal and frequency analysis method used for the above real-time risk analysis models is that of Bayesian network / Bayesian belief network (BN/ BBN) used in four out of the seven studies. This is closely followed by the Fuzzy theory, used in three out of seven studies. Zhang et al. (2020) has used BN along with THERP (Technique for human error rate prediction) and ET (Event tree) for the risk analysis model for human error at the shore control centre of autonomous cargo ship. Utne et al. (2020) has used BBN for building the real-time risk analysis model and to provide a better structure to the STPA (Systems theoretic process analysis) hazard analysis. Yu et al. (2021) has used a BN learning approach to extract static risk data from the Ship risk profile (from new inspection regime) and combine it with the statistical dynamic risk model by using BN, and finally validated using ER (Evidential reasoning). Li et al. (2020) has used the BN to build a dynamic risk analysis model for ship-ice collision risk and combined with ice-monitoring data. While Thieme et al. (2021) has provided a concise overview of several causal & frequency analysis methods along with BBN like: Decision trees (DT), dynamic flowgraph method (DFM), Fault tree analysis (FTA), Markov model and Markov Cell to Cell Mapping Technique (MCCMT). It also introduces to consequence analysis method of event tree analysis (ETA), and simulation method of testing the resilience of autonomous system by failure scenarios and evaluating success of corrective measures with example of Monte Carlo simulations.

Besides, Sahin & Soylu (2020) present a multi-layer multi-criteria decision making algorithm for supply chain optimization which can be applied to other domains like autonomous ship maneuvering. In this study the weights are obtained by using a Fuzzy Analytical hierarchy process (FAHP), while Dijsktra algorithm is used to optimise the layers of risk, cost and performance. Also, the fuzzy method is used by Zhang et al. (2020) and Xue et al. (2019) to decipher expert judgement data in order to prioritise risk influencing factors for decision-making.

The remaining eight studies although not providing a real-time risk analysis model per se, still provide the background context or input to the real-time risk analysis model for autonomous ships or maritime autonomous systems (Figure 9). Chen et al. (2021) provides a comprehensive review of risk analysis methods for autonomous systems like FTA, ETA, BN, variants of BN like: Dynamic BN (DBN), Fuzzy BN (FBN), Copula BN. It also compares the relevance of these methods with reference to the autonomous maritime system of AUV (autonomous underwater vehicle) and concludes that BN based risk analysis methods show superior performance than traditional risk analysis methods of FTA, ETA, FMEA. This is stated to be due to improved clarity in causal relationship amongst risk-variables, and flexibility of BN to provide inferences in both forward and backward directions which suits the updation of knowledge when new information becomes available – which makes it a perfect match for dynamic risk environments. It further concludes that the biggest advantage of BN is that it can be developed with available expertise despite lack of historical information making it versatile for a range of autonomous systems besides AUV's. Other risk analysis methods are also discussed in Chen et al. (2021) like Markov chains which predominantly predict future states based on present state; and the system dynamics method suited for complex dynamic systems capable of understanding non-linear behaviours by using internal feedback loops. Thus, besides Thieme et al. (2021) and Utne et al. (2020) discussed earlier, Chen et al. (2021) also provides a supplementary contextual background to the presented real-time risk analysis study.

SR. NO.	AUTHORS	Title	Year	RISK ANALYSIS METHOD	DOMAIN	PURPOSE	SIGNIFICANCE	RISK MODEL
8	Chen X., Bose N., Brito M., Khan F., Thanyamanta B., Zou T.	A Review of Risk Analysis Research for the Operations of Autonomous Underwater Vehicles	2021	ALL METHODS DISCUSSED	Literature review of risk analysis methods for UAV	Literature review	**Framework for risk model**	**N**
9	Utne, IB; Schjolberg, I; Roe, E	High reliability management and control operator risks in autonomous marine systems and operations	2019	HRM framework for HAZID	HAZID for control room risks in autonomous ships	HAZID for control room risks (remote controlled operations)	Background to risk model	**N**
10	Fan C., Montewka J., Zhang D.	Towards a Framework of Operational-Risk Assessment for a Maritime Autonomous Surface Ship	2021	RPN calculated with FMEA for different LoA's	HAZID during switching of LoA with FMEA, followed by RPN for autonomous ship	Prioritising risk (RPN) during switching of LoA's	Input to risk model	**N**
11	Simon Blindheim, Sebastien Gros, Tor Arne Johansen,	Risk-Based Model Predictive Control for Autonomous Ship Emergency Management	2020	MPC Algorithm (dynamic risk based) for trajectory planning during emergency using heuristic objectives	Decision-making algorithm for moving autonomous ship along pre-planned path during emergency	Technical algorithm for moving ship along pre-planned path during emergency	Input to risk model	**N**
12	Mehdi R.A., Baldauf M., Deeb H.	A dynamic risk assessment method to address safety of navigation concerns around offshore renewable energy installations	2020	Manoeuvring envelope used in place of TTPA/ CPA	Ship manoeuvring near wind farms and/or wind farm supply vessels.	Calculating dynamic risk for collision for ships near wind farms	Input to risk model	**N**

SR. NO.	AUTHORS	Title	Year	RISK ANALYSIS METHOD	DOMAIN	PURPOSE	SIGNIFICANCE	RISK MODEL
13	Yang, X; Utne, IB; Sandoy, SS; Ramos, MA; Rokseth, B	A systems-theoretic approach to hazard identification of marine systems with dynamic autonomy	2020	STPA used for HAZID of Dynamic autonomy of marine systems	HAZID only	HAZID only	Input to risk model	**N**
14	Eriksen, S; Utne, IB; Lutzen, M	An RCM approach for assessing reliability challenges and maintenance needs of unmanned cargo ships	2021	Evaluation of RCM approach for unmanned cargo ships	Maintenance of unmanned cargo ships	Maintenance of unmanned cargo ships	Input to risk model	**N**
15	Baldauf M., Fischer S., Kitada M., Mehdi R.A., Al-Quhali M.A., Fiorini M.	Merging Conventionally Navigating Ships and MASS - Merging VTS, FOC and SCC?	2019	Exploratory discussion of mixed marine traffic. Simulated scenario experiment.	Exploratory discussion of mixed marine traffic. Simulated scenario experiment.	Exploratory discussion of mixed marine traffic. Simulated scenario experiment.	Background to risk model	**N**

Figure 9 - List of LR-III articles continued (without real-time risk model presented)

The level of autonomy (LoA) required for autonomous maritime system varies during the different phases of operation which is referred to as Dynamic autonomy (Yang et al., 2020). Yang et al. (2020) has performed a hazard identification (HAZID) analysis for dynamic autonomy using STPA. Hazards associated with Dynamic autonomy have also been explored by Fan et al. (2021) by using FMEA method of risk analysis based on failure modes derived from an accident simulation model “24 Model”. The RPN for each mode of operation (each LoA) were evaluated based on expert judgements using crisp numbers, based on which recommendations for change of LoA / operation modes were made. The topic of dynamic autonomy has also been explored from view point of human errors in remote /shore control rooms by Utne et al. (2019) during changeover of LoA’s of autonomous systems by applying the HRM (High reliability management) framework to find the real-time human operator performance during transitioning of control between human and autonomous system. This study concluded that the need for real-time risk management is “acute” for remote operators mainly due to the dynamic LoA’s for various autonomous systems.

An interesting take on a scenario of mixed marine traffic of autonomous vessels with manned vessels has been presented by Baldauf et al. (2019) which includes an experimental simulation study of mixed traffic interaction. Some key findings of this paper were the inability to communicate amongst the vessels, and inability to perceive the maneuvers to be done by other ships which are both critical in collision avoidance scenarios. Continuing on the topic of collision avoidance, Mehdi et al. (2020) presents a dynamic risk assessment method to evaluate collision risks while traversing in restricted waters near wind farms which is based on the concept of maneuvering envelope – with the notion that greater the overlaps amongst neighbouring maneuvering envelopes of adjacent ships greater is the collision risk. This dynamic risk was plotted along the path traversed indicating dynamically varying collision risks. Blindheim et al. (2020) has demonstrated the use of a dynamic risk based MPC (Model Predictive Control) algorithm for planning optimal trajectory of autonomous ship through a pre-planned narrow path with grounding risks on both sides. It considers that as the ship trajectory approaches closer to grounding obstacles, the costs associated with operations and risk costs would rise. These were incorporated into the algorithm by path progression cost function, control input cost function and risk cost functions. Thus making it possible to have real-time decision making within regular time-intervals for correcting the ship’s path so as to minimize the costs while maximizing safety.

2.3.2 *Real-time risk analysis (LR-I)*

A quantitative data analysis of the list of journal articles (SC_12 + WoS_02) for exclusion criteria A (n2A) and B (n2B) sourced from Scopus and Web of Science databases comprising of (40 articles+2 articles) and (36 articles + 2 articles) articles respectively is performed using MS Excel.

n2A : [SC_12] & [WoS_02]			n2B : [SC_12] & [WoS_02]		
SUM	**42**		**SUM**	**38**	
	Keyword Instances (No. of articles)	Abstract Instances (No. of articles)		Keyword Instances (No. of articles)	Abstract Instances (No. of articles)
Bayes	22	23	Bayes	23	29
Fuzzy	6	9	Fuzzy	5	8
Monte-Carlo	1	0	Monte-Carlo	1	1
Bow-tie	10	10	Bow-tie	0	1
Event-tree	1	0	Event-tree	0	0
Markov	0	0	Markov	2	2
Digital twin	0	0	Digital twin	1	1
Dynamic risk	12	12	Dynamic risk	3	11
On-line	0	0	On-line	1	2
Real-time	2	9	Real-time	4	12
realtime	1	0	realtime	0	0
Dynamic Bayesian	2	2	Dynamic Bayesian	6	7
Hierarchical Bayesian	1	1	Hierarchical Bayesian	2	2
Copula Bayesian	0	0	Copula Bayesian	0	0
STPA	0	0	STPA	0	0
Ship	1	2	Ship	2	5
Vessel	0	1	Vessel	0	1
Maritime	1	2	Maritime	1	1
Seismic	0	1	Seismic	0	0
Earthquake	1	1	Earthquake	0	0
Process industry	2	2	Process industry	0	1
Chemical	2	12	Chemical	0	6
Drilling	5	6	Drilling	3	4
Power	2	3	Power	0	1
Accident	10	24	Accident	4	17
Collision	1	3	Collision	2	4
Car	0	4	Car	1	4

Figure 10 - Data analysis of 'Real-time risk analysis' articles done in MS Excel

The data analysis is performed by using the ‘Countif’ function whereby word search is performed in abstract and keywords cells of the MS Excel list of shortlisted articles (Figure 10). It is found that the count of text by abstract is a more reliable measure than count of text by keywords since not all keywords are necessarily included in the keyword field of journal articles. A minute possibility of noise still exists in this method; however it nevertheless gives a good indication of the trend that would help in shaping the presented study.

A graphical representation of real-time risk analysis studies by theme is presented in Figure 11. It is observed that real-time risk analysis has been extensively applied in the chemical and process industry with 12 studies/ 42 studies (n2A), and 6 studies/ 38 studies (n2B). This is followed by the oil and gas drilling industry with 6 studies /42 studies (n2A). Whereas in n2B, the second highest studies has marginally shifted to ship industry with 5 studies/ 38 studies – indicating recent interest of real-time risk analysis in shipping industry also indicated previously by the highly limited number of LR-III search results. Another important thing to note is that accident data is found to be of great significance in both n2A and n2B with 24 studies / 42 studies and 17 studies / 36studies respectively.

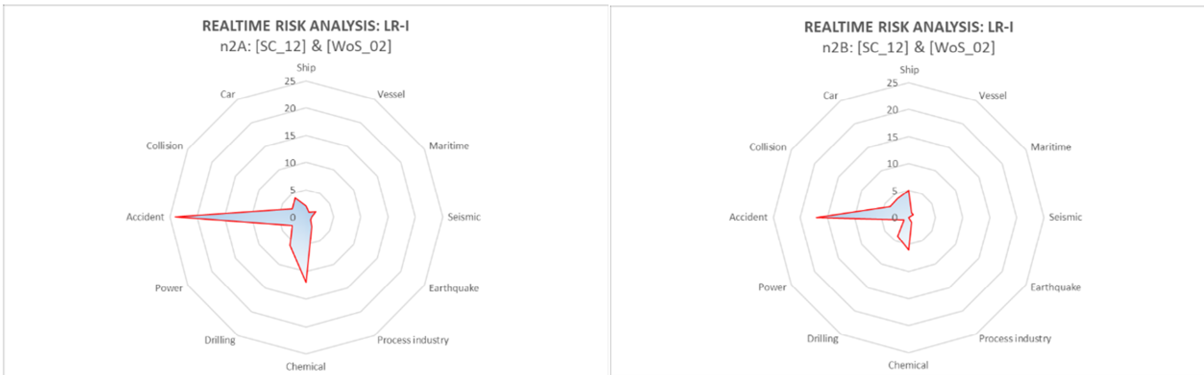


Figure 11 - Distribution of ‘Real-time risk analysis’ study themes (LR-1: n2A and n2B)
(Own graph prepared in MS Excel based on data analysis done in MS Excel)

Similarly a distribution of studies by risk analysis methods employed is shown in Figure 12. The Bayesian network (BN) emerges as the clear choice of majority of the real-time risk analysis studies with 23studies /42studies (n2A) and 29 studies /38 studies (n2B) – further indicating the dominance in the latest four years as well. Though predominantly the BN has been used in its original form, different variations of BN have also been used like Dynamic Bayesian network (DBN), Hierarchical Bayesian, Bayesian dynamic logistic regression, Bayesian conditional logistic model and Object-oriented Bayesian network to name a few.

This is followed by the bow-tie method with 10 studies /42 studies (n2A) and the Fuzzy method with 9 studies /42 studies (n2A). Whereas interestingly in the latest four years bow-tie method is found to have lost favour with a sole result in n2B, while the Fuzzy method has 8 studies /38 studies (n2B).

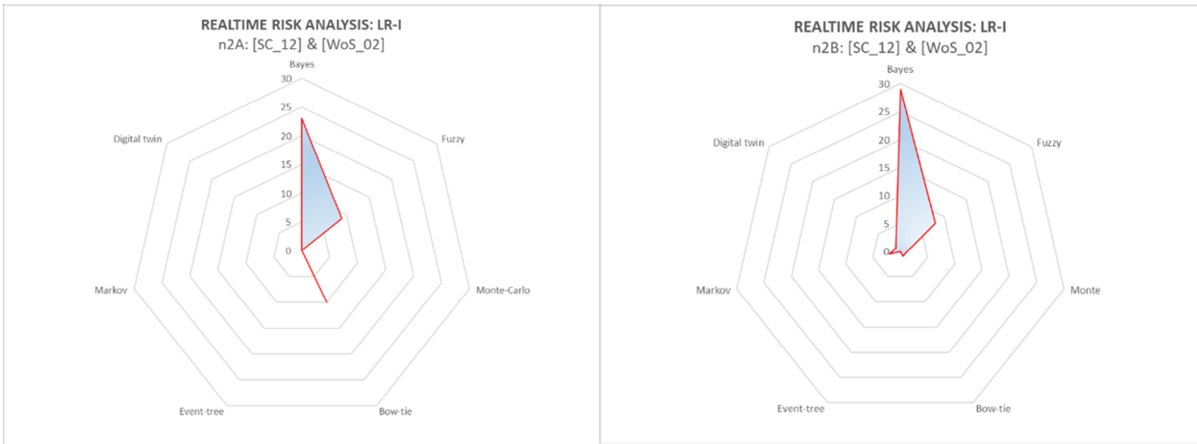


Figure 12 - Distribution of 'Real-time risk analysis' studies by risk analysis method (LR-1: n2A and n2B) (Own graph prepared in MS Excel based on data analysis done in MS Excel)

2.3.3 Autonomous ships (LR-II)

The journal articles (SC_51 + WoS_51) for exclusion criteria A (n2A) and B (n2B) sourced from Scopus and web of Science databases comprising of (36 articles + 2 articles) and (15 articles + 2 articles) respectively are applied quantitative data analysis using MS Excel with 'Countif' function as discussed in the preceding section (Figure 13).

n2_A: SC_51 & WoS_51		
SUM	**38**	
	Keyword Instances (No. of articles)	Abstract Instances (No. of articles)
Bayes	1	1
Fuzzy	5	6
Monte-Carlo	0	0
Bow-tie	0	0
Event-tree	0	0
Markov	0	0
Neural	2	3
Deep learn	0	0
Deep reinforcement learning	0	1
Ant colony	3	3
Dynamic risk	0	0
On-line	0	2
Real-time	0	4
realtime	0	0
Dynamic Bayesian	0	0
risk analysis	0	0
Ship	15	21
Vessel	3	16
Maritime	1	9
MASS	0	0
UAV	0	0
Process industry	0	0
Chemical	0	0
Drilling	0	0
Power	0	1
Accident	2	2
AUV	1	1
autonomous	14	20
unmanned	8	12
Sampling	0	0
Path planning	7	9
route planning	1	1
collision avoidance	15	21
COLREGS	5	7
Autonomous Underwater Vehicle	1	3

n2_B: SC_51 & WoS_51		
SUM	**17**	
	Keyword Instances (No. of articles)	Abstract Instances (No. of articles)
Bayes	0	0
Fuzzy	1	2
Monte-Carlo	0	0
Bow-tie	0	0
Event-tree	0	0
Markov	0	0
Neural	3	4
Deep learn	1	2
Deep reinforcement learning	3	3
Ant colony	0	0
Dynamic risk	0	0
On-line	0	0
Real-time	0	3
realtime	0	0
Dynamic Bayesian	0	0
Ship	10	15
Vessel	2	8
Maritime	3	5
MASS	0	0
UAV	0	0
Process industry	0	0
Chemical	0	0
Drilling	0	0
Power	1	1
Accident	0	1
AUV	0	0
autonomous	11	15
Unmanned	3	1
Sampling	0	0
Path planning	4	3
route planning	0	1
collision avoidance	4	6
COLREGS	1	3
Autonomous Underwater Vehicle	0	0

Figure 13 - Data analysis of 'Autonomous ships' articles done in MS Excel

A graph showing distribution of autonomous ship studies by theme is presented in Figure 14. The most dominant theme in the journal articles for autonomous ships is based on collision avoidance in 21 studies/ 38 studies (n2A), and 6 studies/ 17 studies (n2B). This is followed by path planning in 9 studies/ 38 studies (n2A), and 3 studies/ 17 studies (n2B). Furthermore, path planning and collision avoidance which is compliant with COLREGS is also found to be a repeating theme with 7 studies and 3 studies found in n2A and n2B respectively.

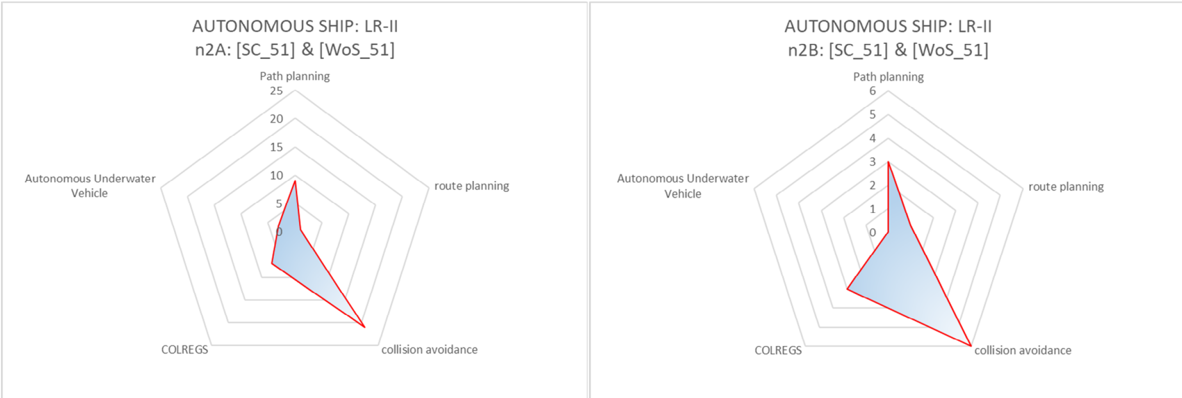


Figure 14 - Distribution of 'Autonomous ship' studies by themes (LR-II: n2A and n2B)
(Own graph prepared in MS Excel based on data analysis done in MS Excel)

A distribution of risk analysis method used in autonomous ship studies is shown in Figure 15. The Fuzzy method is preferred in the study of autonomous ships with 6 studies/ 38 studies (n2A), and 2 studies/ 17 studies (n2B). Whereas the usage of Bayes theorem is negligible in autonomous ship with only 1no. article in n2A, and none in n2B. This is because the predominant themes of collision avoidance and path planning warrant a decision making process which mirrors the human-way of thinking. Fuzzy-logic based systems are more attuned to such human-way of thinking and foster an environment which is human-friendly (Perera et al., 2011), (Perera et al., 2012).

