A risk model for autonomous marine systems focusing on human autonomy - collaboration

Journal:	*Part O: Journal of Risk and Reliability*
Manuscript ID	JRR-16-0140.R1
Manuscript Type:	Special Issue ESREL 2015
Date Submitted by the Author:	13-Feb-2017
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Keywords:	Risk modelling, Autonomous Underwater Vehicles, Human Autonomy Collaboration, BBN, Human Autonomy Interaction, Autonomous Marine System
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A risk model for autonomous marine systems and operation focusing on human - autonomy collaboration

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ABSTRACT:

Autonomous Marine Systems, such as autonomous ships and autonomous underwater vehicles (AUVs), gain increased interest in industry and academia. Expected benefits of AMS in comparison to conventional marine systems are reduced cost, reduced risk to operators, and increased efficiency of such systems. AUVs are applied in scientific, commercial and military applications for surveys and inspections of the sea floor, the water column, marine structures, and objects of interest. AUVs are costly vehicles and may carry expensive payloads. Hence, risk models are needed to assess the mission success before a mission and adapt the mission plan if necessary. The operators prepare and interact with AUVs, in order to carry out a mission successfully. Risk models need to reflect these interactions. This article presents a Bayesian Belief Network (BBN) to assess the Human Autonomy Collaboration Performance (HAC), as part of a risk model for AUV operation. HAC represents the joint performance of the human operators in conjunction with an autonomous system to achieve a mission aim. A case study shows that the HAC can be improved in two ways; (i) through better training and inclusion of experienced operators, and (ii) through improved reliability of autonomous functions and situation awareness of vehicles. It is believed that the HAC BBN can improve AUV design and AUV operations by clarifying relationships between technical, human and organizational factors and their influence on mission risk. The article focuses on AUV, but the results should be applicable to other types of AMS.

Keywords

Risk modelling, autonomous underwater vehicles, human autonomy collaboration, BBN, autonomous marine system, human autonomy interaction

1 Introduction

Autonomous Marine Systems (AMS), including autonomous ships, are the focus of ongoing industrial and academic research and innovation.[1-8] Recently, the Trondheimsfjord in Norway was opened as a test site for autonomous ships.[9] One requirement for AMS to operate in this area, is that the risk has been assessed and it is demonstrated that the risk level is sufficiently low. Research projects, such as MUNIN[10] and AAWA[11] aim to establish concepts for autonomous cargo ships. Several small autonomous boats and vessels are already in use.[6, 12-14] Autonomous underwater vehicles (AUVs) are an examples of AMS, which have been applied for more than two decades. They operate below the water surface and represent an important tool for scientific, commercial and military purposes. They are able to map the sea floor, locate objects of interest, monitor and inspect undersea structures, and measure properties of the seawater.[15] Direct control below the water surface is difficult, due to the impediment of radio signals underwater and the low communication bandwidth of underwater acoustics.[15] AUVs are able to adapt their mission paths to some extent to the environmental conditions to operate in the subsea environment and achieve the previously defined mission aim. Several shapes and types of AUVs exist. Yuh et al.[15] provide an overview of different AUVs and their purposes. In the future, AUV will be increasingly operated together with other autonomous systems, e.g., autonomous aerial vehicles and surface vessels, e.g., for joint monitoring of the environemnt[16, 17]. In order to carry out such operations satisfactorily, AUVs need to be highly reliable. AUVs are expensive assets, often purpose built with a specific payload. A lost or misguided AUV might lead to failure of a mission, if no spare systems are available.[18] Therefore, risk

For Peer Review

models related to mission success (or correspondingly mission failure) are needed for decision support to the human operator.[19]

"Autonomous" does not mean that no personnel will operate them. Autonomy is a system's ability to change its pre-programmed plan of action to achieve its goal.[20] The degree of autonomy designed in a system is described by the level of autonomy (LOA). Several scales of LOA exist, see, for example, [20-22]. Human operators monitor the AMS during a mission. They can change the mission plan, or abort a mission if necessary, e.g., due to unforeseen changes in the operational conditions, or bad vehicle performance.[23] For example, the operators prepare the AUVs and make an overall mission plan, which might be erroneous.[24] Hence, informed risk models need to reflect these interactions. Utne and Schjølberg[25] identify relevant hazards related to human and organizational factors (HOF) for AUV operation that should be considered in risk assessments. Ho et al.[26] discuss AUV operation and associated HOF that are relevant for a successful mission. Existing risk analyses of autonomous marine systems mainly focus on the technical aspects and faults of AUV systems. Expert teams predict mission risk for the AUTOSUB AUVs based on the AUVs' fault logs.[27-30] A Markov model approach assesses the critical phases of operation.[24] Brito and Griffiths[31] present a Bayesian Belief Network (BBN) approach for AUV risk management. Griffiths and Brito[32] apply an expert elicitation process to the fault logs of two REMUS 100 AUVs to predict mission risk for different scenarios.

A few publications focus on autonomous surface vessels. Rødseth and Tjora [33] present a risk based design process for autonomous ships. Based on this approach, Rødseth and Burmeister[34] present a hazard analysis for autonomous ships through a

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scenario approach.[34] They identify risk control options based on these scenarios. These risk control options aim at avoiding hazardous situations, but the interaction with the operators are not a concern. Kretschmann et al.[35, 36] present the qualitative and the coarse quantitative risk assessment for the conceptualized ship of the MUNIN project. Regarding the qualitative risk assessment, they identify human error in remote operation and maintenance, foundering in heavy weather, and security issues as the main hazards. They focus areas of further development. Some risk models for autonomous vessels address heavy weather conditions, such as Ono et al.[37], and Li et al.[38]. Harris et al.[19] review models for risk assessment of AUV and similar systems. They assess the applicability of these models to multi-vehicle operations and conclude that a bottom-up approach to risk assessment is most suitable.

Only a few risk models, however, actually include HOF. Thieme et al.[39] present a risk management framework for AUV, including HOF in a coarse risk assessment of AUV. Thieme et al.[40] also present a qualitative BBN for AUV operation with focus on operator performance. None of the above-mentioned works, however, takes into account the important interaction between human operators and the technical system as a source for potential mission failure, which is addressed in this article.

Risk models considering HOF in AUV operation should treat the human operators and the autonomous system as collaborators, and not as individual or independent systems. Human Autonomy Collaboration (HAC) can be defined as the cooperative and collaborative performance of the human operators and the autonomous system to achieve a goal jointly.[41] Hollnagel[42] argues that a model assessing human-machine systems requires a sound underlying model of the processes that happen during the interaction.

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This should reflect how the joint performance of human and machine is affected by the context and circumstances.[42]

The objective of this article is to present a BBN risk model focusing on HAC for AUV operation. The risk model should benefit users and manufacturers of AUVs and other AMS, to improve the design of these systems and support operator decisions during operation.[43] Since AMS may have similar requirements and demands as AUVs with respect to HAC, the risk model could be adapted to other AMS, as well. The BBN in this article extends the scope of [40], since quantification of the BBN and a case study are included. The case study gives insight into the usefulness and validity of the HAC BBN. The result of the research presented in the article shows that the two most efficient ways of improving HAC are through better training and inclusion of experienced operators, and through improved reliability of autonomous functions and situation awareness of vehicles. The HAC BBN is part of a larger future risk model for AUV operation, which considers environmental interactions, technical system performance, regulatory and customer requirements, and enables assessment of mission success and the effect of risk control.

The next Section describes the development process of the BBN. Then the HAC BBN is presented, including a case study with quantification and validation. The discussion follows, before the last Section concludes the article and states further work.

2 Development of the Bayesian Belief Network

BBNs have been developed for risk assessments in various industries. In the marine domain, BBNs are applied for, e.g., ship collisions[44], ship groundings[45, 46], maintenance work on offshore installations[47, 48], and maritime transport systems[49]. BBNs

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are acyclic directed graphs and consists of nodes and arcs. Nodes have a set of variables, representing the state of the node. Arcs connect parent nodes with child nodes, representing the influence. Arcs are associated with conditional probability tables (CPTs) that determine the child nodes' states based on the parent nodes' states. Input nodes have no parent nodes, they are associated with a default probability to reflect their state. The Bayesian reasoning laws are used to update BBNs.[50] For more specific details on BBN, see, e.g., Jensen and Nielsen[50], or Kjærulff and Madsen[43].

The development of a BBN also includes some challenges. It is important to identify and include all relevant factors that influence risk in a BBN, as well as their relationship. A meaningful BBN model includes well defined nodes, and the problem addressed in the model must lie within a structured domain with causal relationships.[43]

The development of the BBN in this article follows a five-step process:

1. Describe aim and context of the BBN.
2. Gather and group information relevant for the context into nodes.
3. Connect the nodes with directional arcs.
4. Determine the conditional probability tables (CPT) and quantify the model.
5. Test and validate the model.

Steps 1-3 are mainly based on the guidance on construction of BBNs by Jensen and Nielsen[50]. Steps 4 and 5 are adjusted to the purpose of the development of the HAC BBN. The BBN in this article was created with the computer program GeNIe 2.0 by the Decision systems laboratory, University of Pittsburgh, USA[51]. The following sub-sections explain the development process in detail.

2.1 Step 1 - Define aim and context of the risk model

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The aim of the model in the article is to show the relationship between human operator performance and the technical performance of the autonomous system. The aim of the model determines the definition of the top node, which is Human autonomy collaboration performance (HAC). HAC represents the joint performance of the human operator and the autonomous system during a mission of an AUV, its deployment or its retrieval. The presented model shall aid during the planning of an AUV mission to identify potential problems that might arise. The model in this article can also be used as an aid during the design of a system, since it highlights important relationships between the human operators and the technical system. The model shall be seen in the context of the operation of AUV described in the introduction.

Figure 1 shows that an overall risk model for AUV operation should include aspects related to the technical system, environmental conditions, and human and organizational factors, i.e., HAC. Regulations from the authorities, stakeholder requirements, and societal expectations are also issues that need to be considered. The HAC model is the scope of this article, since several works have already focused on the technical system performance and environmental conditions, as mentioned in the introduction. Future work remains to integrate all these aspects into one model.