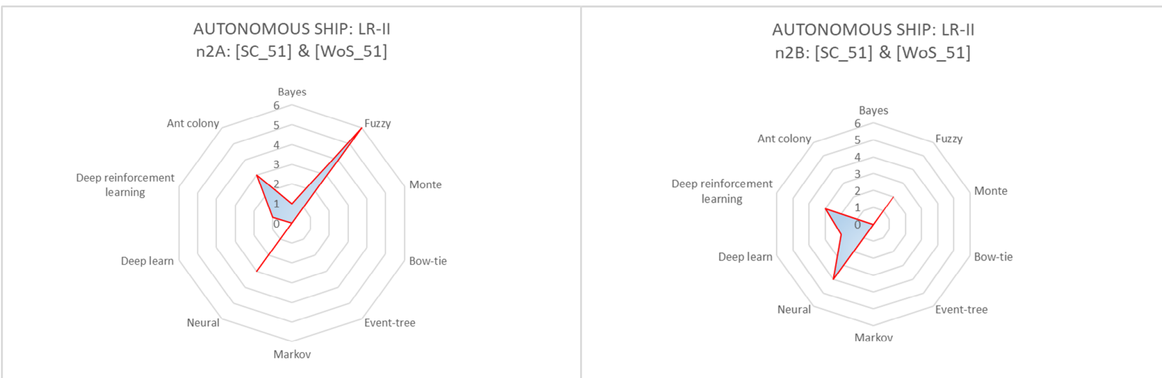


Figure 15 - Distribution of 'Autonomous ship' studies by risk analysis method (LR-II: n2A and n2B)
(Own graph prepared in MS Excel based on data analysis done in MS Excel)

The Neural network method is used in 3 articles/ 38 articles (n2A), and 4 articles/ 17 articles (n2B), with deep learning in 2 articles/ 17 articles (n2B) and deep reinforcement learning (DRL) in 1 article/ 38 articles (n2A), and 3 articles/ 17 articles (n2B). Thus, indicating a marked shift towards use of neural, deep learning and deep reinforcement learning methods in recent times in lieu of Fuzzy methods as can be seen in Figure 15. Neural methods are known for their distinct learning capabilities and have been used successfully in robotics as pointed out by Statheros et al. (2008) in their exploratory study of autonomous ship collision avoidance concepts and technologies. This study by Statheros et al. (2008) is considered as a good reference for collision avoidance concepts and constructs since it provides a very concise overview of the topic and provides diverse approaches to problem solving, and can thereby suitably supplement the development of the proposed real-time risk model.

2.4 Summary and theoretical framework

2.4.1 Unique challenges of Autonomous ships

Implementation of autonomous technologies on ships having level 3 automation does not completely insulate them from human errors. Zhang et al. (2020) states that rather, the place of operator is transformed from ship to shore based control centre (SCC), while the nature of human errors is more from point of view of interaction between the autonomous systems and humans. It further finds that during emergency response situations, the error making probability of operators at remote control centres is higher than in traditional ships. Thereby emphasizing the need for making the SCC's more robust to handle navigational risks and minimizing them.

Utne et al. (2019) highlights that though autonomous systems are normally identified with unmanned systems, some traditional ships which are manned also have systems onboard like the DP systems which possess autonomous control functionalities which can equally be identified as an autonomous system. Autonomous marine systems are characterized by a high prevalence of uncertainties from the ocean environment coupled with limited operational experience of handling such uncertainties (Utne et al., 2019).

This is further complicated by 'Dynamic autonomy' which is the switching of levels of autonomy between different modes of operation like manual, fully-automatic, partial-automatic or remote controlled according to the changing marine environment and within short intervals of time (Yang et al., 2020). Operational modes for autonomous ships are identified by manual control, remote control, autonomous control and fail-safe (or MRC as defined by *DNV-CG-*

0264, (2021), (Fan et al., 2021)). The studies by Fan et al. (2021), Yang et al. (2020), Utne et al. (2019), Utne et al. (2020) have identified that the challenge of quantifying risk in dynamic autonomy of autonomous maritime systems is one area which requires more research and have presented their own attempts at solving it.

An interesting finding of Utne et al. (2019) is that though increased autonomy reduces human effort on one hand, on other hand an emergency situation on such complex autonomous systems would warrant a highly experienced operator capable of understanding nuances of the system and capable of taking evasive actions within short reaction times.

The ship traffic at sea is dynamic in nature, and requires the operator to continuously adapt as per the prevailing traffic environment at sea during navigation (Li et al., 2020). Furthermore, Baldauf et al. (2019) highlights with a mixed traffic simulation experiment of autonomous ships merging with traditional ships that participants in the study expressed their inability to communicate with other ship and desired either direct communication with an operator onboard or the remote operator or some sort of indication from the autonomous ship system itself. This simulation experiment also showed that the more experienced seafarers took strategic and proactive decisions while manoeuvring their ships in the mixed traffic environment. The sum-total of this behaviour exhibited by operators onboard traditional ships can be referred to as human-like manoeuvring of ship. Xue et al. (2019) has presented prioritising of primary risk influencing factors based on decision-making influencing factors to establish a decision-making model that can contribute towards building of an algorithm which can effectively mimic human-like manoeuvring.

Statheros et al. (2008) has similarly emphasised that majority of collision avoidance algorithms despite being intelligent lack the ability to communicate with other ships as well as with traffic control stations. So, as a way around these algorithms then calculate safe distance and the best trajectory to avoid a collision. Statheros et al. (2008) further states that intelligent collision avoidance algorithms with their objective way of thinking, though capable of minimising errors in navigation are still lacking considerably in pattern recognition of obstacles and inability to communicate with surrounding traffic when compared with human abilities.

2.4.2 *Traditional risk analysis and Real-time risk analysis*

Traditional risk analysis is normally based on average risk values which suits decision-making during the design phase, that are not appropriate for operations phase where real-time information is required and the risk model should be able to reflect the dynamics of the system (Thieme et al., 2021). For the autonomous control system to act based on the risk model – it should be able to decide how much risk is acceptable and act accordingly (Thieme et al., 2021).

Traditional risk analysis models possess a static structure that cannot reflect variation in uncertainties over time in complex maritime systems (Chen et al., 2021). Hence in order to capture this dynamic uncertainty, dynamic risk analysis methods (or real-time risk analysis) are required that can continuously monitor abnormal situations and update based on new information the current overall risk (Chen et al., 2021).

Mehdi et al. (2020) points out that in dynamic risk analysis (or real-time risk analysis) the certainty and level of information is higher than in traditional static methods, whereas the availability of resources like time, tools is not considerable due to real-time operation. Thus it concludes that dynamic risk analysis is deterministic rather than probabilistic, whereas traditional risk analysis is probabilistic.

2.4.3 *Concept-map for real-time risk analysis model of autonomous ship:*

Eriksen et al. (2021) has quoted Bertram V. that traditional manned cargo ships have frequent failures in their ship machinery, and despite improvements expected in reliability of autonomous ships, these failures will continue to occur. Thus, it follows that autonomous ships will have some legacy components carried over from traditional manned ships, and some non-legacy components newly introduced in the autonomous ship as shown in Figure 16.

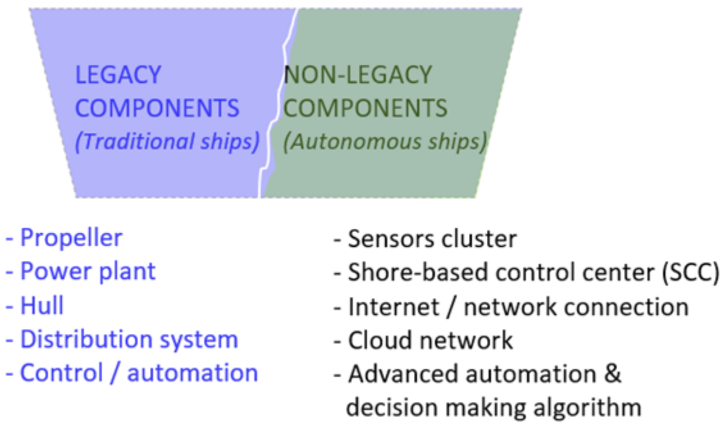


Figure 16 - Proposed classification of autonomous ship's components

The primary goal of maritime risk models is to find the factors which influence the ship's risk level in a particular situation, or a certain spatial area referred to as 'Risk Influencing Factors' (RIF's) (Yu et al., 2021). These RIF's are usually based on historical accident data, or expert judgements, or ship traffic data – which are then integrated into a risk measure by applying probabilistic approach (Yu et al., 2021).

Bayesian network (BN) is essentially a powerful semi-quantitative risk analysis tool which works with mixed data sources: where both quantitative data (relevant when data sources are available) and qualitative data (relevant when data sources are un-available or partially available) sources co-exist (Yu et al., 2021). It is also inferred in the previous section of literature review that BN is a preferred method for solving real-time risk analysis problems.

The typical steps in BN based risk analysis have been concisely summarised by Yu et al. (2021) as: 1) Finding RIF's, 2) Building qualitative BN model, 3) Entering quantitative dependencies and finally 4) converging onto the result. This has been used as the framework for the concept map shown in Figure 17, which is further adapted with necessary linkages for the autonomous ship real-time risk analysis.

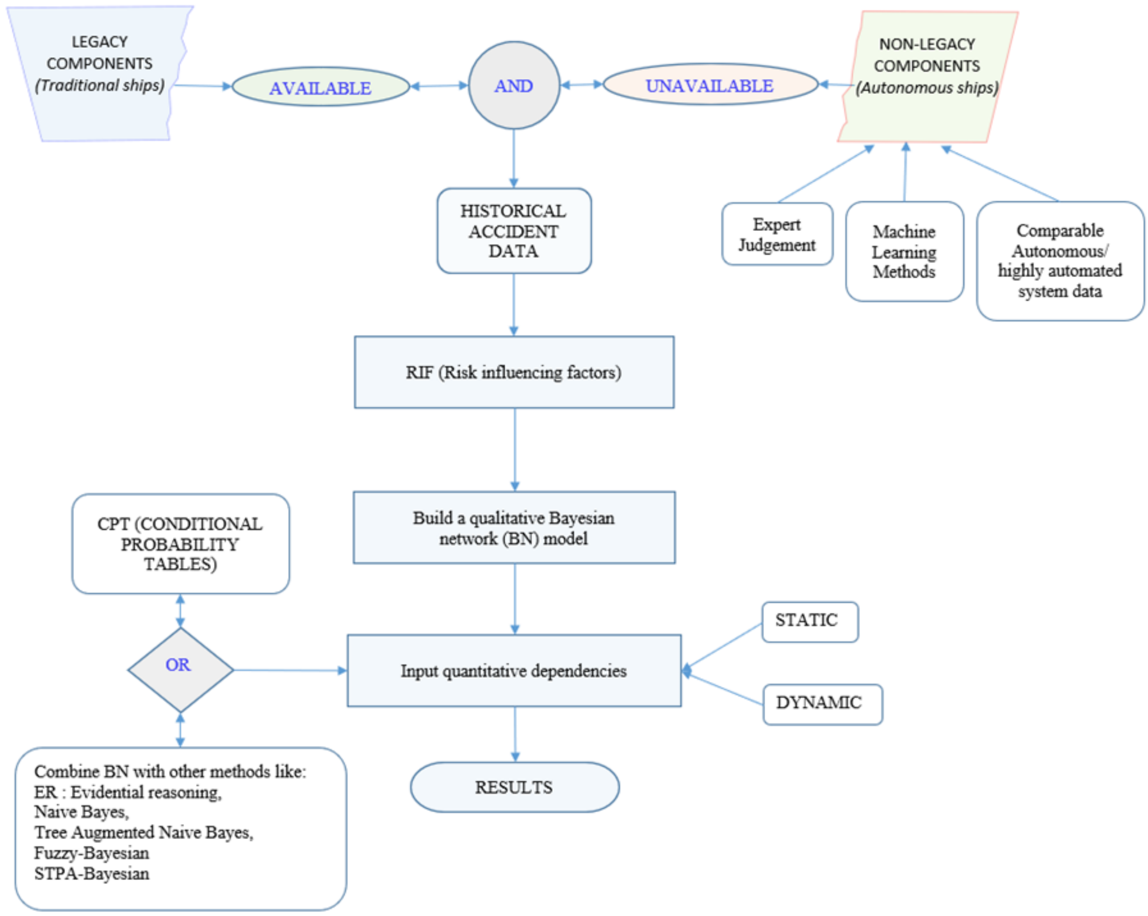


Figure 17 - Concept map for real-time risk analysis of autonomous ship

Historical accident data is an important input to the knowledge base of a BN which relies on quantity and quality of data, however all maritime areas do not have these or have incomplete data (Yu et al., 2021). Autonomous ships being a novel concept, very little to no historical data exists – mainly for the non-legacy components identified in the preceding part of this section.

This missing link in the historical data can be effectively handled by use of expert judgements and knowledge that can contribute with qualitative reasoning (Chen et al., 2021). However, a sole reliance on viewpoint of experts might lead to judgemental uncertainties due to inherent biases, which can be overcome by use of machine learning techniques that have the ability to enhance quantification errors under deficient data circumstances (Chen et al., 2021).

Thieme et al. (2021) has highlighted that highly automated systems have similarity in functions to autonomous systems, with the example of a dynamic positioning controller of an offshore supply vessel as a case-study. Autonomous systems can make decisions for themselves without human intervention, while fully automated systems can similarly perform many functions automatically by themselves with only higher level decision making being done by human (Thieme et al., 2021). Thus, there exists a possibility to extract historical data from comparable autonomous / highly automated systems, which has been incorporated in the presented concept map (Figure 17).

With reference to the BN risk analysis method, a key limitation is caused by the size of conditional probability tables (CPT) which become larger exponentially as the network grows in size and complexity. To get around this limitation, the BN can be combined with other methods like evidential reasoning (ER), Naive Bayes, Tree Augmented Naive Bayes (Yu et al., 2021). Furthermore, Chen et al. (2021) has also discussed variations of BN models as improvements to a classic BN. A BN can incorporate effect of time-dependence by use of Dynamic Bayesian Network (DBN), which updates over time based on new knowledge. A Fuzzy Bayesian Network (FBN) can mitigate the incompleteness or vagueness of available data from expert judgements by employing fuzzy set theory.

With respect to application to real-time risk analysis, Statheros et al. (2008) presents a good argument that while it is possible to develop a highly accurate mathematical model for decision-making, the time taken by such a model to arrive at a decision would make it irrelevant for real-time decision making. Hence, fuzzy logic based methods are stated to have an edge due to its quicker decision making – the reliability of which can be further improved by combining with other methods like Neural methods.

3 Research method

3.1 General introduction

Research method and research design are core central themes of any research project, which presents how a study has been conducted to a level of detail such that it can be repeated by others with comparable results. Research findings have higher credibility if different research studies conducted independently arrive at similar conclusions (Frankfort-Nachmias et al., 2014, p.263).

The research method applied for testing the hypothesis is a case-study approach with Sundbåten autonomous passenger ferry project as the case-study. The Sundbåten project is an ongoing research project between USN and Maritime Robotics for development of an autonomous passenger ferry at Kristiansund, Norway. The result of the hypothesis testing of the presented thesis will form a basis for achieving the mission goal of when the autonomous ferry should warn the onboard captain to take control of the ship. It should be noted that it was primarily the Sundbåten project itself which created the need for performing a research on real-time risk analysis model for autonomous ship as a possible solution to the question of when to call the captain to the bridge.

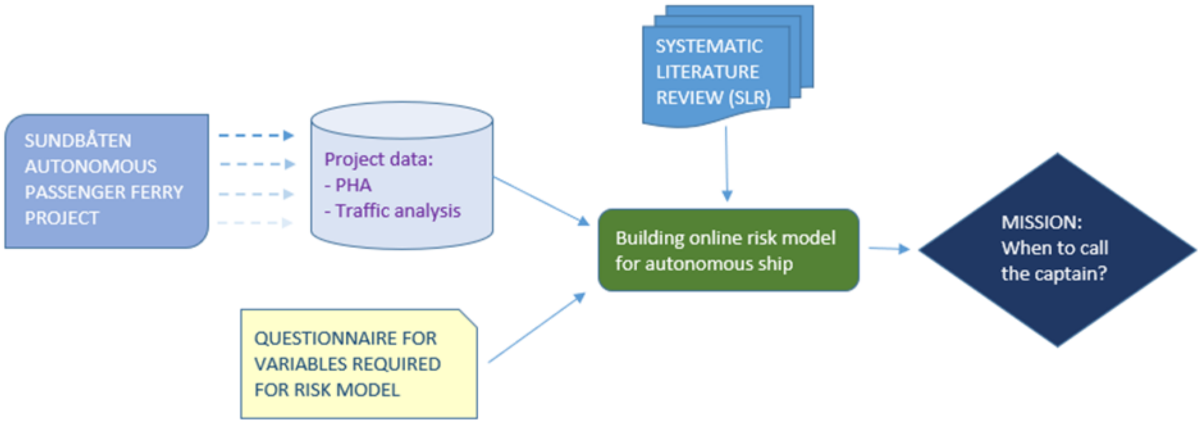


Figure 18 - Research method overview

Since the Sundbåten project is currently underway some data in the form of preliminary hazard analysis (PHA) of the autonomous ship, as well as collected marine traffic data over a period of one-year onboard MS Angvik are available (MS Angvik is a traditional manned ship currently operating on the Sundbåten route which shall be replaced by the autonomous ship). The marine traffic data collected as part of the Marine Traffic Analysis (MTA) primarily consists of AIS transmitting vessels from Kystverket (The Norwegian Coastal administration). This Sundbåten project data of PHA and MTA forms one of the three key building blocks for the real-time risk model, the other two being the theory generated from systematic literature review and results of the expert judgement questionnaire (Appendix F) for variables required for the risk model (Figure 18).

3.2 Research design

Scientific research is based on certain founding principles or assumptions also referred as scientific explanations which answer to the question "why" (Frankfort-Nachmias et al., 2014, p. 7-8). Such explanations can be either deductive or inductive in nature, where explanations based on an existing body of knowledge leading from the whole to part are deductive; whereas those based on fragmented details which when assembled together lead from part to whole are inductive (Gray, 2013, p.16).

In scientific research, the inductive and deductive processes are often complimentary to each other, and it is not possible to have a purely inductive research that completely ignores established theories or ideas of the day (Gray, 2013, p.18). The inductive research design comprises of a combination of inductive and deductive methods as shown in Figure 19 which shows a combined inductive and deductive research design as adapted from Gray, (2013).