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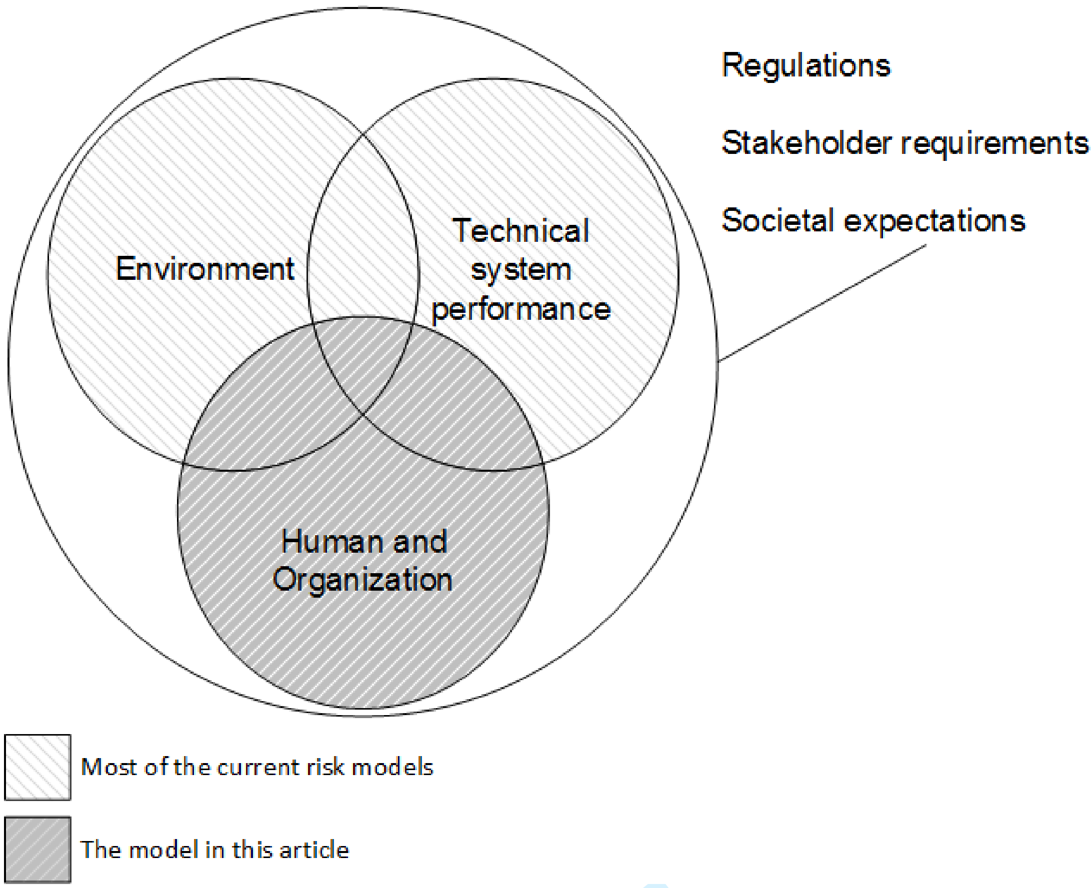

Figure 1 The main aspects to include in an overall risk model for AUV operation. The human autonomy collaboration (HAC) model focuses on the human and organizational part.

2.2 Step 2 - Gather and group relevant information

Literature on human autonomy interaction provides relevant information for the model in this article and determines the basis for the development of the nodes. Based on the definition of HAC, we may group the literature used to develop the model into two overall categories: (i) autonomy and automation, and (ii) human and organizational factors in risk modeling. Table 1 summarizes the details of the literature and the references related to the nodes in the HAC BBN model. Qualitative influence models for use of automated functions were developed by Riley[52] and Parasuraman and Mouloua (cited in [53]). Donmez et al.[54] present a discrete simulation to determine operators'

Review

performance of supervisory control over multiple unmanned aerial vehicles and AUVs. These models are rather coarse and the former two do not contain recent findings. Therefore, it is necessary to aggregate recent findings in this domain and incorporate the considerations for autonomous marine systems, i.e., specifically for AUV operation in this article.

HOFs do not interact linearly.[55] Most methods used in probabilistic safety assessment are not suitable for assessing the HAC performance and a systemic approach is suggested.[42] BBNs are a useful tool for risk modelling, respecting the aforementioned considerations. They are traceable[43], represent dependencies visually, can be used for prognosis and diagnosis.[44] Not only causal but also uncertain dependencies in complex systems can be included.[56]. Existing data and expert judgment can be combined and used to quantify BBN.[43, 44] Furthermore, existing methods, such as fault trees and event trees, can be transformed into BBN, which means that modelling approaches can be combined.[44]

BBNs are also used for human reliability assessment (HRA), for examples, see Mkrtchyan et al.[57] BBN versions of established methods, such as the SPAR-H method[58, 59], are more flexible and can be extended to model performance shaping factors (PSF) with more details, including task specific knowledge. In HRA, the advantages of using BBN are causal and evidential reasoning, incorporation of information from different sources, graphical representation of causal relationships, and the possibility to include probabilistic modelling methods.[57] The existing literature gives confidence that BBN are a suitable tool to model risk of AUV operation, including HOF.

2.3 Step 3 – Connect the nodes

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The arcs in the BBN model are developed based on the findings in the literature and the relationships identified between factors. These findings were merged, in order to determine the network. Some factors have a mutual influence on each other. This makes it difficult to define clearly these arcs. Since BBN are acyclic it is not possible to model mutual influences. In order to resolve mutual influences, the most frequently mentioned direction of influence define these otherwise ambiguous arcs.

2.4 Step 4 - Conditional probability tables and case study

Several ways of CPT elicitation exist, e.g., through theory, observed frequencies or expert estimates.[50] A data driven approach to deriving the CPTs is challenging for the model, since there is lack of data regarding HOF and AUV operation. Only a few investigation reports of loss of AUVs are available, e.g., Strutt [60]. Direct elicitation of CPTs is resource intensive, but methods for reduced effort have been developed.[61] Vinnem et al.[47] use an approach based on building functions to assess CPTs. This process is modified and applied in this article because it reduces the amount of elicitation needed. The process focuses on assessing the strength of influence from parent nodes on their child nodes and on building templates. It is assumed that the parent nodes are independent. The adapted steps from Vinnem et al.'s [47] are: (i) define templates for the CPT assessment based on triangular distributions, (ii) determine the strength of influence of each parent node on the child node, and (iii) combine the templates with the respective weights in the CPT of the parent node. For some nodes, the CPT assessment need to be adapted for the HAC model; more details are given in Section 3.3.

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The data for the input nodes in the model in this article was derived in a case study, with basis in AUV operation in the Autonomous Underwater Robotics (AUR) lab at the Norwegian University of Science and Technology (NTNU).

2.4 Step 5 - Validation

Validation provides assurance that the BBN reflects the system it shall represent and that outputs and mechanisms that produce these outputs reflect the real processes. Validation of BBN is challenging, simply applying a comparison to data or using experts to determine validity might overlook important aspects of model uncertainty.[62] Pitchforth and Mengersen[62, 63] propose a framework to validate BBNs structurally and quantitatively. This framework was chosen for this BBN, since data-driven validation is not possible. The suggested model in this article is compared to existing models, with respect to certain modelling aspects. The framework applies five tests in two categories: expert based validation and databased validation.

Expert based validation consists of the following three tests:[62] (i) face validity assess the BBN's structure in comparison to what the literature or experts predict; (ii) content validity tests, if all relevant factors are included in the model; (iii) convergent and discriminant validity assess if the model is similar to and different enough from other models with a similar aim for a different system. Databased validation considers two aspects[62]: (i) concurrent validity, i.e., the BBN's behavior in comparison to the behavior of (parts of) similar models; and (ii) predictive validity, i.e., the BBN's estimations in comparison to available real world data. As mentioned no comprehensive data is available and therefore databased validation is only limited possible. Details are stated in Section 3.6.

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3 The HAC risk model

3.1 The BBN and description of the nodes

HAC depends on the autonomous functionality designed into the technical system, the human operators, the interaction between the technical system and the human operator, and the organization in which the operators act.[41] An adequate HAC is associated with a high probability for a successful mission. Figure 2 shows the HAC BBN. Table 1 describes the nodes in the BBN, including references to the associated literature. The next paragraphs describe the network in more detail. The literature provides the basis for the arcs and the relations between the nodes.

Human Operator Performance in cooperation with an autonomous system is widely researched. It is influenced by Trust, Reaction Time of the operators, Procedures, Fatigue, Situation Awareness (SA) of Human Operators, Workload, Operators' Training, and Operators' Experience.[26, 52, 53, 55, 64-77] Experience and training refer to all operational aspects of AUV operation. This includes AUV programming, AUV maintenance, AUV deployment and recovery, assessment of the marine environment, and working in the marine environment.

Research of human autonomy collaboration focuses on SA. Low SA of Human Operators is a symptom of low levels of other HOFs.[65] SA of Human Operators is influenced by Trust, Workload, Feedback from the System, Time Delay of Transmission, Communication, and Operators' Training.[26, 53, 65, 73, 76, 78, 79]

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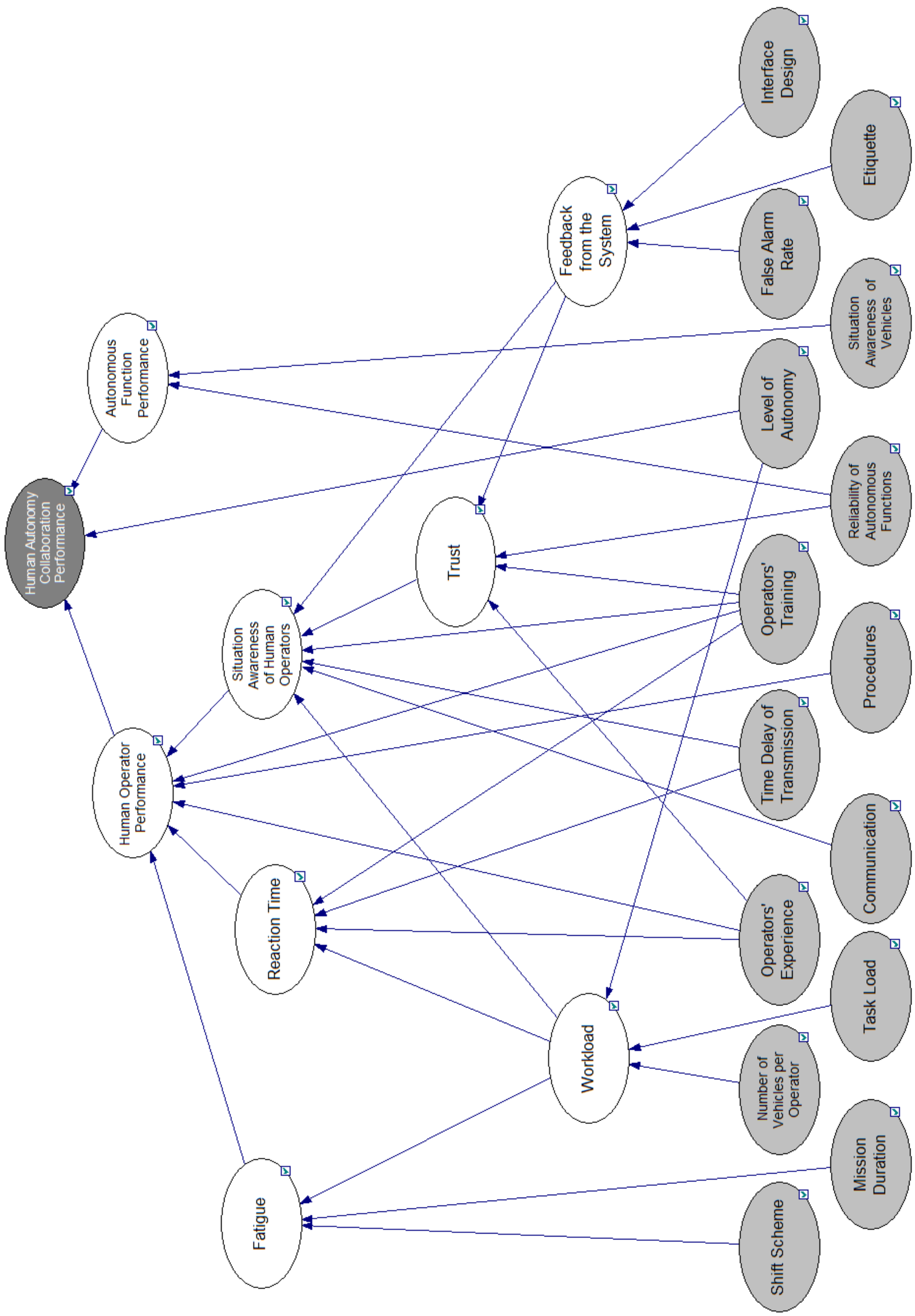

Figure 2 BBN for Human Autonomy Collaboration Performance.
Node color-coding: Light grey – Input nodes, White – Intermediate nodes, Dark grey – HAC node.