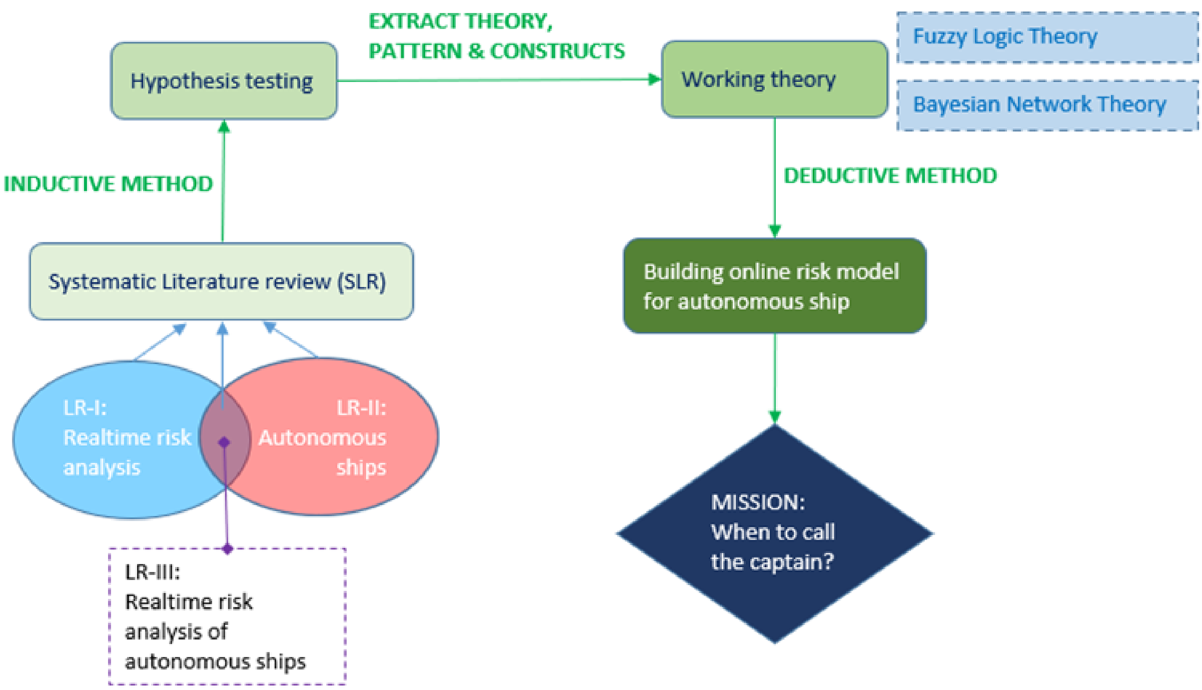


Figure 19 - Research design approach: Combination of inductive & deductive methods (Adapted from (Gray, 2013))

As shown in Figure 19, the literature review inductively provides fragments of information which when assembled together provide emerging patterns and constructs against which the hypothesis is tested. This provides a working theory that is based on existing established theories which are then deductively applied to build the real-time risk model to achieve the mission goal.

The presented research is a mixed method research comprising of qualitative and quantitative research methods. A mixed method research is one in which a hypothesis is tested by using both qualitative and quantitative methods for data collection and analysis (Plano Clark & Ivankova, 2022).

Firstly, the literature review represents the qualitative data collection for building the knowledge base which is further processed quantitatively using word count in MS Excel to extrapolate trends and themes. Secondly, the data of Sundbåten project comprises of both qualitative data by way of preliminary hazard analysis, as well as quantitative data in the form of field observations from MS Angvik ship. Thirdly, the questionnaire for expert judgment from a maritime expert – is structured to address both qualitative and quantitative aspects. The maritime expert has over 10 years of balanced experience with seafaring, ship simulator training and autonomous ships. These three data sources are indicated in the flowchart shown in Figure 18. Thus, the presented research is a mixed method research design comprising of both qualitative and quantitative research methods.

3.3 Ethical considerations

No interviews, field-experiments, lab-experiments or collection of personal information have been conducted in this research study. Project data comprising of PHA (Preliminary hazard analysis) and Marine traffic analysis (MTA) along with allied project discussions from "Sundbåten" project of USN/ Maritime Robotics has been used with a pre-condition that the collected data will not be shared, since the project is currently underway. The requisite Non-disclosure agreement (NDA) is signed with Maritime Robotics.

Confidentiality of project documents has not affected the quality of the study performed since the expert judgements and governing trends from data have been incorporated in the risk model. The only limitation is that the used project data cannot be explicitly shared in this report which if present increases the reliability of the report to the reader.

4 Analysis & Results

4.1 Framework for the real-time risk model

Building-on the concept-map for real-time risk analysis indicated in Figure 17, a framework is required to operationalise it into an actual working model. A top-down approach has been considered starting from the top similar to the STPA inspired top-down approach used in Utne et al. (2020). The top level being what is the real-time risk model expected to answer: which is when to call the onboard-captain to take control of the ship from its autonomous system. In order for the model to do that, a decision-making mechanism is required to be set-up which can collate existing risks and evaluate based on the sum-total of the prevailing risks at that instant of time.

The three over-arching risk themes for the risk influencing factors (RIF) have been identified as environmental risk, traffic or obstruction risk and ship condition risk based on Utne et al. (2020), Thieme et al. (2021) and Chen et al. (2021). Similarly, the PHA data from Sundbåten project as well as the typical navigational hazards for autonomous ships as identified by *DNV-CG-0264*, (2021) also corroborate with these three themes.

The above three risk themes have been presented in Figure 20, along with the identified underlying risk influencing factors based on literature review. It can be inferred that the ship condition risk is a very broad risk category covering all risks relevant to the ships primary components: both technical as well as human related.

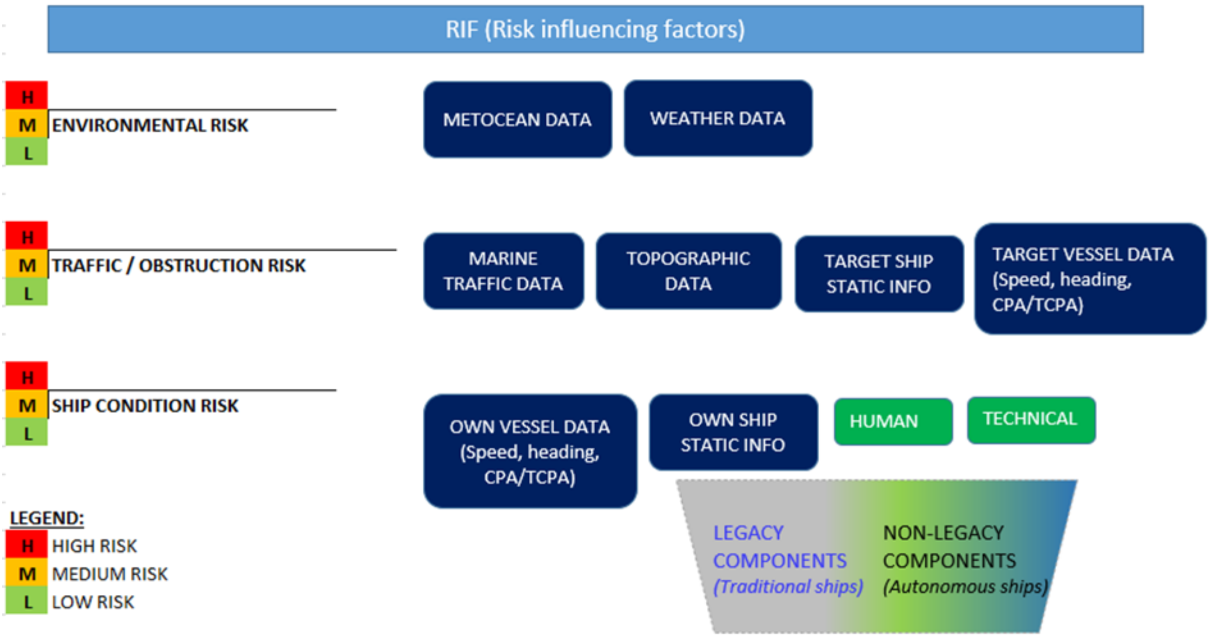


Figure 20 - Real-time risk model: Top level decision making layout

As previously entailed in the concept map, the ship's components are classified as legacy component and non-legacy components. The former being components from traditional manned-ships with available historical data, while the latter being components specific to autonomous ships with partial or no historical data. Thus, the traditional reliability based risk models are suited for legacy components, while Bayesian or real-time data based risk models are suited for non-legacy components. Eriksen et al., (2021) states that reliability based methods are generally applicable for reliability and maintenance of components on unmanned ships, however highlights that the biggest challenge is faced by long voyage ships (typically cargo ships) due to lack of corrective maintenance opportunities onboard the ship due to unmanned (or partially manned) operations.

4.2 Fuzzy-logic based decision-making: Top level

At the top level, each of the three risk themes are assigned a 3-level risk value: low (L), medium (M) and high (H) as shown in Figure 20. In order to mimic human-like decision making, a fuzzy-logic based decision making system is incorporated.

Matlab R2022a software has been used to build the fuzzy inference system at top level, using its graphical user interface: 'Fuzzy logic toolbox' as shown in Figure 21. Each of the three risk themes are represented as input variables (in yellow boxes) as Environmental risk (ENVIRO), Traffic/ obstruction risk (TRAFFIC_OBST) and ship condition risk (SHIP_COND). In order to incorporate human-interpretation of linguistic terms of low risk (L), medium risk (M) and high risk (M): three membership functions are built as triangular membership functions for each L, M and H risk levels based on the questionnaire (Figure 22).

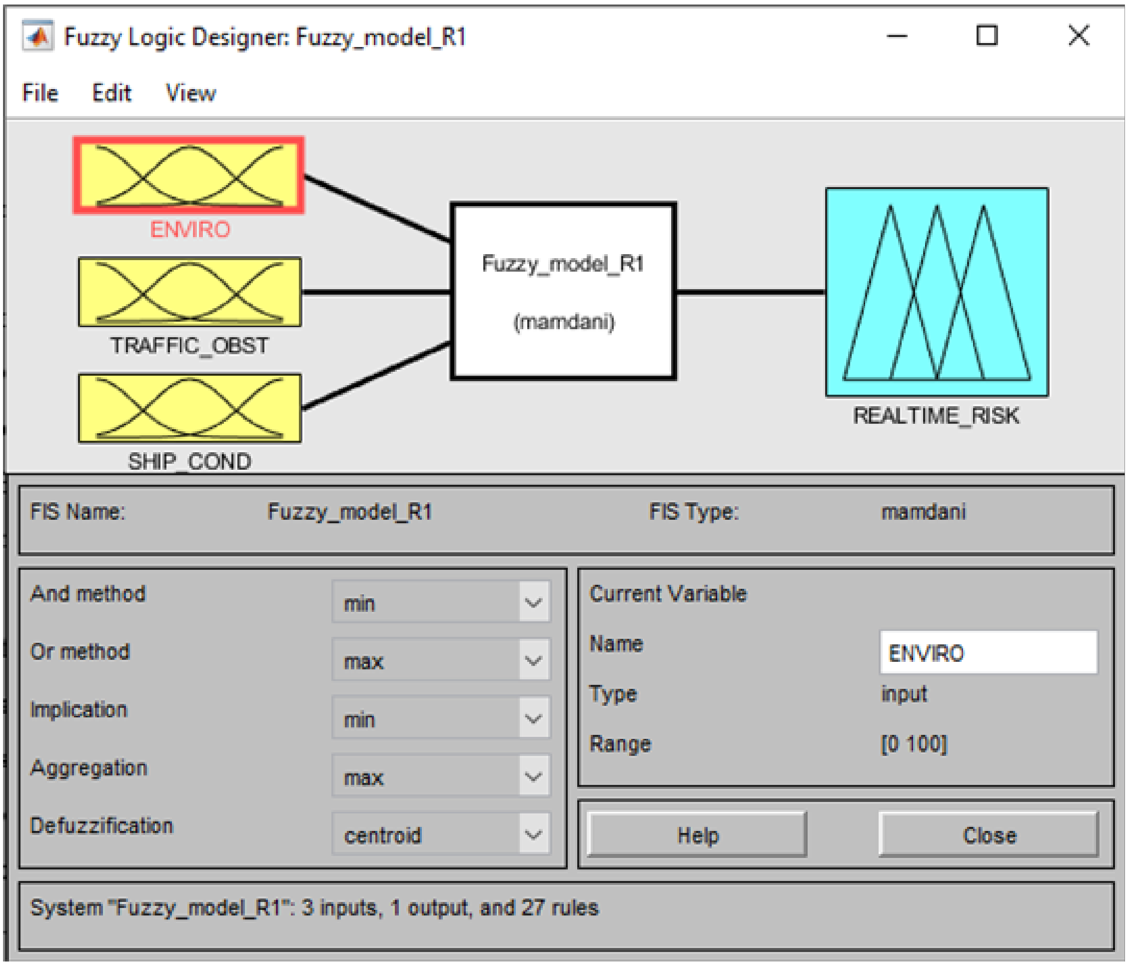


Figure 21 - Matlab Fuzzy logic designer tool showing risk evaluation at top level

A rule-based decision making based on 'Mamdani Fuzzy inference system' is then entered at the next step indicated by white coloured box in Figure 21. The rules are then defined inside the rule editor box using boolean operator 'and'. A simplified view of these are presented using MS Excel in Figure 22 showing the three input variables, and the output variable. Each of the three risk themes of environmental risk, traffic/ obstruction risk and ship condition risk can take three possible values of L,M or H at input end. Thus resulting in a total number of 3 x 3 x 3 = 27nos. of fuzzy rules at input end. These rules for fuzzy decision making as shown in Figure 22 are self-explanatory. For example the first entry of L,L,L at input ends translates to VL at output end. Meaning that when environmental risk is "low", 'and' traffic/ obstruction risk is "low", 'and' ship condition risk is "low", then the total risk is "very low". The rules are designed such that traffic/ obstruction risk is scaled ahead, followed by environmental risk and finally followed by ship-condition risk based on the expert judgement data from questionairre (Appendix F). The reasoning behind this is that in terms of likelihood of the risk to cause a near-collision or total collision scenario is the highest for traffic/ obstruction risk followed by environmental risk and then lastly the ship-condition risk. This effect is visible in the output 'Surface plot' shown in Figure 25.

The output variable (in blue box) is defined as a five-level risk namely: Very Low (VL), Low (L), Medium (M), High (H) and Very High (VH) – as five triangular membership functions as shown in Figure 21 and Figure 24. The reason behind using a narrower five-level risk for output is to get more risk levels so that the change in risks is magnified thereby providing crucial reaction time for the onboard operator, which is not possible with a broader three-level risk output. While the rationale for using a broader three-level risk at input end (Figure 23) is that it enables fewer number of combinations for rules which sufficiently defines the five-level risk output. This approach also confirms with Castillo et al. (1997) which states the problem of exponential increase of rules when input variables increase beyond four to five variables which are quantified as fuzzy sets. It also states the problem of transparency of model which gets lower when the number of rules become larger and/or longer – adversely impacting its readability. The three-level input risk variables (L/M/H) are defined as triangular membership functions Figure 23 in the Fuzzy logic toolbox based on the expert judgement data from questionairre (Appendix F) such that the traffic/ obstruction risk has the lowest risk threshold, followed by environment risk and lastly the ship-condition risk in increasing order of risk threshold levels.

The final output of Mamdani fuzzy inference system is done by aggregating the fuzzy values for each of the three risk themes one-by-one at each of the 27 nos. of rules. The fuzzified values at each of the rules are aggregated together to provide a single fuzzified value. Then this value is de-fuzzified by centroid-method to achieve the final crisp-value of risk. This final crisp-value of risk gives the total risk value, which is the total real-time risk value, based on which the decision whether to call or not call the captain is made. It should be noted that defuzzification by centroid method creates an upper & lower bound for the output variable (real-time risk membership function) corresponding to the centroid location. Hence, the range for the output variable (real-time risk) membership function is calibrated such that its lower bound tends to zero when all 3 input variables are zero, and similarly its upper bound tends to 100 when all 3 input variables are 100. This is shown in Figure 24, where the output variable (real-time risk) membership function has a range of [-12 to 128].

The fuzzy logic toolbox creates a 'Surface plot' output of Mamdani Fuzzy inference system which displays the total risk level in different scenarios as shown in Figure 25.

RULES FOR FUZZY DECISION MAKING

INPUT			OUTPUT
(3-level risk value)			(5-level risk value)
ENV	TRAFF	SHIP	STATUS
L	L	L	VL
M	M	M	H
H	H	H	VH
M	L	L	L
H	L	L	M
L	M	L	M
L	H	L	H
L	L	M	L
L	L	H	M
M	M	L	H
M	H	L	VH
H	M	L	H
H	H	L	VH
L	M	M	H
L	M	H	H
L	H	M	H
L	H	H	VH
M	L	M	M
H	L	H	H
M	L	H	M
H	L	M	H
M	M	H	H
M	H	M	VH
M	H	H	VH
H	M	H	H
H	M	M	VH
H	H	M	VH

Figure 22 – Simplified version of rules for fuzzy decision-making presented in MS Excel

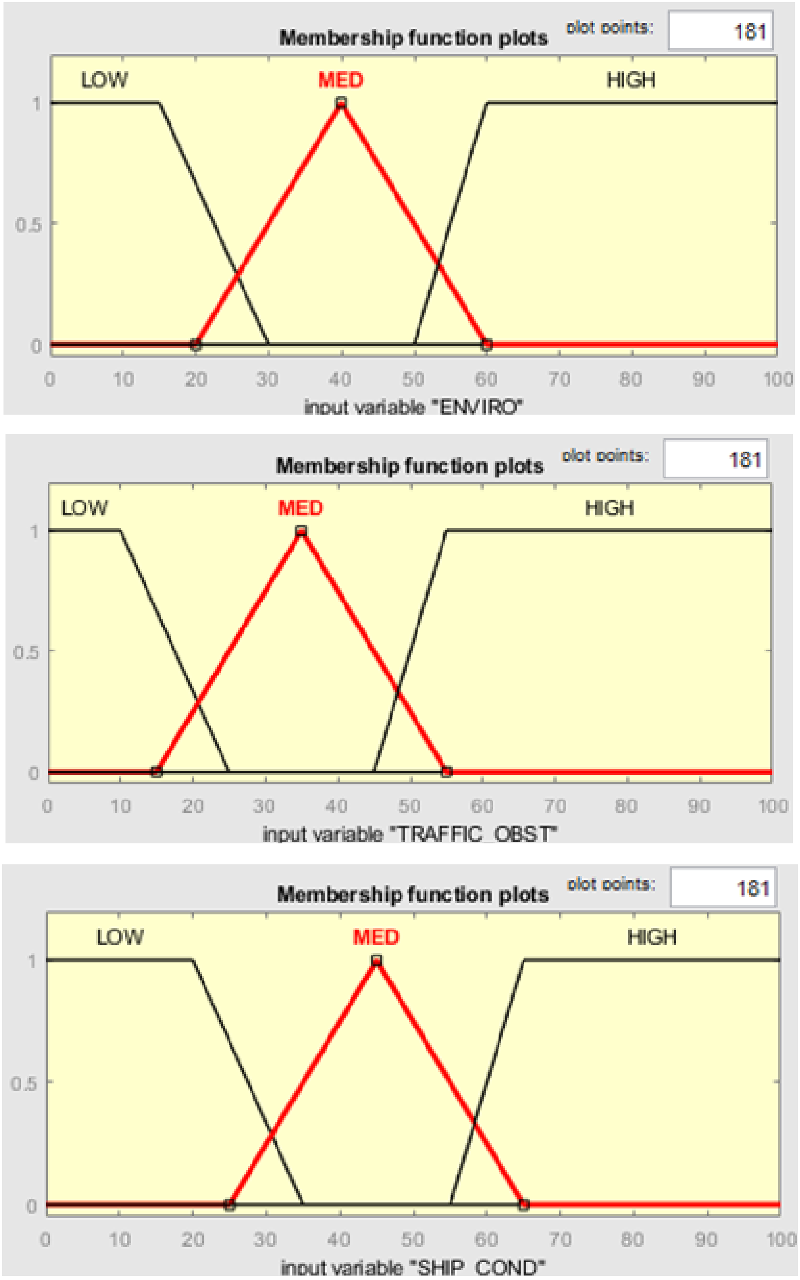


Figure 23 - 3-level input risk membership function

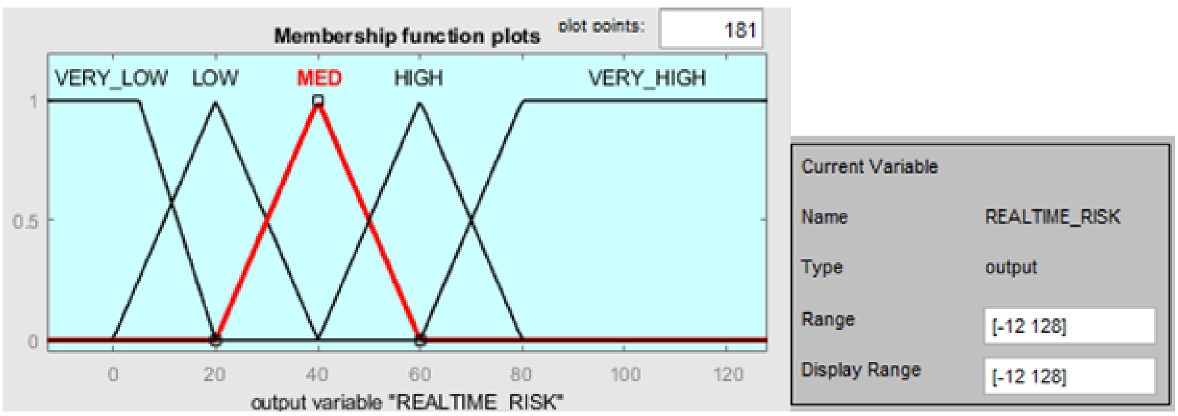


Figure 24 – 5-level output risk membership functions

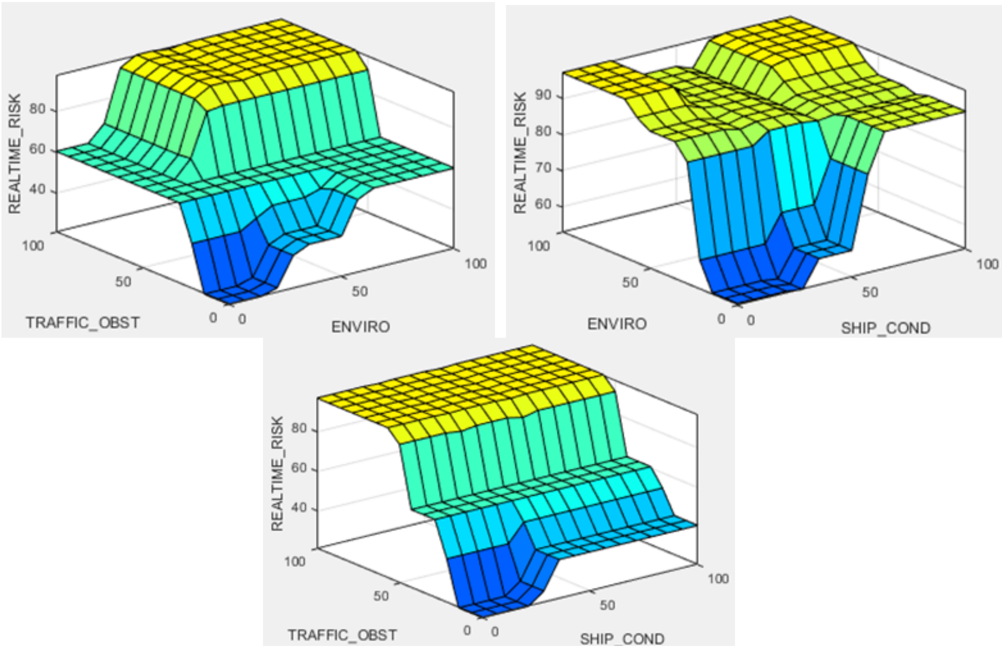


Figure 25 – 'Surface plot' output of Mamdani Fuzzy inference system indicating total risk level in different scenarios (Matlab Fuzzy logic toolbox output)

4.3 Bayesian network model: Bottom level

The bottom level decision-making which shall feed into the top-level decision-making is built based on Bayesian network (BN) model as shown in Figure 26. The reason behind choosing a BN model for bottom level is that as we go from top to bottom, we dive into a layered and complex network of variables (or risk influencing factors). The use of BN model allows the risk model to be built on incomplete information which gets updated based on latest available evidence (for example from the sensors) that can be entered anywhere in the network propagating through the model either from cause to effect (forward) or effect to cause (backward) providing an updated probability distribution for every variable in the network (Fenton & Neil, 2012).

This enables the fuzzy-logic based top level model to be fed with always the latest information from the BN-based bottom model, thereby enabling the risk model to be real-time in the true sense. At the same time, the use of fuzzy-logic at top level allows for quicker decision-making which suits real-time situations as also identified by Statheros et al. (2008). This essence of time in emergency situations on complex autonomous ships by virtue of short reaction times is highlighted by Utne et al. (2019), and also by Zhang et al. (2020) in the context of delayed perception at shore control centres.

Furthermore, the key advantage of BN model is the pictorial representation of the causal factors by nodes which are interconnected by links / arrows thereby indicating which variables are connected and which ones are independent, combined with its ability to quantify uncertainty explicitly in a transparent manner (Fenton & Neil, 2012).

Due to the limited time-resource, only the traffic / obstruction risk is explored further in the bottom level risk model (highlighted in blue box in Figure 26 and Figure 31). The reason for choosing the traffic /obstruction risk is that amongst the three risk themes, it is the most researched topic in the field of autonomous ships and maritime systems.

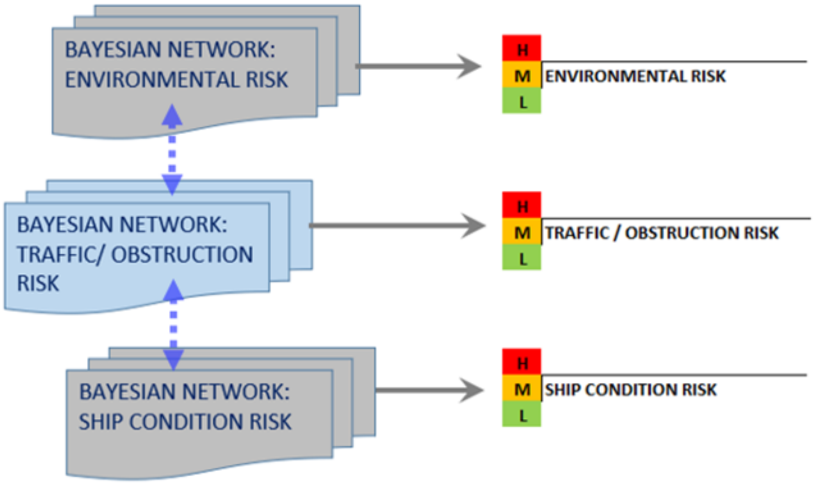


Figure 26 - Real-time risk model: Bottom level decision making data link

As shown in Figure 26, each of the three risk themes have corresponding Bayesian networks which feed them their respective risk figures. The top-down approach is continued while building the BN using a hierarchical structure which improves readability and provides clarity besides minimising the number of parents for any node as recommended by Fenton & Neil, (2012).

Continuing the split in three themes (at top level) by building corresponding sets of three Bayesian networks (at bottom level) besides providing the data link, also has a crucial advantage of splitting which avoids explosion of combinations encountered in very large Bayesian networks as pointed out by Fenton & Neil, (2012). However, the interlinking of some of the under-lying nodes (or RIF's) of the three BN's is still possible as indicated by the blue dashed arrows in Figure 26 maintaining homogeneity of the total risk analysis model.

4.3.1 Bayesian network model: For traffic/ obstruction risk

The Bayesian network (BN) model for traffic/ obstruction risk is built using the ‘GeNIe’ software, v3.0.6518.0 (32-bit) for Bayesian network modelling by ‘BayesFusion, LLC’.

The risk influencing factors (RIF’s) which form the nodes of the BN model (Figure 27) are a combination of sources from literature review as well as some new RIF’s. The new RIF’s identified are: presence of small leisure boats, high tides causing floating debris, removal of floating debris, crossing of maritime traffic lanes, 2-way communication and COLREG compliance – which are found to be unique and hitherto not discussed in earlier BN risk model studies for autonomous ships. The structure of BN, causation links between RIF’s and resulting events, as well as grouping of sub-risks are not based on previous studies and has been newly developed as part of this thesis.

Some RIF’s are adapted from the risk model proposed by Utne et al., (2020) and the technology modules for autonomous navigation functions of unmanned ships identified by *DNV-CG-0264*, (2021). The RIF for crossing of maritime traffic lanes is derived from Rule 10(c) of *COLREGS*, (2016) which explicitly recommends vessels to avoid crossing of traffic lanes as far as feasible and if necessary to do so, advises to cross at 90 degrees to traffic flow, thereby abductively implying the inherent risks of crossing maritime traffic lanes.

The data analysis & processing of the preliminary marine traffic analysis (MTA) data collected over a period of one year onboard the passenger ferry MS Angvik as part of Sundbåten project is currently in early stages. Discussions which were part of the MTA provided an interesting observation that small leisure crafts are a risk factor, since they neither have AIS transmitting devices nor they use VHF radio, and very often violate COLREG give way rules leading to near-collision situations. Therefore, small leisure crafts have been considered as RIF in the BN model (Figure 27). Similarly, it is found from the MTA discussions that during times of high tide some debris like wood planks, ropes, tree stumps are often noticed at the sea thus being possible sources of obstruction. However, these are picked by the port authorities once alerted by captains. Hence, tides and status of debris removal are some other RIF’s which are included in the BN model (Figure 27). Similarly, Sundbåten route crosses maritime traffic lanes several times in a day and hence crossing of maritime traffic lanes as also been identified as a major risk in the BN risk model.

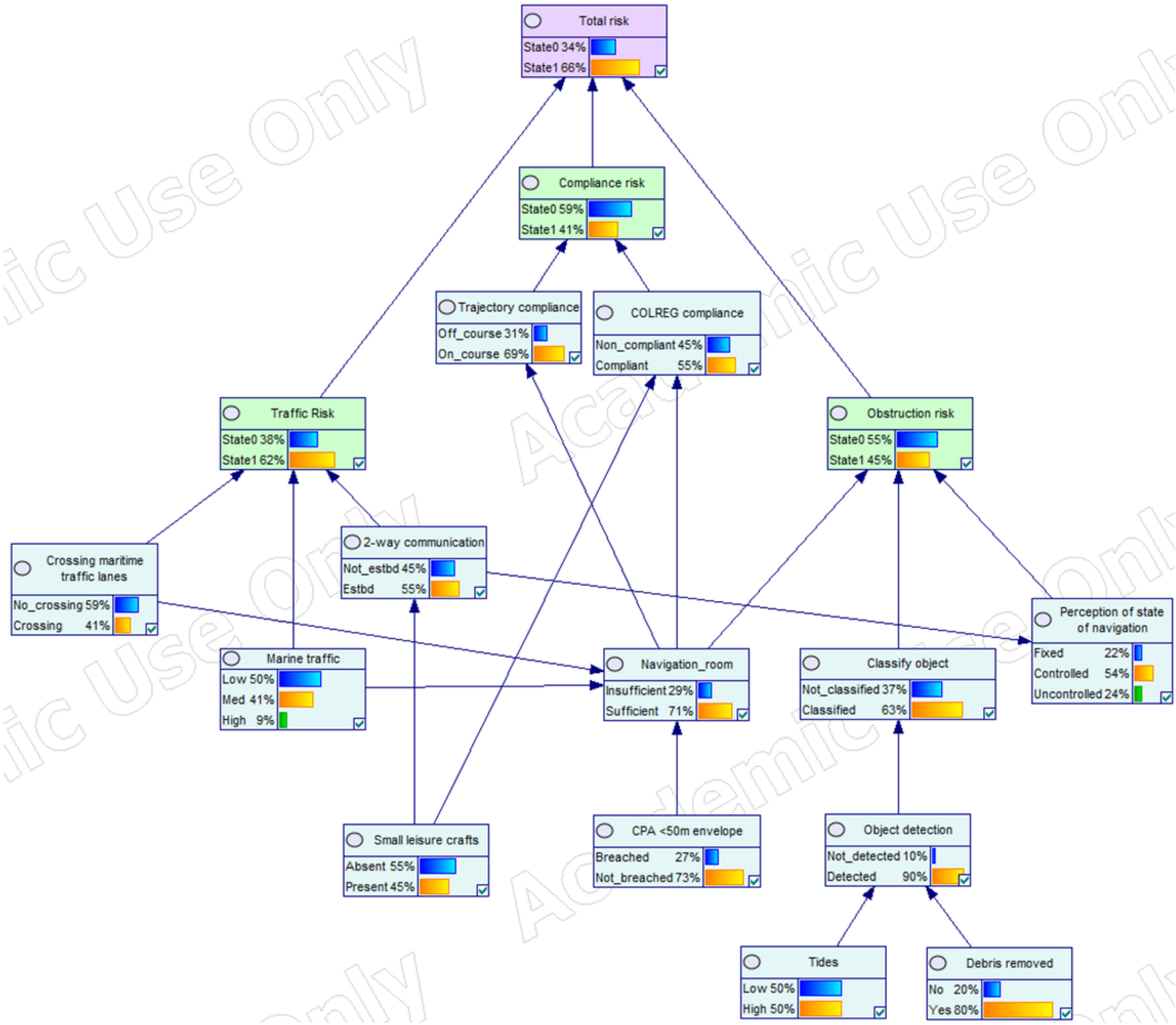


Figure 27 - Traffic /Obstruction risk BN model with prior beliefs applied at root nodes (no evidence updated)

The splitting concept is further carried down into the traffic/ obstruction risk BN by splitting into three main sub-risks (in green boxes) namely: traffic risk, obstruction risk and compliance risk (Figure 27). This limits the number of parents for any node to three simplifying the BN structure. The traffic risk covers risk associated with marine traffic, obstruction risk implies risk of obstruction to path traversed by the ship and compliance risk caters to risk reflected by degree of conformance to rules or to trajectory prompts. The RIF's within these three sub-risks are further interconnected wherever cause-effect relation exists.

The interconnection of underlying RIF's with those of adjoining BN's of environmental risk and ship condition risk are excluded in this model since the focus is only on traffic/obstruction risk. For example, the trajectory compliance requires interconnection with environmental risk and ship condition risk since these affect the ship's compliance to trajectory which are shown in the risk model proposed by Utne et al., (2020).

4.3.2 Bayesian network model: Parameters

Prior belief: P(H)

A prior belief *P(H)* represents our prior knowledge or belief regarding the probability of occurrence of a hypothesis *(H)* (Fenton & Neil, 2012). The hypothesis referred here implies the variable or RIF. The prior belief is based on historical data or expert judgements (Zhang et al., 2020). The prior beliefs and their sources considered in the BN model are presented in Figure 28. These are primarily based on the historical maritime traffic analysis (MTA) data collected over a period of one year onboard MS Angvik (for Sundbåten project), while some are assumed as stated in Figure 28. The prior belief probabilities are applied to the root nodes (or bottom-most nodes without any parent) of BN model as shown in Figure 27.

Posterior belief: P(H | E)

A posterior belief *P(H | E)* is the updated probability of occurrence of the hypothesis *(H)* (variable or RIF), due to occurrence of a new evidence *(E)* (Fenton & Neil, 2012). The occurrence of new evidence *(E)* can be updated in any of the nodes in the BN model inside the GeNIe software, which updates the probability distribution of the BN, yielding posterior beliefs.

Likelihood of evidence: *P(E | H)*

The likelihood of evidence *P(E | H)* implies how likely the particular evidence *(E)* is to be seen for the given hypothesis *(H)* (Fenton & Neil, 2012).

Prior belief: *P(E)*

A prior belief *P(E)* represents our prior knowledge or belief regarding the probability of occurrence of a evidence *(E)* (Fenton & Neil, 2012).

Bayes Theorem

A simplified formulation for finding the posterior belief *P(H | E)* is provided by the Bayes theorem which is as under (Fenton & Neil, 2012):

$$P(H \mid E) = \frac{P(E \mid H) \quad x \quad P(H)}{P(E)}$$

Description	**Quantity** *Nos.*	**Prior belief** *(% Frequency)*	**Source**
Average round trips in a day (summertime)*	22	-	Kystdatahuset (KD)
Crossing maritime traffic lanes	9	41 %	Kystdatahuset (KD)
Marine traffic: High	2	9 %	MTA
Marine traffic: Medium	9	41 %	MTA
Marine traffic: Low	11	50 %	MTA
Small leisure crafts: Absent	12	55 %	
Small leisure crafts: Present #	10	45 %	Assumed based on KD & MTA data
CPA <50m envelope: Breached	6	27 %	MTA
CPA <50m envelope: Not Breached	16	73 %	MTA
Tides: Low	-	50 %	Kartverket
Tides: High	-	50 %	Kartverket
Debris removed (by Port authorities): No **	-	20 %	Assumed **
Debris removed (by Port authorities): Yes	-	80 %	

Notes:

- MTA: Marine traffic analysis onboard MS Angvik
- "One Round-trip" implies starting from point A and returning back to starting point A

* - Summer time considered due to more trips

- MTA statistics have some reliability issues; however, it still provides indication of trends

\# - Small leisure craft in summertime, indicates average number of unique crafts in a day.

- Object detection is dependent on condition of mainly non-legacy items like sensor clusters which are part of "Ship condition risk" hence prior belief is assumed

** - Port authorities are alerted by captains about debris, which is then immediately cleaned. Debris like wood planks, wood logs, rope (sometimes) typically noticed after high tides (MTA).

Figure 28 - Prior beliefs considered (MTA: Marine traffic analysis onboard MS Angvik (for Sundbåten project))

Conditional Probability Tables *(CPT)*

The root nodes of BN model as shown in Figure 27, are connected by corresponding child nodes in a network leading up to the top level nodes. Similar to the prior belief probabilities at the root nodes, the subsequent chain of child nodes have conditional probability tables which have probabilities conditioned on the prior probability of parent nodes connecting into that child node (Fenton & Neil, 2012).

The CPT's for top level BN nodes are shown in Figure 29, while those for bottom level BN nodes are shown in Figure 30. The conditional probabilities for the CPT's have been entered mainly based on MTA and its discussions. A detailed list of conditional probability values is provided in Appendix F. These CPT values are sourced from MTA, and reviewed by expert judgement.

Node properties: Total risk

Traffic Risk	State0				State1			
Obstruction risk	State0		State1		State0		State1	
Compliance risk	State0	State1	State0	State1	State0	State1	State0	State1
State0	0.95	0.3	0.4	0.25	0.3	0.15	0.15	0.05
State1	0.05	0.7	0.6	0.75	0.7	0.85	0.85	0.95

Node properties: Traffic Risk

Crossing mariti...	No_crossing						Crossing					
Marine traffic	Low		Med		High		Low		Med		High	
2-way communi...	Not_estbd	Estbd	Not_estbd	Estbd	Not_estbd	Estbd	Not_estbd	Estbd	Not_estbd	Estbd	Not_estbd	Estbd
State0	0.3	0.95	0.2	0.35	0.1	0.25	0.25	0.4	0.15	0.3	0.05	0.2
State1	0.7	0.05	0.8	0.65	0.9	0.75	0.75	0.6	0.85	0.7	0.95	0.8

Node properties: Obstruction risk

Classify object	Not_classified						Classified					
Navigation_room	Insufficient			Sufficient			Insufficient			Sufficient		
Perception of state of navigation	Fixed	Controlled	Uncontrolled	Fixed	Controlled	Uncontrolled	Fixed	Controlled	Uncontrolled	Fixed	Controlled	Uncontrolled
State0	0.25	0.35	0.2	0.65	0.7	0.4	0.3	0.4	0.25	0.7	0.75	0.45
State1	0.75	0.65	0.8	0.35	0.3	0.6	0.7	0.6	0.75	0.3	0.25	0.55

Node properties: Compliance risk

Trajectory compliance	Off_course		On_course	
COLREG compliance	Non_compliant	Compliant	Non_compliant	Compliant
State0	0.15	0.75	0.25	0.95
State1	0.85	0.25	0.75	0.05

Figure 29 - CPT's for top level BN nodes

Node properties: Trajectory compliance

General | Definition | Observation Cost | Format | Documentation | User properties | Value

Navigation_room	Insufficient	Sufficient
Off_course	0.95	0.05
On_course	0.05	0.95

Node properties: COLREG compliance

General | Definition | Observation Cost | Format | Documentation | User properties | Value

Navigation_room	Insufficient		Sufficient	
Small leisure crafts	Absent	Present	Absent	Present
Non_compliant	0.1	0.95	0.05	0.9
Compliant	0.9	0.05	0.95	0.1

Node properties: Navigation_room

General | Definition | Observation Cost | Format | Documentation | User properties | Value

Marine traffic	Low				Med				High			
Crossing maritime traffic lanes	No_crossing		Crossing		No_crossing		Crossing		No_crossing		Crossing	
CPA <50m envelope	Breached	Not_breached	Breached	Not_breached	Breached	Not_breached	Breached	Not_breached	Breached	Not_breached	Breached	Not_breached
Insufficient	0.25	0.05	0.35	0.15	0.45	0.25	0.55	0.35	0.95	0.75	0.98	0.85
Sufficient	0.75	0.95	0.65	0.85	0.55	0.75	0.45	0.65	0.05	0.25	0.02	0.15

Node properties: Classify object

General | Definition | Observation Cost | Format | Documentation | User properties | Value

Object detection	Not_detected	Detected
Not_classified	1	0.3
Classified	0	0.7

Node properties: Object detection

General | Definition | Observation Cost | Format | Documentation | User properties | Value

Tides	Low		High	
Debris removed	No	Yes	No	Yes
Not_detected	0.1	0.05	0.5	0.05
Detected	0.9	0.95	0.5	0.95

Node properties: 2-way communication

General | Definition | Observation Cost | Format | Documentation | User properties | Value

Small leisure crafts	Absent	Present
Not_estbd	0.05	0.95
Estbd	0.95	0.05

Figure 30 - CPT's for bottom level BN nodes

4.4 *Real-time risk model: Bottom level + Top level*

The final concluding step in the building of real-time risk model is to combine the Bayesian network model at bottom level with the fuzzy logic risk model at the top level to arrive at 'one' real-time risk value. This is represented by the flowchart shown in Figure 31, which shows the flow of risk information from the Bayesian risk model to the Fuzzy logic model which yields the resulting real-time risk level on a five-level risk scale.