Table 1 Definition and description of the nodes included in the Human Autonomy Collaboration (HAC) BBN.

Node	Description	Factor mentioned in
Autonomous Function Performance	Node summarizing the performance of autonomous functions of the system.	N/A
Communication	Information exchange between operators to fulfil the assigned mission.	73, 78, 79
Etiquette	"Set of prescribed and proscribed behaviours that permits meaning and intent to be ascribed to actions"[69] of the system.	26, 53, 69, 70
False Alarm Rate	Rate of status messages that contain erroneous information.	53, 64, 71, 78
Fatigue	"Inability [of the operator] to function at the desired level due to incomplete recovery from the demands of prior work and other waking activities."[80]	45, 53, 74, 80
Feedback from the System	Node summarizing the way a system gives feedback, to the operators, on status, intentions and actions.	53, 55, 64, 65, 67, 70, 71, 73, 81
Human Autonomy Collaboration Performance	Node summarizing the overall performance of operators in conjunction with the autonomous functions of the system to achieve the mission goal.	N/A
Human Operator Performance	Node summarizing the nodes that influence the human operators' performance.	55, 65-67, 69-71, 73, 76, 79
Interface Design	Design principles applied to the physical and virtual interfaces of the system.	53, 59, 70, 78, 81, 82
Level of Autonomy	The degree of the systems' ability to make independent decisions. This depends on the type of operation to be carried out and the type of AUV. This relationship is not further included in the model.	26, 54, 67, 71, 72, 74, 76
Mission Duration	The duration of use and operation of AUVs for a mission. It also depends on the type of mission, type of vehicle and the environmental condition. These interactions are not modelled, since they would require that environmental and technical aspects are fully included in the model.	68
Number of Vehicles per Operator	Number of AUVs and AUV types, one operator operates concurrently.	26, 54, 55, 67, 71, 72, 74, 79, 83
Operators' Experience	Level of experience of the operators with operation of the AUVs. This includes experience with AUV programming, AUV maintenance, AUV deployment and recovery, assessment of the marine environment, and working in the marine environment.	53, 59, 65, 69, 77
Operators' Training	The amount of relevant training operators received for operation of AUVs. Relevant training includes training with respect to AUV programming, AUV deployment and recovery, AUV maintenance, the marine operation environment and working in the marine environment.	53, 59, 64, 65
Procedures	Provided documentation that prescribes operation and provides guidance to operator.	59, 75
Reaction Time	Time the operators need to react to a situation that needs their attention.	64, 71, 72, 78
Reliability of Autonomous Functions	The system's ability to perform its functions as required during the time of use. This includes mission relevant and diagnostic functions.	53, 64, 67, 69-71, 78, 81
Shift Scheme	Pattern, which determines the operators' working and resting time.	45, 68, 80

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Node	Description	Factor mentioned in
SA of Human Operators	Perception and comprehension of the AUVs' state and situation during operation by the operator, and projection of the future state.	26, 53, 65, 71, 72, 76, 78, 84
SA of Vehicles	The vehicles' ability to perceive information, interpret, integrate and assess relevance of that information, and predict the future with this information and prior background knowledge.	85
Task Load	Number of tasks that have to be executed concurrently by one operator. This evaluation should include the consideration of complexity of tasks.	53, 55, 59, 64, 70, 72, 73, 78
Time Delay of Transmission	Time that a message needs from the AUV to the operators or vice versa.	26
Trust	"Users' willingness to believe information from a system or make use of it" [69]	26, 53, 64, 67, 69, 70, 77, 78, 81
Workload	The work demand encountered by the operators during AUV operation.	26, 53-55, 64, 65, 67, 69, 72, 74, 76-79, 81, 83

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Trust in the system is built with time through the Operators' Experience with the system.[81] Trust also depends on the operators' Workload, Feedback of the System, and Reliability of Autonomous Functions.[26, 53, 67, 69, 70, 78, 81] Workload and Time Delay of Transmission influences the Reaction Time of operators.[26, 64, 71, 72, 78] Operators' Experience and Training determine familiarity with the systems and influence the Reaction Time. The Operators' Workload depends on the amount and kind of tasks they have to carry out.[54] In the model, Workload is determined through the LOA, Task Load, and Number of Vehicles per Operator.[26, 53-55, 66, 67, 71-73, 78, 79]

Gander et al.[80] highlight the necessity to consider fatigue in risk management. Akhtar and Utne[45] analyse the influence of fatigue on risk in maritime transport. Fatigue depends on the Workload, Mission Duration, and the Shift Scheme.[45]

Feedback of the System summarizes the system's way of presenting information to the operators, through Etiquette, False Alarm Rate, and Interface Design, c.f. [26, 53, 70, 78, 81]. SA of Vehicles and Reliability of Autonomous Functions constitute the Autonomous Function Performance. Autonomous functions are those functions that the AUV carries out to finish a mission successfully. This includes mission relevant functions, e.g., sensing of the environment, data recording, and diagnostic functions, which are necessary for the AUV to follow and adapt its mission plan to achieve the most satisfactory mission outcome. SA of Vehicles influences the Autonomous Function Performance, since it is the AUVs' ability to perceive and analyze their own situation and predict their future situation.[85] A low Reliability of Autonomous Functions implies that the system does not execute its functions when needed and in the right way.