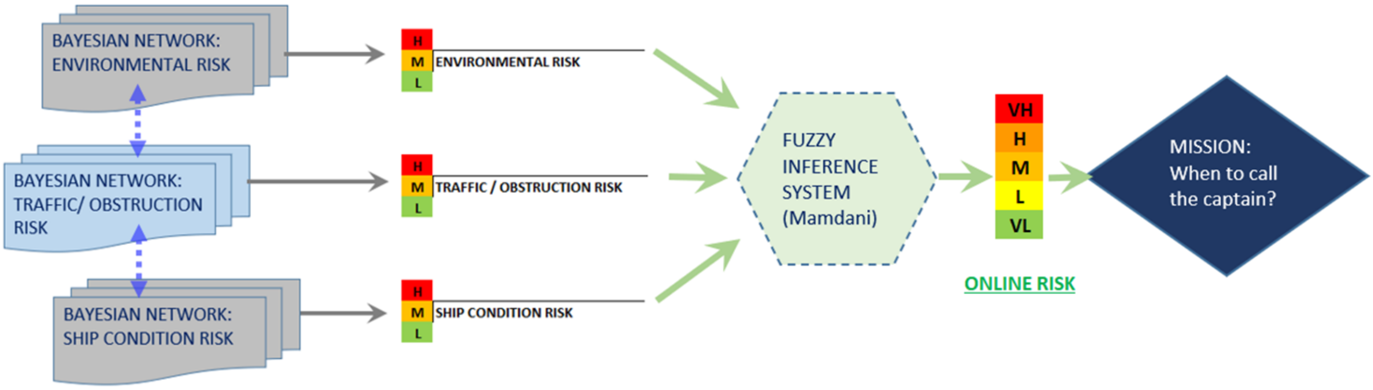


Figure 31 - Schematic flowchart showing complete real-time risk model

This five-level real-time risk scale is linked to the autonomous control system of the ship such that it provides a warning to the captain at pre-determined risk levels such that sufficient reaction time is available for the onboard captain to assemble at the bridge of the vessel.

5 Results

The results for the real-time risk analysis model are presented with typical worst case (or pessimistic) scenario and best case (or optimistic) scenario. While the base case scenario is as presented in the preceding section in Figure 27 with prior beliefs, with 66% traffic/ obstruction risk.

5.1 *Results: Bottom level – BN model*

5.1.1 Scenario A (Optimistic)

The results for scenario A for the bottom level BN model for traffic/ obstruction risk is presented in Figure 32 by updating evidence at root node such that a best case scenario is simulated with minimal risks. The BN nodes with updated evidence are indicated in the BN model by "**underlined bold text**" (for example: "**No crossing**"). This yields a total traffic/ obstruction risk of 31%.

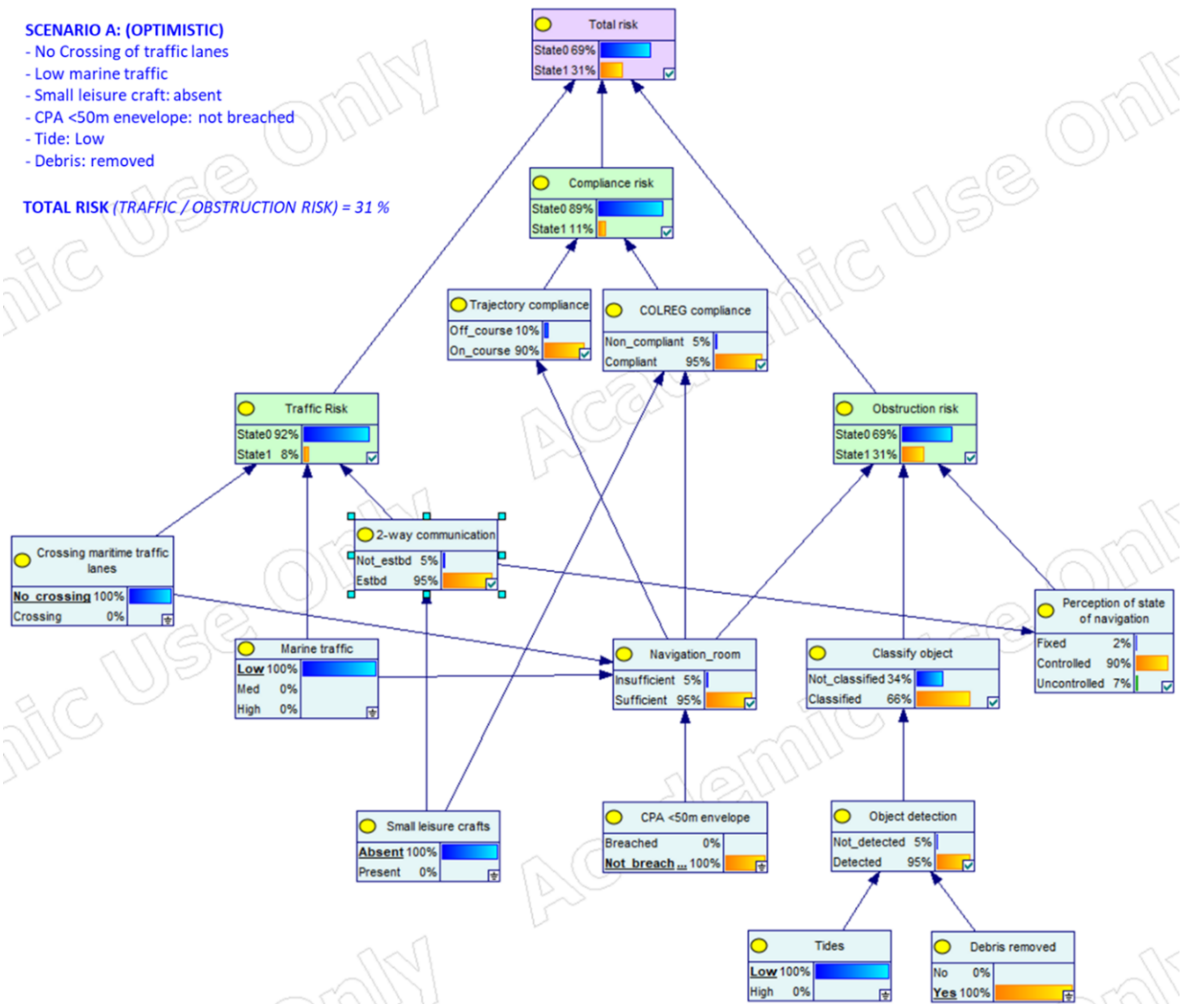


Figure 32 - Results: BN model: Traffic/ obstruction risk: 31% {Scenario A, Optimistic}

5.1.2 *Scenario B (Pessimistic)*

Similarly, the results for scenario B for the bottom level BN model for traffic/ obstruction risk is presented in Figure 33 by updating evidence at root node such that a worst case scenario is simulated with maximal risks. The BN nodes with updated evidence are indicated in the BN model by "**underlined bold text**" (for example: "**Crossing**"). This yields a total traffic/ obstruction risk of 89%.

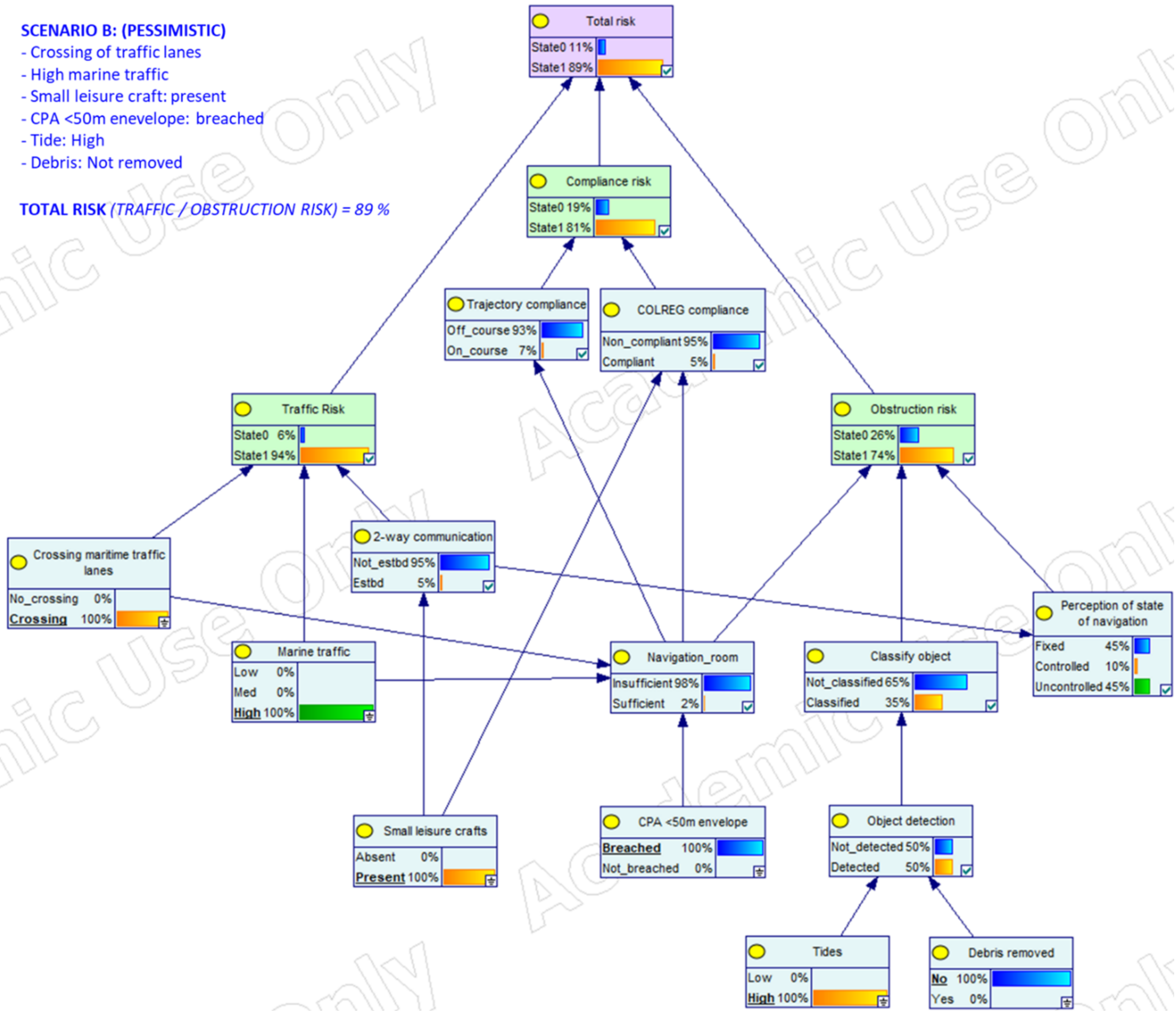


Figure 33 - Results: BN model: Traffic/ obstruction risk: 89% {Scenario B, Pessimistic}

5.2 *Results: Top level – Fuzzy model*

At the top level, the BN Scenario A and B values are transferred to the corresponding theme of traffic/ obstruction risk in the fuzzy model. However, since the other two bottom level BN models for environmental risk and ship condition risk are not implemented in this study – hypothetical values are assumed to simulate and test the results obtained by the real-time risk model.

5.2.1 Scenario A (Optimistic)

The results for scenario A for the top level fuzzy model is presented in Figure 34 by entering the traffic/ obstruction risk value of 31% (from BN model) along with the hypothetical low risk values of 20% each at environmental and ship risks respectively such that a best case scenario is simulated with minimal risks. The real-time risk value for each of the fuzzy rules is visible in blue colour (at right side), which is aggregated to achieve a final real-time risk value of 40.6%.

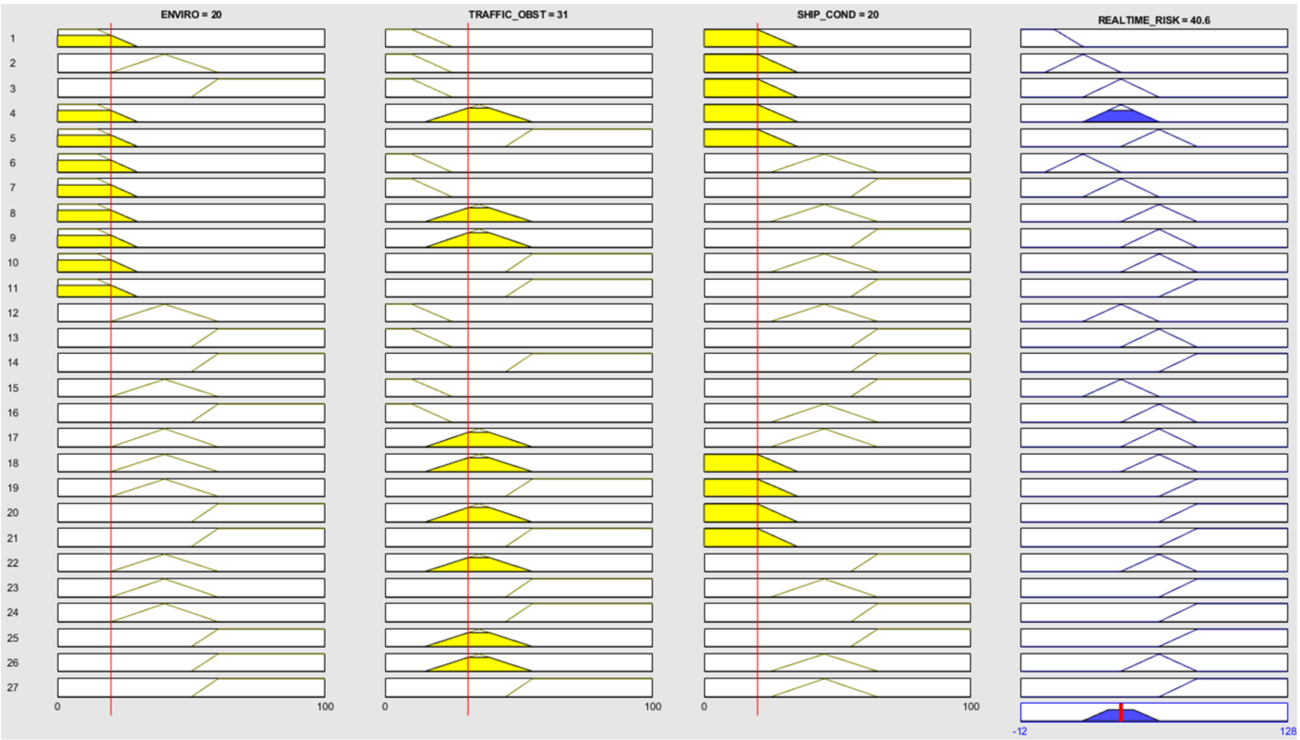


Figure 34 – Results: Fuzzy model: Total Real-time risk: 40.6 % {Scenario A, Optimistic}

5.2.2 Scenario B (Pessimistic)

Similarly, the results for scenario B for top level fuzzy model for traffic/ obstruction risk is presented in Figure 35 by entering the traffic/ obstruction risk value of 89% (from BN model) along with the hypothetical high risk values of 90% each at environmental and ship risks respectively such that a worst case scenario is simulated with maximal risks. The real-time risk value for each of the fuzzy rules is visible in blue colour (at right side), which is aggregated to achieve a final real-time risk value of 99.3%.

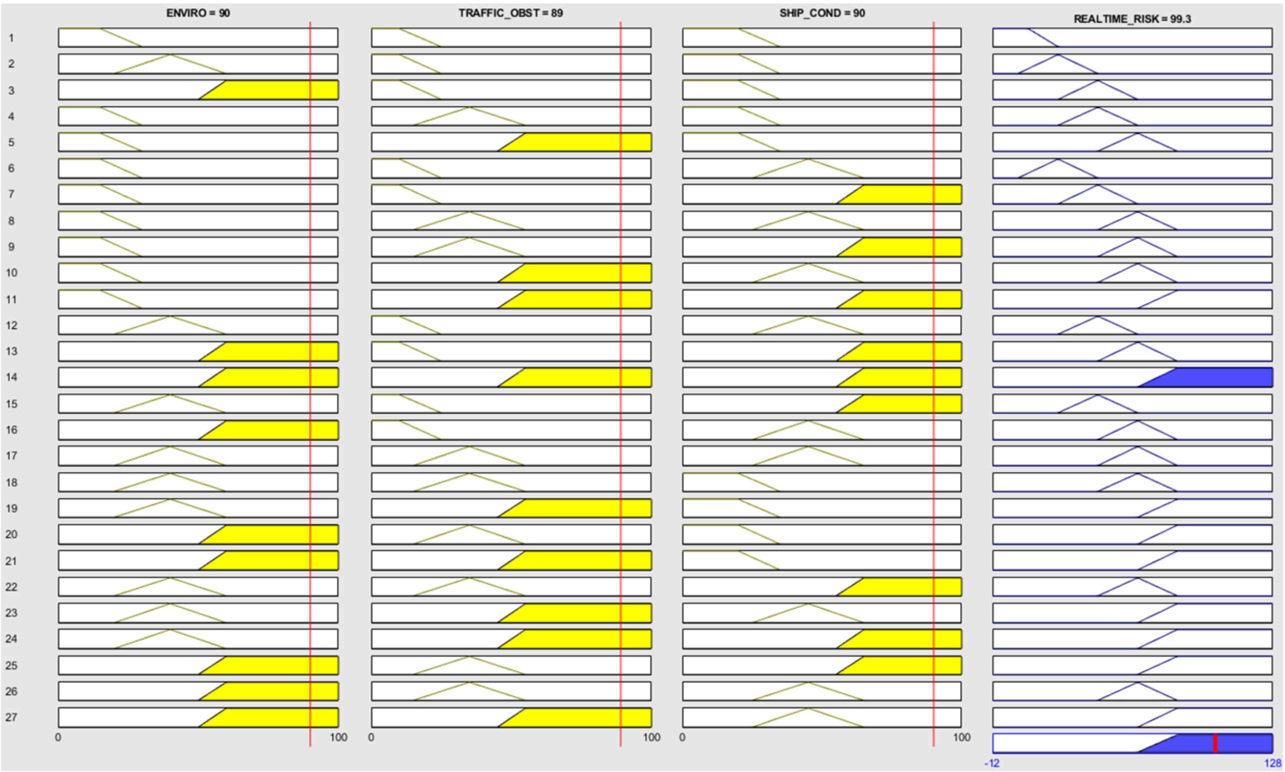


Figure 35 – Results: Fuzzy model: Total Real-time risk: 99.3 % {Scenario B, Pessimistic}

5.3 Validation of Results: Sensitivity analysis

Sensitivity analysis is a means of verifying to what degree a particular output changes when changes are made to input variables, thereby enabling to identify the input variables which when changed cause the most variation in output (most sensitive) as well as those which have the least effect on output (least sensitive) (Castillo et al., 1997).