3.2 States of the nodes

Table 2 presents the proposed states for the nodes described in Table 1. Proposals of evaluation criteria are given for the input nodes. The states are arranged from "worst" to "best" states, except for LOA, and Trust. States that need clarification are described below.

Table 2 Proposed states for the nodes in the Human Autonomy Collaboration Performance BBN

Node	Proposed states
Autonomous Function Performance	Low; Medium; High
Communication	Low; Adequate; High (e.g., no communication of relevant information; communication of relevant information; clear and unambiguous communication of all relevant information)
Etiquette	Disruptive; Mediocre; Good (e.g., intrusive messages with abstract information; messages partly fulfil design criteria from [70] p. 102; messages fulfil design criteria from [70] p. 102)
False Alarm Rate	High; Medium; Low (e.g., more than one of 1000 status updates is erroneous; one status update of between 1000 and 10000 is erroneous; less than one of 10000 status updates is erroneous)
Fatigue	High; Medium; Low
Feedback from the System	Poor; Mediocre; Good
Human Autonomy Collaboration Performance	Inadequate; Adequate
Human Operator Performance	Low; Medium; High

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Node	Proposed states
Interface Design	Poor; Mediocre; Good (e.g., no interface design principles applied; ecological interface design principles partly applied; ecological interface design principles fully applied, c.f. [70])
Level of Autonomy	LOA 1 – Manual Control; LOA 2 – Action Support; LOA 3 – Batch Processing; LOA 4 – Shared Control; LOA 5 – Decision Support; LOA 6 – Blended Decision Making; LOA 7 – Rigid System; LOA 8 – Automated Decision Making; LOA 9 – Supervisory Control; LOA 10 – Full autonomy (based on [66])
Mission Duration	Long; Medium; Short (e.g., more than eight hours; between four and eight hours; less than four hours)
Number of Vehicles per Operator	High; Medium; Low (e.g., more than three vehicles or vehicle types; between two and three vehicles or two vehicle types; less than two vehicles)
Operators' Experience	Low; Medium; High (e.g., less than half a year, between half a year and one year; more than one year)
Operator' Training	Low; Adequate; High (e.g., operators have not attended required trainings; operators have gone through required training; additional to required trainings, additional training was attended)
Procedures	Poor; Adequate, Good (e.g., procedures are incomplete; procedures are covering all expectable situations; procedures are well written covering all expectable situations and give guidance in case of unforeseen events)
Reaction Time	Long; Medium; Short
Reliability of Autonomous Functions	Low; Mediocre; High (e.g., ≤ 95%, > 95% and ≤ 99%, > 99%)
Shift Scheme	Variable working hours; 8-4-4-8; 12-12 or 6-6 (hours on and off duty, based on [45])
SA of Human Operators	Low; Medium; High
SA of Vehicles	Low; Medium; High (e.g., basic perception of the environment; interpretation, integration and ranking of perceived information; prediction of future situations, with available knowledge and perceptions, based on [84])
Task Load	High; Medium; Low (e.g., more than three nominal tasks, or more than one moderately complex tasks, or one or more highly complex tasks; between two and three nominal tasks, or one moderately complex task; two or less nominal tasks)
Time Delay of Transmission	Long; Medium; Short (e.g., more than 40 seconds, between 40 and 20 seconds, shorter than 20 seconds)
Trust	Distrust; Adequate; Overreliance
Workload	High; Medium; Low

The HAC node has the states "Inadequate" and "Adequate". This represents the combined expected performance of the operators and the AUV system. An "Adequate" HAC can be expected to contribute to a higher probability of mission success. An "Inadequate" HAC is associated with a lower expected performance, e.g., errors by the operators or inadequate decisions by the autonomous system. It has a negative influence

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on mission success, and the probability for negative mission outcomes increases, e.g., loss of an AUV.

The "Low" states of Reliability of Autonomy Functions is based on the assumption that a reliability below 95 % is not acceptable and performance decreases strongly below 95 %.[67] No manual control or correction is possible. Therefore, this threshold was selected. The states "Medium" and "High" are exemplarily given.

The states of Shift Scheme in Table 2 need explanation: Akhtar and Utne[45] show that in the presence of other fatigue related factors, the "8-4-4-8" scheme contributes more to fatigue than the shift schemes "12-12 or 6-6". Variable working hours, however, may lead to more fatigue.

3.3 Quantification of the Bayesian Belief Network

The process for CPT assessment was adapted from Vinnem et al.[47] The first step (i) is to define the templates used for CPT elicitation, which are based on a triangular distribution. Table 3 shows the CPT templates for assessment of the child nodes. The strength of influence defines the spread in the template for a given parent state. In this article, two strengths (low and high) are used. The templates are based on discretized triangular functions, which is a simplification from the original process in Vinnem et al.[47], due to limited data available. A high influence template has a lower spread over the range of states. The range of states is referred to as Worst, Intermediate, and Best. These states correspond to the states presented in Table 2.

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Table 3 Discretized CPT templates for low and high strength of influence. Worst, intermediate, and best represent the states generically.

Parent's state	Child's states	Low strength template	High strength template
Worst	Worst	0.60	0.90
	Intermediate	0.30	0.09
	Best	0.10	0.01
Intermediate	Worst	0.20	0.05
	Intermediate	0.60	0.90
	Best	0.20	0.05
Best	Worst	0.10	0.01
	Intermediate	0.30	0.09
	Best	0.60	0.90

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In the second step (ii), the strength of influence of each parent node is assessed for the child node. For example, the Autonomous Function Performance has the parents Reliability of Autonomous Functions and SA of Vehicles, with corresponding states in Table 2. The strength of influence from Reliability of Autonomous Functions is rated high, since AUVs are highly dependent on the correct performance of their functions to execute a mission. SA of Vehicles is also rated as highly influential, since the operational picture is highly relevant for the AUVs to carry out their assigned functions appropriately.

The strength of influence also determines the weight of each parent node. A low strength of influence is associated with a weight of 1. A high strength of influence is associated with a weight of 3. The weights for each parent node are normalized with the total sum of all weights. The templates for each parent node are multiplied with their normalized weights to build a child node's CPT. For a given combination of the parent nodes' states, the weighted templates are added together and inserted in the respective column of the child node's CPT. This represents the third step (iii) of Vinnem et al.'s approach. In the above example, the high strength templates in Table 3 are used.

As an example of the elicitation process, consider the node Autonomous Function Performance. The strength of influence is considered the same for both parent nodes; i.e., Reliability of Autonomous Functions and SA of Vehicles, and therefore, they are equally weighted. Table 4 shows the resulting CPT for the node Autonomous Function Performance. A short example demonstrates the calculation, the combination of states was chosen in order to clearly distinguish the contribution from the parents. For example, the CPT entry for "Low" Autonomous Function Performance for the combination of "Mediocre" Reliability of Autonomous Functions and "Low" SA of Vehicles is 0.475. Both, Reliability of Autonomous Functions and SA of Vehicles have a high influence on Autonomous Function Performance. Therefore, they are associated with a weight of "3" and the high strength templates in Table 3. The entry in the CPT is the sum of the contribution from the "Low" Autonomous Function Performance multiplied with the normalized weight $\left(0.05 \cdot \frac{3}{3+3} = 0.025\right)$ and the contribution from "Mediocre" Reliability of Autonomous Functions multiplied with the normalized weight$\left(0.9 \cdot \frac{3}{3+3} = 0.45\right)$. This process is repeated for all possible combinations of the two parent nodes' states for each state of Autonomous Function Performance. Appendix 1 contains the other strength of influence assessments of the parent nodes on the child nodes.

Table 4 CPT of Autonomous Function Performance. Abbreviations: L – Low, M – Medium, and H – High.

Reliability of Autonomous Functions		L			Mediocre			H		
SA of Vehicles		L	M	H	L	M	H	L	M	H
State of Autonomous Function Performance	L	0.900	0.475	0.455	0.475	0.050	0.030	0.455	0.030	0.010
	M	0.090	0.495	0.090	0.495	0.900	0.495	0.090	0.495	0.090
	H	0.010	0.030	0.455	0.030	0.050	0.475	0.455	0.475	0.900

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A few CPTs need a separate process; i.e., the HAC node, Trust, and Workload. The CPT for the HAC node needs a separate process, as the templates cannot be applied and the LOA needs to be considered separately. Table 5 shows the CPT template used for the HAC node, since the templates from Table 3 are not suitable for translating directly the states “Low”, “Medium” and “High” to “Inadequate” and “Adequate”. In Table 5, “Low” Performance of the Human Operator and the Autonomous System is mainly associated with an “Inadequate” HAC. Similarly, a “Medium” performance is mainly associated with an “Adequate” HAC. A “High” performance is strongly associated with an “Adequate” state.

Table 5 CPT template for determination of the CPT of the Human Autonomy Collaboration Performance node

HAC state	State of Autonomous Function Performance or Human Operator Performance		
	Low	Medium	High
Inadequate	0.90	0.10	0.01
Adequate	0.10	0.90	0.99

The LOA, by definition, proportions the influence from the human operator and the autonomous system on decision-making and performance. Hence, LOA determines the weight of the Human Operator Performance in relation to Autonomous Function Performance. Table 6 shows the LOA dependent weights. They are based on the assumption that the human operators have most influence on the state of HAC when the AUV has a low LOA. Their influence decreases with increasing LOA. However, the Autonomous Function Performance is not negligible at LOA 1, nor the Human Operator Performance at LOA 10.

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Table 6 Proposed weights for building the CPT for Autonomy Collaboration Performance depending on LOA

LOA	Weight for Autonomous Function Performance	Weight for Human Operator Performance
1	0.05	0.95
2	0.15	0.85
3	0.25	0.75
4	0.35	0.65
5	0.45	0.55
6	0.55	0.45
7	0.65	0.35
8	0.75	0.25
9	0.85	0.15
10	0.95	0.05

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The building of the CPT for Trust needs considerations, due to its three states. The literature [53, 69, 70, 81] shows how “Distrust”, “Overreliance” and “Adequate” Trust are formed. The states of Reliability of Autonomous Functions (“Low”, “Mediocre” and “High”) are directly associated with the respective formation of “Distrust”, “Adequate” Trust and “Overreliance”. “Poor” Feedback from the system leads to “Distrust”. A “Good” Feedback will lead to an “Adequate” level of Trust. Consequently, “Mediocre” feedback will lead to “Overreliance”, since the operator might overlook cues. “Low” Operators’ Experience leads to “Distrust”. “High” Operators’ Experience creates an “Adequate” level of Trust. “Medium” Operators’ Experience is associated with “Overreliance”. Similarly, “High” Operators’ Training creates “Adequate Trust”. “Low” Operators Training leads to “Distrust”. “Adequate” Training is associated with “Overreliance”, since not all situations that would require the operators’ attention are trained. This means that Trust has two states that have a negative influence on the operator[53, 69, 70]. These are “Distrust” and “Overreliance”. Hence, the template for the “worst” state is used for both “Distrust” and “Overreliance” to build the CPT for SA of Human Operators.