5.3.1 *Sensitivity: BN model*

BN risk models need to be validated to ensure robustness and reliability of the model (Yu et al., 2021). Sensitivity analysis is a validation technique for verifying the network's sensitivity to changes in node variables (Utne et al., 2020). As shown in Figure 36, sensitivity analysis is performed (in GenIE) considering the top node "MasterRisk" as the target output node against which input node variables will be tested by varying values within a range. The nodes with deepest shade of red imply nodes which have highest sensitivity, while the ones with lightest shade of red indicate the least sensitive nodes, and the transient shades in between indicate the moderate sensitivities.

This is further simplified by the Tornado diagram (Figure 37) created by GeNIe which ranks the top ten input node variables from most sensitive to least sensitive, while the length of bar indicates the rate of change in the target node as the input node parameter is changed within a range of +/-10%. The bar being coded red for negative changes and green for positive changes.

Thus, the posterior probability distribution for the target node "MasterRisk" (or total risk) to occur *(State 1)* – change in parameter of "Smallcrafts" variable node will have the most effect. If the "Smallcrafts" node has a state 'absent' meaning there are no small crafts, then decrease *(red bar)* in probability value for 'absent' state by -10% increases the posterior probability distribution for "MasterRisk" to 0.678 from current value of 0.66. Similarly, an increase *(green bar)* in probability for 'absent' state by +10% decreases the posterior probability distribution for "MasterRisk" to 0.647 from current value of 0.66. Thereby resulting in a maximum sensitivity of 0.262 for "Smallcrafts" node, which is the highest for the network. This is followed by the "Traffic" node with a maximum sensitivity of 0.151. Thus, implying that minor change in marine traffic and/ or minor change in small leisure craft traffic has the highest potential to alter the "MasterRisk" (or Total risk). Or in other words, to control the "MasterRisk" (or Total risk) the most efficient treatment is to control the marine traffic and/ or small leisure craft traffic. This observation perfectly aligns with the MTA (Marine traffic analysis) observations for increase in marine traffic over the last year at Sundbåten's route, as also the frequent near-collision risks experienced with small leisure crafts, thereby validating the BN model's behaviour.

Amongst the three sub-risk nodes of "R01" (Traffic risk), "R02" (Obstruction risk) and "R03" (Compliance risk) – highest maximum sensitivity of 0.129 is noted for "R03" (Compliance risk), followed by 0.081 for "R02" (Obstruction risk) and closely followed by 0.076 for "R01" (Traffic risk). This is visible by the shades of red noted in Figure 36. Thus, indicating that at the higher level of sub-risks – to control the "MasterRisk" (or Total risk) the optimum solution is to control the compliance risk first, and if required the other two: obstruction risk and/or traffic risk can be controlled. Similar to the preceding paragraph, this observation as well corroborates with MTA observation of small leisure crafts very frequently violating COLREG compliance (give-way rules) – further confirming sanity of the results obtained.

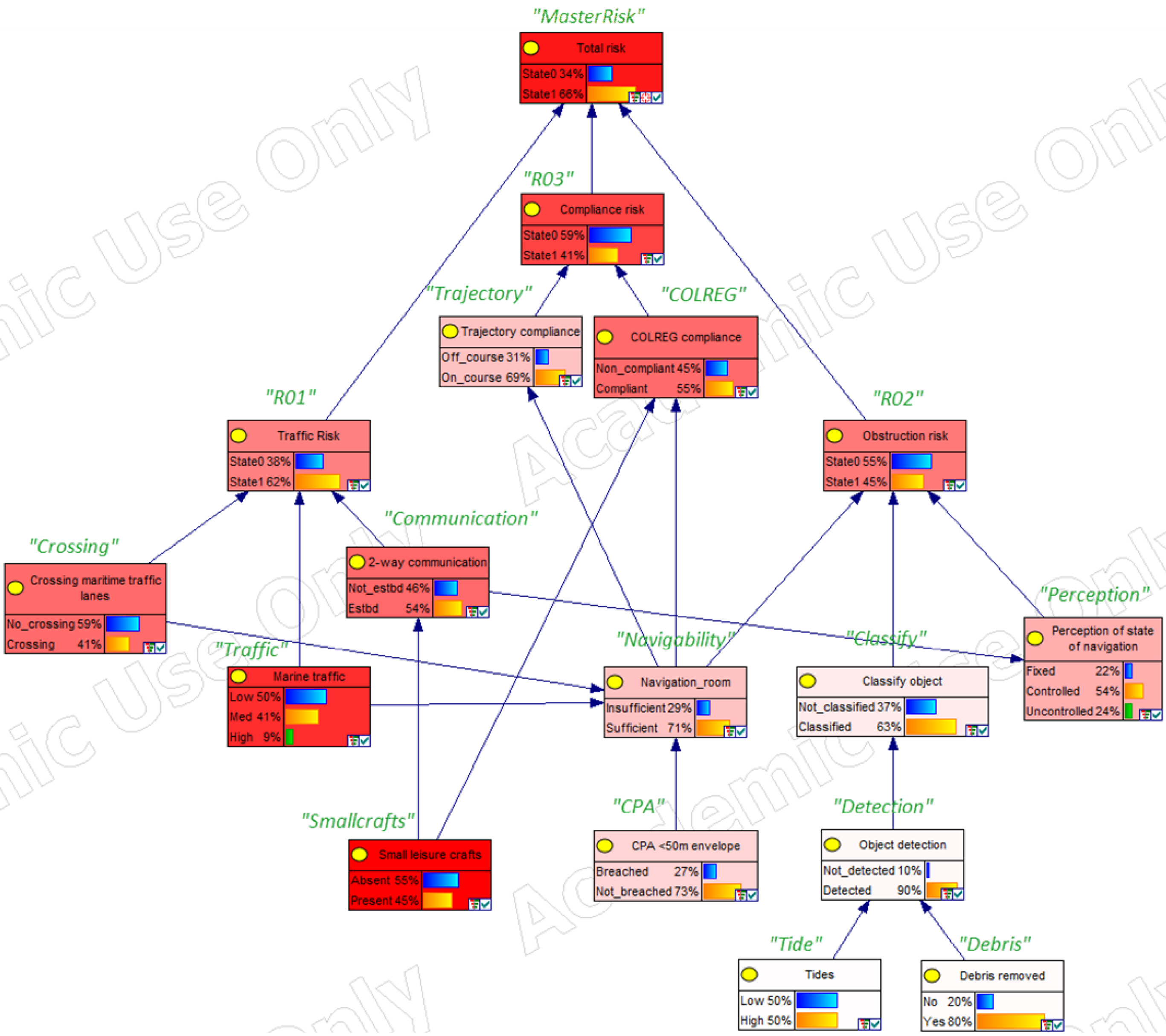


Figure 36 - Sensitivity analysis - BN model (Node variable names marked in "green font")

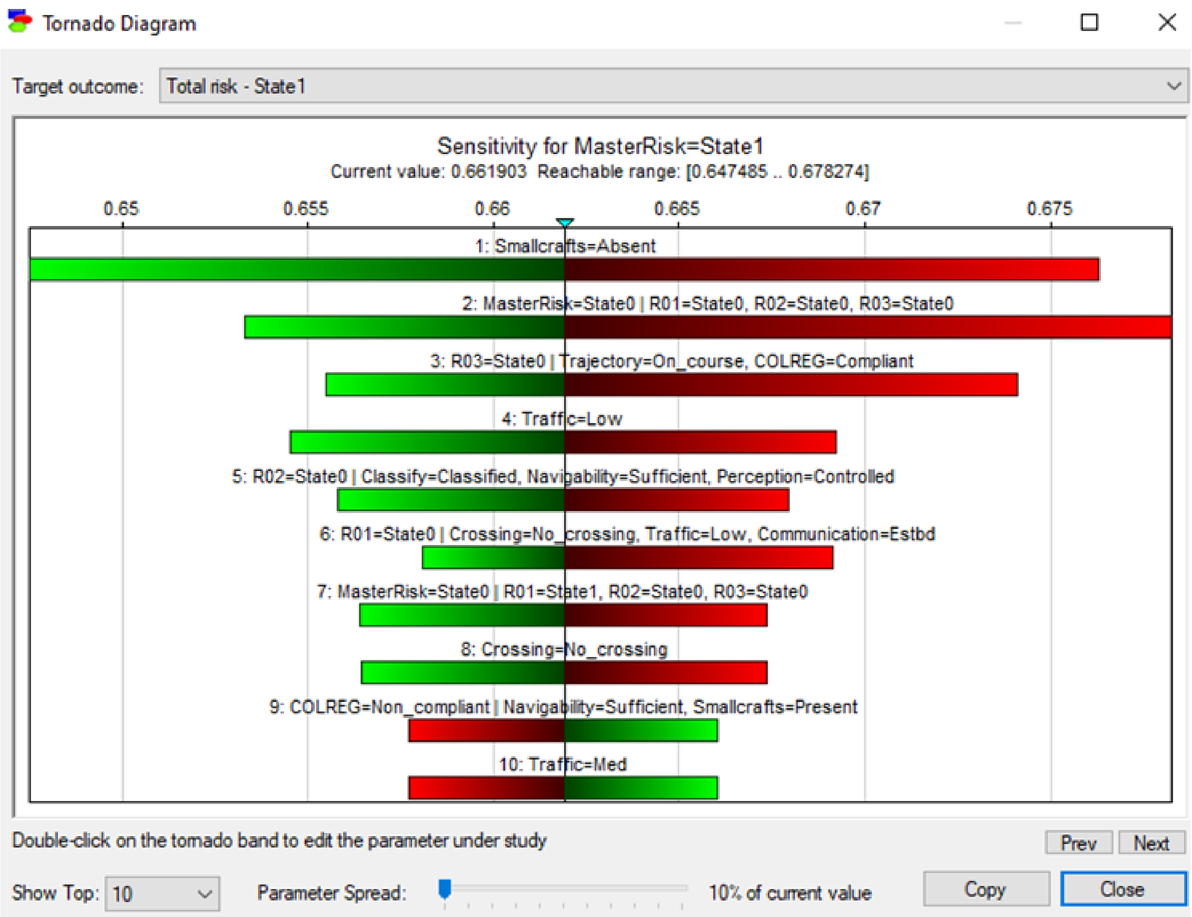


Figure 37 - Sensitivity analysis - BN model: Tornado diagram (with node variable names)

5.3.2 *Sensitivity: Fuzzy model*

The sensitivity for Fuzzy model is well represented by the surface plots previously shown in Figure 25.

Additionally, Castillo et al. (1997) states the issues of completeness and consistency for rule-based fuzzy systems. Completeness implies that the rule-based fuzzy model should be built such that for any random input variable at least one of the defined set or rules is activated – which is reflected by the surface plots. Consistency means the rules should not be duplicated giving similar conclusions, which has been ensured in the fuzzy model by checking the rules in a simplified excel table that provides improved readability and striking out duplicates. Consistency also implies divergent conclusions for similar rules indicating conflicting rules – this is verified from the surface plots for unnatural peaks or troughs.

6 Discussion

The presented real-time risk analysis model and its methodology are discussed in light of existing research studies from literature review, the applied theories, finally followed by findings of the conducted study and its validity.

The field of real-time risk analysis as applied to autonomous ships is an area of emerging technology which is reflected by the sparse number of research articles on the topic. Efforts at building real-time risk models for autonomous ships have largely been at a localized level of assessing risk within a specific domain like human error assessment, ship maneuvering risks, ship collision risk, decision making; and/ or limited to hazard identification (HAZID) and prioritizing them. This enabled a high-level of detailed analysis specific for the domain of interest as a subset of the global real-time risk assessment of autonomous ships. However, a real-time risk model capable of assessing the risk at a global level as a sum of these detailed subsets is lacking. Though there do exist a couple of research articles which offer useful guidelines regarding building real-time risk model and integrating it at the top supervisory level of control system of autonomous ships. These have been used as important building blocks during development of the presented real-time risk model.

The mission of the real-time risk model to answer the question of when to alert the captain to take control of the ship from its autonomous system – steered this study in the direction of global real-time risk assessment of the autonomous ship as a whole, unlike domain-specific real-time risk models of the past. The underpinning framework for the developed real-time risk model though built for a small passenger ferry (Sundbåten project case-study), is still valid for all types of autonomous ships. It is a scalable risk model and can be built in a modular way and then interconnected. Therefore, speedy implementation of real-time risk models is possible for autonomous ships of varying complexities and size by splitting resources to work simultaneously on different risk modules.

The Bayesian network (BN) theory of risk assessment is a well-grounded theory that can work effectively with partial historical data and has been used successfully in process and chemical plants, and oil and gas drilling industry with some recent applications in shipping industry. Its strength and flexibility as a method as enunciated in theory is further confirmed by the results obtained in the BN real-time risk model, as also the ease with which the latest evidence once updated in any of the BN nodes gets propagated through the entire network. Besides, the BN transparently displays its causation and frequency logic, thereby boosting its reliability as a method to the user / reader.

In the field of maritime autonomous systems and autonomous ships, a key attribute is the desire to have human-like decision-making and human-like maneuvering. Human-like behavior of the system would mimic the way a manned-ship would behave thereby enabling parity of unmanned / partially manned ships with those of manned ships – in effect achieving equivalent safety of autonomous ships.

This human-centric behavior is achievable by use of Fuzzy logic method – which provides computational equivalence to human linguistic terms for real-scenarios. In research within autonomous ships, Fuzzy logic method has been the method of choice in lieu of Bayesian network methods and predominantly used in collision avoidance and path planning. While for research studies within real-time risk analysis for autonomous ships, BN methods and fuzzy methods are placed on an even keel. The use of fuzzy logic method for real-time risk analysis of autonomous ships has been mainly used to collate expert judgement data at upstream level (or bottom level of risk model) collected by questionnaire or survey so as to assist in prioritizing risk influencing factors for decision-making.

However, in the real-time risk model presented in this report the fuzzy-logic does not directly collect expert judgement data. Instead it collects fuzzy set values for the three input variables of environmental risk, traffic/ obstruction risk and ship condition risk from the top node of BN model at a downstream level (or topmost level of risk model). These are then subjected to a rule-based fuzzy inference system in which rules with varying combinations of linguistic risk levels of low, medium and high for the three input variables are coded into the system along with their corresponding 5-level output variables (very low, low, medium, high, very high) to mimic human rationale during decision-making. At the output end the fuzzy system then gives the de-fuzzified aggregated risk value as a single crisp number. The advantage of a single crisp number (based on human-rationale) is the simplicity in programming the supervisory control of ship to give warnings to the onboard captain based on a single all-encompassing value.

Thus the presented real-time risk model is a good template based on which future studies can be initiated. Due to the modular structure of the real-time risk model, it is possible to have simultaneous multi-pronged studies to build several domain-specific BN models which can then be assembled together using the presented framework for unifying the data to achieve a single real-time risk value.

6.1 Limitations

6.1.1 Validity: Internal & external

The internal validity of real-time risk model is sufficiently established by conducting sensitivity analysis checks on the BN and fuzzy models, as shown in preceding section. It is developed based on expert judgements which were part of the Sundbåten project documents (both PHA and MTA discussions which included captains working on Sundbåten route amongst other experienced seafarers) which improves internal validity. Additionally, as part of the thesis a maritime expert with 10+ years of all-round experience in seafaring, ship simulator training and autonomous ships has shared expert opinion via the expert judgement questionnaire (Appendix F). The MTA data analysis software used in the Sundbåten project has some reliability issues which would get transferred to the BN risk model by way of prior-beliefs. However, this will not adversely affect the results since BN is a robust method which allows partial truths to be updated once evidence is updated. Besides, the expert judgement questionnaire also mitigates some of these risks.

The real-time risk model in the current form (as-is) is valid for similar small-sized passenger ferry ships with updation of prior-beliefs based on region of operation of the ferry. The overall framework for the real-time risk model is also valid for other types of autonomous ships and is a scalable model that can be built in modular way and interconnected.

However, since the bottom level sub-risks of environmental risk and compliance risk are not evaluated as part of this study, hypothetical values have been used in order to elicit a response from the risk model. The use of ship simulator was subject to availability of time and resources, hence could not be used. External and internal validity of the risk model can be boosted by testing it against the ship simulator results to validate findings of risk model against actual scenarios.

6.1.2 Reliability

The real-time risk model is repeatable in its current form and gives same results, for similar sized passenger ferries operating in similar regions. For using it on other ships or regions, the prior beliefs and conditional probability tables used in BN model would require some updation. Similarly, the rules used in rule-based fuzzy inference system could require tweaking to suit other regions and ship types.

6.1.3 Other limitations

Information technology and internet of things (IoT) which are key enablers for the ships autonomy have not been explored in this study from point of view of associated risks – particularly cyber-security risks. Some purists believe that having direct-communication between vessels for collision avoidance situations is contrary to the very basis for COLREG rules which is not having communication at all (Mehdi et al., 2020). A similar view is expressed by the maritime expert that co-existence of COLREG compliance and having 2-way communication can be counter-productive since direct communication in collision avoidance scenarios can cause more harm. The expert also states that there is a risk of mis-communication or communicating with the wrong ship and in worst case proceeding with maneuvers communicated to the wrong ship. Similarly, an argument exists that COLREG does not cover all possible maneuvers and combination of environmental and traffic risks (Baldauf et al., 2019). These aspects of COLREG and two-way communication and their co-existence need to be explored in detail in future.

7 Conclusion

The research study performed for implementation of real-time risk analysis for autonomous ships successfully converges to the desired solutions as shown in (Figure 38).

The dual goals of the thesis which were set out in the beginning of the research have been successfully achieved. Firstly, a sound body of knowledge for real-time risk analysis of autonomous ships based on the systematic literature review (SLR) is established; and secondly the mission goal of creating a robust real-time risk analysis model capable of alerting the onboard captain of the ship to take control of the autonomous vessel is achieved.

The developed risk analysis model is one of a kind which covers the entire global view of real-time risk for the complete autonomous ship package. Further its modular architecture coupled with the single aggregated real-time risk figure simplifies efforts towards linking with supervisory control of the autonomous ship, thereby making it highly flexible and scalable.

7.1 Issues for further research

The bottom level sub-risks of environmental risk and compliance risk need to be included in future studies to achieve a cohesive risk model with internal causal relationships amongst the RIF's within all the three sub-risks. To further boost the model's reliability its results can be compared with ship simulator and the outcomes can be compared for different scenarios.

The academic state of the art for the subject of real-time risk analysis in autonomous shipping has been extensively covered in this study. However, inclusion of an industry-based perspective on its state of the art is desirable to gauge readiness of the maritime industry and different approaches currently been employed by them.

A possible area of research is to incorporate artificial learning into the BN model and Fuzzy model so that the real-time risk-model is capable of learning and adapting for situations. Thereby making it possible to train the real-time risk model either based on its interactions with the ship simulator or the actual ship during operation. Neural networks for example have had a sound basis in the field of robotics as found during the systematic literature review phase of this report.

Research question	Answers to research questions	Reference
RQ1.1	Real-time risk analysis has been extensively used in chemical and process, oil and gas drilling industries. A recent interest in its application to maritime shipping industry is observed, with very limited peer reviewed journal studies.	2.3.2
RQ1.2	The main advantage of using real-time risk analysis in lieu of traditional risk analysis method is that it is capable of working with partial or no historical data, however with a higher certainty and level of information at its disposal by virtue of it being in a live operations phase rather than traditional risk analysis which works in design phase. Thus, the real-time risk model always gives the latest risk picture when it gets new evidence. Whereas traditional risk analysis methods are static and do not get updated with changed circumstances.	2.4.2
RQ1.3	The most commonly used methods for real-time risk analysis of autonomous ships are Bayesian networks (BN) and their variations, and Fuzzy logic networks. Whereas in autonomous ships in general, the Fuzzy logic methods are more commonly used than BN.	2.3.1
RQ2.1	The real-time risk model for autonomous passenger ferry is prepared by first preparing a concept map based on the systematic literature review. Thereafter, the risk model framework is designed as a combination of top-level (or high-level) and bottom-level (or detailed level). The bottom-level risk model is built using Bayesian network modelling while the top-level risk model is based on Rule-based Fuzzy inference system. This structure of risk-model gives it a flexible and modular architecture enabling the model to be built simultaneously.	2.4.3, 4
RQ2.2	Three RIF's are identified for developing the real-time risk model at the top-level namely: environmental risk, traffic/ obstruction risk and ship-condition risk. At bottom-level the traffic/ obstruction risk is explored further, and three over-arching RIF's are identified namely: Traffic risk, Obstruction risk and compliance risk. These over-arching RIF's subsequently have 13 RIF's in total which are connected based on causation-relationships amongst them.	4
RQ2.3	Six unique RIF’s are identified namely: presence of small leisure boats, high tides causing floating debris, removal of floating debris, crossing of maritime traffic lanes, 2-way communication and COLREG compliance – which are found to be unique and previously not discussed in earlier BN risk model studies for autonomous ships.	4.3.1

Figure 38 - Answers to research questions

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Note: *For extended reference list please refer to Appendices*

Appendices

Appendix A: Search queries

LR-I : [SC12]

```
(
ALL ( "online risk" )
OR ALL ( "on-line risk" )
OR ALL ( "real-time risk" )
OR ALL ( "realtime risk" )
OR ALL ( "dynamic risk" )
)
W/50 (
"monitoring"
OR "analysis"
OR "assessment"
)
ANDNOT SRCTITLE(medical)
ANDNOT SRCTITLE(medicine)
ANDNOT SRCTITLE(diabetes)
ANDNOT SRCTITLE(biomedical)
AND (
LIMIT-TO ( SRCTYPE,"j" )
)
AND (
LIMIT-TO ( DOCTYPE,"ar" )
)
AND (
LIMIT-TO ( SUBJAREA,"ENGI" )
OR LIMIT-TO ( SUBJAREA,"DECI" )
OR LIMIT-TO ( SUBJAREA,"MULT" )
OR LIMIT-TO ( SUBJAREA,"CENG" )
OR LIMIT-TO ( SUBJAREA,"ENER" )
)
AND (
LIMIT-TO ( LANGUAGE,"English" )
)
```

LR-II : [SC51]

```
TITLE-ABS-KEY ("autonomous")
OR TITLE-ABS-KEY ("self-driving")
OR TITLE-ABS-KEY ("unmanned")
OR TITLE-ABS-KEY ("un-manned")
W/0 (
"ship"
OR "vessel"
OR "boat"
OR "barge"
)
)
ANDNOT SRCTITLE(medical)
ANDNOT SRCTITLE(medicine)
ANDNOT SRCTITLE(diabetes)
ANDNOT SRCTITLE(biomedical)
ANDNOT ALL("blood vessel")
ANDNOT ALL("aerial vehicle")
ANDNOT ALL("aviation")
ANDNOT ALL("aeroplane")
ANDNOT ALL("flight")
AND (
LIMIT-TO ( SRCTYPE,"j" )
)
AND (
LIMIT-TO ( DOCTYPE,"ar" )
)
AND (
LIMIT-TO ( SUBJAREA,"ENGI" )
OR LIMIT-TO ( SUBJAREA,"DECI" )
OR LIMIT-TO ( SUBJAREA,"MULT" )
OR LIMIT-TO ( SUBJAREA,"CENG" )
OR LIMIT-TO ( SUBJAREA,"ENER" )
)
AND (
LIMIT-TO ( LANGUAGE,"English" )
)
```

LR-III : [SC101]

```
(
ALL ("autonomous")
OR ALL ("self-driving")
OR ALL ("unmanned")
OR ALL ("un-manned")
W/0 (
"ship"
OR "vessel"
OR "boat"
OR "barge"
OR "surface vehicle"
)
)
AND (
ALL ( "online risk" )
OR ALL ( "on-line risk" )
OR ALL ( "real-time risk" )
OR ALL ( "realtime risk" )
OR ALL ( "dynamic risk" )
OR ALL ( "operational risk" )
)
W/50 (
"monitoring"
OR "analysis"
OR "assessment"
)
ANDNOT SRCTITLE(medical)
ANDNOT SRCTITLE(medicine)
ANDNOT SRCTITLE(diabetes)
ANDNOT SRCTITLE(biomedical)
ANDNOT ALL("blood vessel")
ANDNOT ALL("aerial vehicle")
ANDNOT ALL("aviation")
ANDNOT ALL("aeroplane")
ANDNOT ALL("flight")
AND (
LIMIT-TO ( SRCTYPE,"j" )
)
AND (
LIMIT-TO ( DOCTYPE,"ar" )
)
AND (
LIMIT-TO ( SUBJAREA,"ENGI" )
OR LIMIT-TO ( SUBJAREA,"DECI" )
OR LIMIT-TO ( SUBJAREA,"MULT" )
OR LIMIT-TO ( SUBJAREA,"CENG" )
OR LIMIT-TO ( SUBJAREA,"ENER" )
)
AND (
LIMIT-TO ( LANGUAGE,"English" )
)
```

Figure A1 - Search queries used in Scopus (SC)

LR-I: [WoS_02]	TS=(("online risk" OR "on-line risk" OR "real-time risk" OR "realtime risk" OR "dynamic risk") NEAR/50 ("monitoring" OR "analysis" OR "assessment")) NOT SO=("medical" OR "medicine" OR "diabetes" OR "biomedical") *and Articles (Document Types) and English (Languages) and Engineering or Operations Research Management Science or Transportation or Automation Control Systems or Construction Building Technology or Nuclear Science Technology or Instruments Instrumentation or Robotics or Metallurgy Metallurgical Engineering (Research Areas)*
LR-II: [WoS_51]	TS=(("autonomous" OR "self-driving" OR "unmanned" OR "un-manned") NEAR/0 ("ship" OR "vessel" OR "boat" OR "barge")) NOT SO=("medical" OR "medicine" OR "diabetes" OR "biomedical") NOT TS=("blood vessel" OR "aerial vehicle" OR "aviation" OR "aeroplane" OR "flight") *and Articles (Document Types) and English (Languages) and Engineering or Operations Research Management Science or Transportation or Automation Control Systems or Construction Building Technology or Nuclear Science Technology or Instruments Instrumentation or Robotics or Metallurgy Metallurgical Engineering (Research Areas)*
LR-III: [WoS_101]	ALL=(("autonomous" OR "self-driving" OR "unmanned" OR "un-manned")) AND ALL=(("online risk" OR "on-line risk" OR "real-time risk" OR "realtime risk" OR "dynamic risk")) NOT SO=("medical" OR "medicine" OR "diabetes" OR "biomedical") NOT ALL=("blood vessel" OR "aerial vehicle" OR "aviation" OR "aeroplane" OR "flight") *and Articles (Document Types) and English (Languages) and Engineering(All) or Operations Research Management Science or Transportation Science Technology or Engineering Multidisciplinary (Research Areas)*

Note: All text in grey colour & italics font is manually added filters inside WoS. This text cannot be copied as a query in WoS and has to be applied as manual filters. Text in black can be copied as a query inside WoS.

Figure A2 - Search queries used in Web of Science (WoS)

Appendix B: References from LR-I : [SC12] : Exclusion Criteria A

Sr. No.	Authors	Title	Year	Source title	Cited by
1	Khakzad N., Khan F., Amyotte P.	Dynamic safety analysis of process systems by mapping bow-tie into Bayesian network	2013	Process Safety and Environmental Protection	344
2	Khakzad N., Khan F., Amyotte P.	Quantitative risk analysis of offshore drilling operations: A Bayesian approach	2013	Safety Science	259
3	Khakzad N., Khan F., Amyotte P.	Dynamic risk analysis using bow-tie approach	2012	Reliability Engineering and System Safety	222
4	Zio E.	Challenges in the vulnerability and risk analysis of critical infrastructures	2016	Reliability Engineering and System Safety	215
5	Kalantarnia M., Khan F., Hawboldt K.	Dynamic risk assessment using failure assessment and Bayesian theory	2009	Journal of Loss Prevention in the Process Industries	181
6	Meel A., Seider W.D.	Plant-specific dynamic failure assessment using Bayesian theory	2006	Chemical Engineering Science	154
7	Goerlandt F., Montewka J.	A framework for risk analysis of maritime transportation systems: A case study for oil spill from tankers in a ship-ship collision	2015	Safety Science	153
8	Abimbola M., Khan F., Khakzad N.	Dynamic safety risk analysis of offshore drilling	2014	Journal of Loss Prevention in the Process Industries	147
9	Li X., Chen G., Zhu H.	Quantitative risk analysis on leakage failure of submarine oil and gas pipelines using Bayesian network	2016	Process Safety and Environmental Protection	140
10	Bhandari J., Abbassi R., Garaniya V., Khan F.	Risk analysis of deepwater drilling operations using Bayesian network	2015	Journal of Loss Prevention in the Process Industries	139

Sr. No.	Authors	Title	Year	Source title	Cited by
11	Zio E.	The future of risk assessment	2018	Reliability Engineering and System Safety	135
12	Yazdi M., Kabir S.	A fuzzy Bayesian network approach for risk analysis in process industries	2017	Process Safety and Environmental Protection	117
13	Jia G., Taflanidis A.A.	Kriging metamodeling for approximation of high-dimensional wave and surge responses in real-time storm/hurricane risk assessment	2013	Computer Methods in Applied Mechanics and Engineering	106
14	Kalantarnia M., Khan F., Hawboldt K.	Modelling of BP Texas City refinery accident using dynamic risk assessment approach	2010	Process Safety and Environmental Protection	100
15	Khakzad N., Khan F., Paltrinieri N.	On the application of near accident data to risk analysis of major accidents	2014	Reliability Engineering and System Safety	92
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17	Aqlan F., Mustafa Ali E.	Integrating lean principles and fuzzy bow-tie analysis for risk assessment in chemical industry	2014	Journal of Loss Prevention in the Process Industries	83
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19	Yang Y., Khan F., Thodi P., Abbassi R.	Corrosion induced failure analysis of subsea pipelines	2017	Reliability Engineering and System Safety	81
20	Feng Y., Wu W., Zhang B., Li W.	Power system operation risk assessment using credibility theory	2008	IEEE Transactions on Power Systems	81

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22	Goerlandt F., Khakzad N., Reniers G.	Validity and validation of safety-related quantitative risk analysis: A review	2017	Safety Science	78
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28	Amin M.T., Imtiaz S., Khan F.	Process system fault detection and diagnosis using a hybrid technique	2018	Chemical Engineering Science	67

Sr. No.	Authors	Title	Year	Source title	Cited by
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30	Yeo C., Bhandari J., Abbassi R., Garaniya V., Chai S., Shomali B.	Dynamic risk analysis of offloading process in floating liquefied natural gas (FLNG) platform using Bayesian Network	2016	Journal of Loss Prevention in the Process Industries	58
31	Tsang Y.P., Choy K.L., Wu C.H., Ho G.T.S., Lam C.H.Y., Koo P.S.	An Internet of Things (IoT)-based risk monitoring system for managing cold supply chain risks	2018	Industrial Management and Data Systems	57
32	Stroeve S.H., Blom H.A.P., Bakker G.J.	Contrasting safety assessments of a runway incursion scenario: Event sequence analysis versus multi-agent dynamic risk modelling	2013	Reliability Engineering and System Safety	55
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35	Beroggi G.E.G.	Operational Risk Management: A New Paradigm for Decision Making	1994	IEEE Transactions on Systems, Man and Cybernetics	53
36	Paltrinieri N., Khan F., Amyotte P., Cozzani V.	Dynamic approach to risk management: Application to the Hoeganaes metal dust accidents	2014	Process Safety and Environmental Protection	52

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38	Faghih-Roohi S., Ong Y.-S., Asian S., Zhang A.N.	Dynamic conditional value-at-risk model for routing and scheduling of hazardous material transportation networks	2016	Annals of Operations Research	51
39	Rathnayaka S., Khan F., Amayotte P.	Accident modeling and risk assessment framework for safety critical decision-making: Application to deepwater drilling operation	2013	Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability	50
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Appendix B2: References from LR-I : [WoS02] : Exclusion Criteria A

Sr. No.	Authors	Article Title	Source Title	Times Cited, WoS Core	Year
1	Khan, F; Hashemi, SJ; Paltrinieri, N; Amyotte, P; Cozzani, V; Reniers, G	Dynamic risk management: a contemporary approach to process safety management	CURRENT OPINION IN CHEMICAL ENGINEERING	78	2016
2	Zarei, E; Azadeh, A; Khakzad, N; Aliabadi, MM; Mohammadfam, I	Dynamic safety assessment of natural gas stations using Bayesian network	JOURNAL OF HAZARDOUS MATERIALS	107	2017

Appendix C: References from LR-I : [SC12] : Exclusion Criteria B

Sr. No.	Authors	Title	Year	Source title	Cited by
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2	Chang Y., Wu X., Zhang C., Chen G., Liu X., Li J., Cai B., Xu L.	Dynamic Bayesian networks based approach for risk analysis of subsea wellhead fatigue failure during service life	2019	Reliability Engineering and System Safety	48
3	Galagedarage Don M., Khan F.	Dynamic process fault detection and diagnosis based on a combined approach of hidden Markov and Bayesian network model	2019	Chemical Engineering Science	48
4	Islam R., Khan F., Abbassi R., Garaniya V.	Human Error Probability Assessment During Maintenance Activities of Marine Systems	2018	Safety and Health at Work	48
5	Lee J., Cameron I., Hassall M.	Improving process safety: What roles for digitalization and industry 4.0?	2019	Process Safety and Environmental Protection	47
6	Zhang Q., Zhou C., Tian Y.-C., Xiong N., Qin Y., Hu B.	A Fuzzy Probability Bayesian Network Approach for Dynamic Cybersecurity Risk Assessment in Industrial Control Systems	2018	IEEE Transactions on Industrial Informatics	45
7	Zhang L., Wu S., Zheng W., Fan J.	A dynamic and quantitative risk assessment method with uncertainties for offshore managed pressure drilling phases	2018	Safety Science	44
8	Hossain M., Abdel-Aty M., Quddus M.A., Muromachi Y., Sadeek S.N.	Real-time crash prediction models: State-of-the-art, design pathways and ubiquitous requirements	2019	Accident Analysis and Prevention	43
9	Yuan J., Abdel-Aty M.	Approach-level real-time crash risk analysis for signalized intersections	2018	Accident Analysis and Prevention	40

Sr. No.	Authors	Title	Year	Source title	Cited by
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11	Abaei M.M., Abbassi R., Garaniya V., Chai S., Khan F.	Reliability assessment of marine floating structures using Bayesian network	2018	Applied Ocean Research	38
12	Essa M., Sayed T.	Full Bayesian conflict-based models for real time safety evaluation of signalized intersections	2019	Accident Analysis and Prevention	37
13	Arbabzadeh N., Jafari M.	A Data-Driven Approach for Driving Safety Risk Prediction Using Driver Behavior and Roadway Information Data	2018	IEEE Transactions on Intelligent Transportation Systems	37
14	Alyami H., Yang Z., Riahi R., Bonsall S., Wang J.	Advanced uncertainty modelling for container port risk analysis	2019	Accident Analysis and Prevention	36
15	Yazdi M., Nedjati A., Abbassi R.	Fuzzy dynamic risk-based maintenance investment optimization for offshore process facilities	2019	Journal of Loss Prevention in the Process Industries	35
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17	Zeng T., Chen G., Yang Y., Chen P., Reniers G.	Developing an advanced dynamic risk analysis method for fire-related domino effects	2020	Process Safety and Environmental Protection	33
18	Li X., Chen G., Khan F., Xu C.	Dynamic risk assessment of subsea pipelines leak using precursor data	2019	Ocean Engineering	33
19	Zhou Y., Li C., Zhou C., Luo H.	Using Bayesian network for safety risk analysis of diaphragm wall deflection based on field data	2018	Reliability Engineering and System Safety	33
20	Szlapczynski R., Krata P.	Determining and visualizing safe motion parameters of a ship navigating in severe weather conditions	2018	Ocean Engineering	33

Sr. No.	Authors	Title	Year	Source title	Cited by
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22	Katrakazas C., Quddus M., Chen W.-H.	A new integrated collision risk assessment methodology for autonomous vehicles	2019	Accident Analysis and Prevention	32
23	Li X., Chen G., Jiang S., He R., Xu C., Zhu H.	Developing a dynamic model for risk analysis under uncertainty: Case of third-party damage on subsea pipelines	2018	Journal of Loss Prevention in the Process Industries	32
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25	Dimitriou L., Stylianou K., Abdel-Aty M.A.	Assessing rear-end crash potential in urban locations based on vehicle-by-vehicle interactions, geometric characteristics and operational conditions	2018	Accident Analysis and Prevention	31
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27	Guo X., Zhang L., Liang W., Haugen S.	Risk identification of third-party damage on oil and gas pipelines through the Bayesian network	2018	Journal of Loss Prevention in the Process Industries	30
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29	Zeng Z., Zio E.	Dynamic Risk Assessment Based on Statistical Failure Data and Condition-Monitoring Degradation Data	2018	IEEE Transactions on Reliability	29
30	Guo C., Khan F., Imtiaz S.	Copula-based Bayesian network model for process system risk assessment	2019	Process Safety and Environmental Protection	28

Sr. No.	Authors	Title	Year	Source title	Cited by
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32	Wang J., Kong Y., Fu T.	Expressway crash risk prediction using back propagation neural network: A brief investigation on safety resilience	2019	Accident Analysis and Prevention	27
33	Yazdi M.	Footprint of knowledge acquisition improvement in failure diagnosis analysis	2019	Quality and Reliability Engineering International	27
34	Yang D.Y., Frangopol D.M.	Probabilistic optimization framework for inspection/repair planning of fatigue-critical details using dynamic Bayesian networks	2018	Computers and Structures	26
35	Dinis D., Teixeira A.P., Guedes Soares C.	Probabilistic approach for characterising the static risk of ships using Bayesian networks	2020	Reliability Engineering and System Safety	25
36	Yuan J., Abdel-Aty M., Wang L., Lee J., Yu R., Wang X.	Utilizing bluetooth and adaptive signal control data for real-time safety analysis on urban arterials	2018	Transportation Research Part C: Emerging Technologies	25

Appendix C2: References from LR-I : [WoS02] : Exclusion Criteria B

Sr. No.	Authors	Article Title	Source Title	Times Cited, WoS Core	Year
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2	Kanes, R; Marengo, MCR; Abdel-Moati, H; Cranefield, J; Vechot, L	Developing a framework for dynamic risk assessment using Bayesian networks and reliability data	JOURNAL OF LOSS PREVENTION IN THE PROCESS INDUSTRIES	26	2017

Appendix D: References from LR-II : [SC51] : Exclusion Criteria A

Sr. no.	Authors	Title	Year	Source title	Cited by
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8	Perera L.P., Ferrari V., Santos F.P., Hinostroza M.A., Guedes Soares C.	Experimental Evaluations on Ship Autonomous Navigation and Collision Avoidance by Intelligent Guidance	2015	IEEE Journal of Oceanic Engineering	104
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11	Pan C.-Z., Lai X.-Z., Yang S.X., Wu M.	An efficient neural network approach to tracking control of an autonomous surface vehicle with unknown dynamics	2013	Expert Systems with Applications	90
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13	Tam C., Bucknall R.	Cooperative path planning algorithm for marine surface vessels	2013	Ocean Engineering	87
14	Xue Y., Clelland D., Lee B.S., Han D.	Automatic simulation of ship navigation	2011	Ocean Engineering	84
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17	Sutulo S., Guedes Soares C.	An algorithm for offline identification of ship manoeuvring mathematical models from free-running tests	2014	Ocean Engineering	80
18	Song R., Liu Y., Bucknall R.	Smoothed A* algorithm for practical unmanned surface vehicle path planning	2019	Applied Ocean Research	76
19	Tam C., Bucknall R.	Path-planning algorithm for ships in close-range encounters	2010	Journal of Marine Science and Technology	76
20	Lyu H., Yin Y.	COLREGS-Constrained Real-Time Path Planning for Autonomous Ships Using Modified Artificial Potential Fields	2019	Journal of Navigation	74

Sr. no.	Authors	Title	Year	Source title	Cited by
21	Chen X., Wang S., Shi C., Wu H., Zhao J., Fu J.	Robust ship tracking via multi-view learning and sparse representation	2019	Journal of Navigation	74
22	Song R., Liu Y., Bucknall R.	A multi-layered fast marching method for unmanned surface vehicle path planning in a time-variant maritime environment	2017	Ocean Engineering	73
23	Shin J., Kwak D.J., Lee Y.-I.	Adaptive path-following control for an unmanned surface vessel using an identified dynamic model	2017	IEEE/ASME Transactions on Mechatronics	67
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27	Peng Z., Wang J., Wang D., Han Q.-L.	An Overview of Recent Advances in Coordinated Control of Multiple Autonomous Surface Vehicles	2021	IEEE Transactions on Industrial Informatics	62
28	Huang Y., Chen L., van Gelder P.H.A.J.M.	Generalized velocity obstacle algorithm for preventing ship collisions at sea	2019	Ocean Engineering	60
29	He Y., Jin Y., Huang L., Xiong Y., Chen P., Mou J.	Quantitative analysis of COLREG rules and seamanship for autonomous collision avoidance at open sea	2017	Ocean Engineering	60
30	Abilio Ramos M., Utne I.B., Mosleh A.	Collision avoidance on maritime autonomous surface ships: Operators' tasks and human failure events	2019	Safety Science	58
31	Peng Z., Wang D., Li T., Han M.	Output-feedback cooperative formation maneuvering of autonomous surface vehicles with connectivity preservation and collision avoidance	2020	IEEE Transactions on Cybernetics	57
32	Escario J.B., Jimenez J.F., Giron-Sierra J.M.	Ant colony extended: Experiments on the travelling salesman problem	2015	Expert Systems with Applications	56

Sr. no.	Authors	Title	Year	Source title	Cited by
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34	Lazarowska A.	A new deterministic approach in a decision support system for ship's trajectory planning	2017	Expert Systems with Applications	53
35	Kretschmann L., Burmeister H.-C., Jahn C.	Analyzing the economic benefit of unmanned autonomous ships: An exploratory cost-comparison between an autonomous and a conventional bulk carrier	2017	Research in Transportation Business and Management	52
36	Shen H., Hashimoto H., Matsuda A., Taniguchi Y., Terada D., Guo C.	Automatic collision avoidance of multiple ships based on deep Q-learning	2019	Applied Ocean Research	50

Appendix D2: References from LR-II : [WoS51] : Exclusion Criteria A

Sr. no.	Authors	Article Title	Source Title	Times Cited, WoS Core	Year
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2	Naeem, W; Irwin, GW; Yang, AL	COLREGs-based collision avoidance strategies for unmanned surface vehicles	MECHATRONICS	118	2012

Appendix E: References from LR-II : [SC51] : Exclusion Criteria B

Sr. no.	Authors	Title	Year	Source title	Cited by
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2	Wu B., Cheng T., Yip T.L., Wang Y.	Fuzzy logic based dynamic decision-making system for intelligent navigation strategy within inland traffic separation schemes	2020	Ocean Engineering	48
3	Chen L., Hopman H., Negenborn R.R.	Distributed model predictive control for vessel train formations of cooperative multi-vessel systems	2018	Transportation Research Part C: Emerging Technologies	47
4	Chen Z., Chen D., Zhang Y., Cheng X., Zhang M., Wu C.	Deep learning for autonomous ship-oriented small ship detection	2020	Safety Science	42
5	Fan C., Wróbel K., Montewka J., Gil M., Wan C., Zhang D.	A framework to identify factors influencing navigational risk for Maritime Autonomous Surface Ships	2020	Ocean Engineering	42
6	Ramos M.A., Thieme C.A., Utne I.B., Mosleh A.	Human-system concurrent task analysis for maritime autonomous surface ship operation and safety	2020	Reliability Engineering and System Safety	42
7	Zhao L., Roh M.-I.	COLREGs-compliant multiship collision avoidance based on deep reinforcement learning	2019	Ocean Engineering	42
8	Chiang H.-T.L., Tapia L.	COLREG-RRT: An RRT-Based COLREGS-Compliant Motion Planner for Surface Vehicle Navigation	2018	IEEE Robotics and Automation Letters	41
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Sr. no.	Authors	Title	Year	Source title	Cited by
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11	Guo S., Zhang X., Zheng Y., Du Y.	An autonomous path planning model for unmanned ships based on deep reinforcement learning	2020	Sensors (Switzerland)	29
12	Haseltalab A., Negenborn R.R.	Model predictive maneuvering control and energy management for all-electric autonomous ships	2019	Applied Energy	29
13	Zhang X., Wang C., Liu Y., Chen X.	Decision-making for the autonomous navigation of maritime autonomous surface ships based on scene division and deep reinforcement learning	2019	Sensors (Switzerland)	28
14	Lyu H., Yin Y.	Fast path planning for autonomous ships in restricted waters	2018	Applied Sciences (Switzerland)	26
15	Peng Z., Jiang Y., Wang J.	Event-Triggered Dynamic Surface Control of an Underactuated Autonomous Surface Vehicle for Target Enclosing	2021	IEEE Transactions on Industrial Electronics	25

Appendix E2: References from LR-II : [WoS51] : Exclusion Criteria B

Sr. no.	Authors	Article Title	Source Title	Times Cited, WoS Core	Year
1	Banda, OAV; Kannos, S; Goerlandt, F; van Gelder, PHAJM; Bergstrom, M; Kujala, P	A systemic hazard analysis and management process for the concept design phase of an autonomous vessel	RELIABILITY ENGINEERING & SYSTEM SAFETY	33	2019
2	Komianos, A	The Autonomous Shipping Era. Operational, Regulatory, and Quality Challenges	TRANSNAV-INTERNATIONAL JOURNAL ON MARINE NAVIGATION AND SAFETY OF SEA TRANSPORTATION	25	2018

Appendix F: Expert judgement questionnaire

Expert judgement sources:

MEx - Maritime expert having > 10 years of balanced experience with seafaring, ship simulator training and autonomous ships

MTA - Sundbåten Project Marine Traffic Analysis (MTA) data/ discussions

23-May-2022, DPF

0 INTRODUCTION:

The purpose of this questionaire is to provide inputs for developing of an online risk analysis model, capable of providing decision-making support for the onboard captain on the autonomous ship. The high level aim of this online risk analysis model is to provide a realtime warning to the onboard captain when a high risk situation is about to be encountered by the autonomous ship, thereby improving safety of the autonomous ship.

1 REVIEWER'S LINGUISTIC INTERPRETATION OF RISK LEVELS: **Source: MEx** ***.....................For Fuzzy model***

Reviewer to express their own 'linguistic' interpretation of low, medium and high risk bands based on occurence probabilities for each of the following 3 risks: (E), (O) & (S)

Reviewer to note that these are not technical definitions of risk bands. Instead they are their own generic usage of words "low risk", "medium risk" & "high risk".

Reviewer can choose to have same risk bands for each of the 3 risks: (E), (O) & (S), or they can choose to have different risk bands for each of the 3 risks.

The intention behind this excercise is to replicate the reviewers judgement during their decision making process while operating a vessel: when they decide a certain event is low risk, or medium risk or high risk.

*(**For example** .: L:<=20%, M:40%; H:>=75%...means:*
- According to the reviewer when they say a certain risk is a "low risk", it means that in their mind they think that this particular risk has less than & equal to 20% probability of occurence;
- Similarly, they feel that a certain risk is "high risk", it means that in their mind they think that that particular risk has an occurence probability of more than or equal to 75%;
- Whereas, everything in between the two extremes they identify as "medium risk" with a peak value of occurence probability of 40%

	PROBABILITY OF OCCURENCE		
	LOW RISK (L)	MEDIUM RISK (M)	HIGH RISK (H)
ENVIRONMENTAL RISK (E) *(Adverse weather/ metocean conditions risk)*	<=__15__%	__40__%	>=__60__%
OBSTRUCTION RISK (O) *(Traffic/ obstruction risk)*	<=__10__%	__35__%	>=__55__%
SHIP CONDITION RISK (S) *(Risk of reduced or impaired functionality of ship)*	<=__20__%	45 %	>=__65__%

Note : <= : Less than or equal to
>= : Greater than or equal to

2 OPEN-ENDED FEEDBACK: Source: MEx

Reviewer to identify and state the top 5 highly probable risks while sailing on short round-trips (15-20mins) for passenger ferry or similar, based on their experience:

Risk 1	:	Collision
Risk 2	:	Loss of propulsion/ ctrl....
Risk 3	:	collision into fixed object
Risk 4	:	strong winds
Risk 5	:	

3 LIKELIHOOD OF OCCURENCE OF RISK: TOP LEVEL *......[Total Online Risk]* Source: MEx *.....................For Fuzzy model*

Sr. No.	Occurence of events	(E) Environmental risk *(Implies collsion risk due to environmental factors)*	(O) Traffic/ obstruction risk *(Implies collsion risk due to traffic/ obstruction)*	(S) Ship condition risk *(Implies collsion risk due to ship condition)*	Likelihood of causing Total online Risk (score 1 to 5) *(1: Not likely; 2: Likely; 3: Moderately likely; 4: Moderate to high; 5: Highly likely)*
3.1	Occurence of only (E) environmental risk during sailing of ship: (E) only	X	-	-	3
3.2	Occurence of only (O) traffc/obstruction risk during sailing of ship: (O) only	-	X	-	4
3.3	Occurence of only (S) ship condition risk during sailing of ship: (S) only	-	-	X	2
3.4	Combined occurence of environmental risk & obstruction risk during sailing of ship: (E)+ (O)	X	X	-	5
3.5	Combined occurence of traffc/obstruction & ship condition risk during sailing of ship: (O)+ (S)	-	X	X	4
3.6	Combined occurence of environmental risk & ship condition risk during sailing of ship: (E) + (S)	X	-	X	3
3.7	Combined occurence of all risks: environmental, obstruction & ship condition risk during sailing: (E)+(O)+(S)	X	X	X	5

4 LIKELIHOOD OF OCCURENCE OF RISKS: BOTTOM LEVEL *......[Total traffic/ obstruction risk node]* Source: MTA (reviewed by MEx) *.....................For BN model*

Sr. No.	Occurence of events	(O) Traffic/ obstruction risk			Likelihood of causing top event at node (%)
		Traffic risk *(implies Traffic/ obstruction risk due to marine traffic)*	Obstruction risk *(implies Traffic/ obstruction risk due to other objects/ obstructions)*	Compliance risk *(implies Traffic/ obstruction risk due to partial or no compliance to trajectory commands or COLREG rules)*	
4.1	Occurence of only traffic risk during sailing of ship	X	-	-	70 %
4.2	Occurence of only obstruction risk during sailing of ship	-	X	-	60 %
4.3	Occurence of only compliance risk during sailing of ship	-	-	X	70 %
4.4	Combined occurence of traffic risk & obstruction risk during sailing of ship	X	X	-	85 %
4.5	Combined occurence of obstruction risk & compliance risk during sailing of ship	-	X	X	75 %
4.6	Combined occurence of traffic risk & compliance risk during sailing of ship	X	-	X	85 %
4.7	Combined occurence of traffic risk, obstruction risk & compliance risk during sailing of ship	X	X	X	95 %
4.8	'NO' occurence of traffic risk, and 'NO' obstruction risk, or compliance risk during sailing of ship	-	-	-	5 %

5	LIKELIHOOD OF OCCURENCE OF RISKS: BOTTOM LEVEL ......*[Traffic risk node]* Source: MTA (reviewed by MEx) ....*For BN model*				
Sr. No.	Occurence of events	Traffic risk			Likelihood of causing top event at node
		Crossing maritime traffic lane *(implies Traffic risk due to crossing traffic lanes)*	Marine traffic *(implies Traffic risk due to marine traffic)*	2-way communication *(implies Traffic risk due to partial or no 2-way communication between ships)*	
5.1	Occurence of traffic risk only due to crossing of marine traffic lanes during sailing of ship	X	-	-	60 %
5.2	Occurence of traffic risk only due to marine traffic during sailing of ship	-	X	-	75 %
5.3	Occurence of traffic risk only due to poor or no 2-way communication amongst ships	-	-	X	70 %
5.4	Combined occurence of marine traffic risk & crossing marine traffic lanes risk	X	X	-	80 %
5.5	Combined occurence of marine traffic risk & 2-way communication risk	-	X	X	90 %
5.6	Combined occurence of crossing marine traffic lanes & 2-way communication risk	X	-	X	75 %
5.7	Combined occurence of crossing marine traffic lanes risk, marine traffic risk & 2-way communication risk	X	X	X	95 %
5.8	'NO' occurence of crossing marine traffic lanes risk, and NO' marine traffic risk, and NO' 2-way communication risk	-	-	-	5 %

6	LIKELIHOOD OF OCCURENCE OF RISKS: BOTTOM LEVEL ......*[Obstruction risk node]* Source: MTA (reviewed by MEx) ....*For BN model*				
Sr. No.	Occurence of events	Obstruction risk			Likelihood of causing top event at node
		Classify object *(implies Obstruction risk due to failure to classify object)*	Navigation room *(implies Obstruction risk due to insufficient navigation room)*	Perception of navigational state *(implies Obstruction risk according to perception of navigational state)*	
6.1	Occurence of obstruction risk only due to non-classification/non-identification of object	X	-	-	30 %
6.2	Occurence of obstruction risk only due to insufficient navigation room	-	X	-	60 %
6.3	- Occurence of obstruction risk only due to perception of navigational state as 'fixed' (non-movable object)	-	-	X	30 %
6.4	- Occurence of obstruction risk only due to perception of navigational state as 'controlled' (controlled motion of object)	-	-	X	25 %
6.5	- Occurence of obstruction risk only due to perception of navigational state as 'uncontrolled' (uncontrolled motion of object)	-	-	X	55 %
6.6	Combined occurence of non-classification/non-identification of object & insufficient navigation room	X	X	-	65 %
6.7	- Combined occurence of insufficient navigation room & perception of navigational state as 'fixed'	-	X	X	70 %
6.8	- Combined occurence of non-classification/non-identification of object & perception of navigational state as 'fixed'	X	-	X	30 %
6.9	- Combined occurence of non-classification/non-identification of object, insufficient navigation room & perception of navigational state as 'fixed'	X	X	X	75 %
6.10	- Combined occurence of insufficient navigation room & perception of navigational state as 'controlled'	-	X	X	60 %
6.11	- Combined occurence of non-classification/non-identification of object & perception of navigational state as 'controlled'	X	-	X	25 %
6.12	- Combined occurence of non-classification/non-identification of object, insufficient navigation room & perception of navigational state as 'controlled'	X	X	X	65 %
6.13	- Combined occurence of insufficient navigation room & perception of navigational state as 'uncontrolled'	-	X	X	75 %
6.14	- Combined occurence of non-classification/non-identification of object & perception of navigational state as 'uncontrolled'	X	-	X	55 %
6.15	- Combined occurence of non-classification/non-identification of object, insufficient navigation room & perception of navigational state as 'uncontrolled'	X	X	X	80 %

7	LIKELIHOOD OF OCCURENCE OF RISKS: BOTTOM LEVEL ......*[Compliance risk node]*	Source: MTA (reviewed by MEx)		*....................For BN model*
Sr. No.	Occurence of events	Compliance risk		Likelihood of causing top event at node
		Trajectory compliance *(implies Compliance risk due to non-compliance to trajectory)*	**COLREG compliance** *(implies Compliance risk due to non-compliance to COLREG)*	
7.1	Occurence of Compliance risk only due to non-compliance of trajectory	X	-	**25 %**
7.2	Occurence of Compliance risk only due to non-compliance of COLREG	-	X	**75 %**
7.3	Combined occurence of trajectory non-compliance & COLREG non-compliance	X	X	**85 %**
7.4	Combined occurence of trajectory compliance & COLREG compliance	X	X	**5 %**

8	LIKELIHOOD OF OCCURENCE OF RISKS: BOTTOM LEVEL ......*[Trajectory Compliance node]*	Source: MTA (reviewed by MEx)	*....................For BN model*
Sr. No.	Occurence of events	Trajectory Compliance risk	Likelihood of causing top event at node
		Navigation room *(implies Trajectory Compliance risk due to navigation room)*	
8.1	Occurence of trajectory compliance risk when navigation room is insufficient	X	**95 %**
8.2	Occurence of trajectory compliance risk when navigation room is sufficient	X	**5 %**

9	LIKELIHOOD OF OCCURENCE OF RISKS: BOTTOM LEVEL ......*[COLREG Compliance risk node]*	Source: MTA (reviewed by MEx)		*....................For BN model*
Sr. No.	Occurence of events	COLREG Compliance risk		Likelihood of causing top event at node
		Navigation room *(implies COLREG Compliance risk due to navigation room)*	**Small leisure crafts** *(implies COLREG Compliance risk due to small leisure crafts)*	
9.1	Occurence of COLREG Compliance risk only when navigation room is insufficient	X	-	**10 %**
9.2	Occurence of COLREG Compliance risk only due to presence of small leisure crafts	-	X	**90 %**
9.3	Combined occurence of insufficient navigation room & presence of small leisure crafts	X	X	**95 %**
9.4	'NO' occurence of insufficient navigation room, and 'NO' presence of small leisure crafts	-	-	**5 %**

10	LIKELIHOOD OF OCCURENCE OF RISKS: BOTTOM LEVEL ......*[Navigation room node]*	Source: MTA (reviewed by MEx)			....................*For BN model*
Sr. No.	**Occurence of events**	**Navigation room risk**			**Likelihood of causing top event at node**
		Marine traffic *(implies Navigation room risk due to marine traffic)*	**Crossing maritime traffic lane** *(implies Navigation room risk due to crossing traffic lanes)*	**CPA < 50m envelope** *(implies Navigation room risk due to breaching of envelope CPA<50m)*	
10.1	Occurence of Navigation room risk only due to marine traffic during sailing of ship	X	-	-	75 %
10.2	Occurence of Navigation room risk only due to crossing of marine traffic lanes during sailing of ship	-	X	-	15 %
10.3	Occurence of Navigation room risk only due to breaching of CPA envelope <50m	-	-	X	25 %
10.4	Combined occurence of marine traffic risk & crossing marine traffic lanes risk	X	X	-	85 %
10.5	Combined occurence of crossing marine traffic lanes risk & risk of breaching of CPA envelope <50m	-	X	X	35 %
10.6	Combined occurence of marine traffic risk & risk of breaching of CPA envelope <50m	X	-	X	95 %
10.7	Combined occurence of marine traffic risk, crossing marine traffic lanes risk & risk of breaching of CPA envelope <50m	X	X	X	98 %
10.8	'NO' occurence of marine traffic risk, and 'NO' crossing marine traffic lanes risk, and 'NO' risk of breaching of CPA envelope <50m	-	-	-	5 %

11	LIKELIHOOD OF OCCURENCE OF RISKS: BOTTOM LEVEL ......*[Classify object node]* Source: MTA (reviewed by MEx)		....................*For BN model*
Sr. No.	**Occurence of events**	**Classify object risk** **Object detection** *(implies Classify object risk due to object detection)*	**Likelihood of causing top event at node**
11.1	Occurence of Classify object risk <u>when object is not detected</u>	X	100 %
11.2	Occurence of Classify object risk <u>when object is detected</u>	X	30 %

12	LIKELIHOOD OF OCCURENCE OF RISKS: BOTTOM LEVEL ......*[Object detection risk node]*	Source: MTA (reviewed by MEx)		....................*For BN model*
Sr. No.	**Occurence of events**	**Object detection risk**		**Likelihood of causing top event at node**
		Tides *(implies Object detection risk due to high sea tide)*	**Debris removal** *(implies Object detection risk due to non-removal of debris at sea)*	
12.1	Occurence of Object detection risk due to high sea tide only	X	-	5 %
12.2	Occurence of Object detection risk due to non-removal of debris at sea only	-	X	10 %
12.3	Occurence of Object detection risk due to Combined occurence of high sea tide & non-removal of debris at sea	X	X	50 %
12.4	'NO' occurence of high sea tide, and 'NO' non-removal of debris at sea	-	-	5 %

13 LIKELIHOOD OF OCCURENCE OF RISKS: BOTTOM LEVEL *……[2-way communication node]* **Source: MTA (reviewed by MEx)** *…………………For BN model*

Sr. No.	Occurence of events	2-way communication risk **Small leisure crafts** *(implies 2-way communication risk due to small leisure crafts)*	Likelihood of causing top event at node
13.1	Occurence of 2-way communication risk when small leisure crafts are present at sea	X	95 %
13.2	Occurence of 2-way communication risk when small leisure crafts are absent at sea	X	5 %

14 ADDITIONAL COMMENTS BY REVIEWER (IF ANY):