The CPT for Workload needs additional assumptions due to its parent LOA. A lower LOA implies more work for the human operators. Hence, “LOA 1” to “LOA 3” were associated with a “High” Workload. “LOA 4” to “LOA 7” imply cooperation in execution of the operation and a “Medium” Workload. “LOA 8” to “LOA 10” represent the best possible state, and imply a “Low” Workload, since autonomous functions carry out most of the work

3.4 Case study

NTNU operates one REMUS 100 AUV, designed and produced by Hydroid, through its Advanced Underwater Robotics Laboratory (AUR Lab)[86]. The AUV is used for testing scientific equipment, surveys of the seabed, biological and physical studies of the fjords of Norway. The data in the case study is mainly derived from earlier work, c.f. [39, 87] and supplemented with information from the AUR Lab, the supplier[88] and other publications[32, 89, 90]. The case study focuses on the operation phase of the mission to have sufficient data. Deployment and retrieval can be assessed by changing the states of the input nodes, according to the operators and mission states. However, insufficient information is available for these phases and a quantification in the case study is impossible.

Table 7 summarizes the states for the input nodes and related references used in the case study. LOA, Shift Scheme and Number of Vehicles are deterministic, their state is known, and hence the probability is set to 1. Thieme[87] presents the rating of PSF for the SPAR-H method by two operators of the AUR Lab. Six undesired events are related to operators interacting with the REMUS 100 AUV. These events are: AUV is not properly monitored, Unexpected behavior is not detected, Existing faults are not

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completely solved before deployment, Faults are not recognized during planning phase or before deployment, Wrong use of software leads to wrongly implemented parameters, and Implementation of mission path or map is done wrongly. For a detailed description, see [87]. The PSF of these events were assessed to be in either a low or poor state, an adequate or nominal state, or a good or helpful state. It was assumed that these ratings of the PSF correlate to the generic states in this article; Worst, Intermediate and Best, respectively. The number of ratings was normalized over these states. The PSF ratings were used for the nodes Communication, Etiquette, Interface Design, Operators' Experience, Operators' Training, Procedures, and Task Load.

Table 7 States of the input nodes for the case study. For states without available reference (N.A. – not available), assumptions had to be made based on experiences in the AUR Lab.

Node	States			Comment	Ref.
	Worst	Inter-mediate	Best		
Communication	0.001	0.749	0.250	Based on the PSF ratings of work processes.	87
Etiquette	0.167	0.750	0.083	Based on the PSF ratings of Ergonomics/ HMI.	87
False Alarm Rate	0.200	0.600	0.200	No data is available. A Medium False Alarm Rate is assumed, with low confidence.	N.A.
Interface Design	0.167	0.750	0.083	Based on the PSF ratings of Ergonomics/ HMI.	87
Level of Autonomy		LOA 7		AUV are pre-programmed, the software for programming assists in planning and mission implementation. This corresponds to LOA7.	N.A.
Mission Duration	0.050	0.900	0.050	Missions were in average between four and five hours (assuming a speed of 1.5 m/s and length of 25 km).	39, 87
Number of Vehicles per Operator	0.000	0.000	1.000	The AUR Lab operates one REMUS 100 AUV.	39, 87
Operators' Experience	0.667	0.250	0.083	Based on the PSF ratings of Experience/ Training.	87
Operators' Training	0.667	0.250	0.083	Based on the PSF ratings of Experience/ Training.	87
Procedures	0.001	0.166	0.833	Based on the PSF ratings of Procedures.	87
Reliability of Autonomous Functions	0.200	0.600	0.200	Griffiths et al.[32] report that 14.8 % of mission were aborted preliminary by the REMUS 100. The exact reasons are not stated. Therefore, it is assumed that Reliability of Autonomous	32

For Peer Review

				Functions is mainly Mediocre, with low certainty.	
Shift Scheme	0.000	0.000	1.000	Normally operators work a 12–12 shift scheme.	N.A.
SA of Vehicles	0.050	0.900	0.050	The AUV is equipped with various sensors. Based on measurements it assesses its own situation with simple reasoning. Therefore, it is assumed medium with high certainty.	88, 89
Task Load	0.001	0.916	0.083	Based on the PSF ratings of Complexity.	87
Time Delay of Transmission	0.010	0.090	0.900	Messages can be delayed by more than ten seconds. It was assumed that only a low percentage is delayed by more than 20 seconds.	90

For states of the nodes that have zero probability, since the operators in [87] did not use corresponding PSF ratings, a small probability was inserted in the current case study to reflect uncertainty. For the other states, available information from [32, 39, 87-90] was used to assess the most likely state. For some nodes no references were available (marked with N.A.). These nodes are False Alarm Rate, LOA, and Shift Scheme. For these states assumptions were made based on the experience with the AUR Lab. Based on the strength of knowledge, the strength of influence templates from Table 3 were used to derive the input probabilities.

Using the probabilities from Table 7 for the input nodes and updating the network in GeNIe, gives a probability of 28.5 % for an "Inadequate" HAC state, and a probability of 71.4 % for an "Adequate" HAC state. The probability of mission success decreases with an increased probability of "Inadequate" HAC (cf. Figure 1). Hence, the results of the case study imply that there is room for improvement. The HAC should be as "Adequate" as possible. A sensitivity analysis in the next section gives input to how the state of HAC could be improved.

3.5 Sensitivity Analysis

For Peer Review

GeNIe 2.0 was used to conduct a sensitivity analysis. The built in sensitivity analysis function of GeNIe 2.0 varies each node over the whole range and assesses the impact of this change on the target node. The target node for the sensitivity analysis is in this case the Human Autonomy Performance Collaboration node. Figure 3 shows the analysis results. Intensive red areas indicate a higher influence of nodes. The most influential input nodes on the HAC node are Autonomous Function Performance, Reliability of Autonomous Functions, SA of Vehicles, Operators' Training, and Operators' Experience. The nodes LOA, Shift Scheme, and Number of Vehicles per Operator are deterministic and depend on the mission. Hence, their influence could not be assessed during the sensitivity analysis. Figure 4 shows the effect of changing the states of each node in the case study on the probability of "Adequate" HAC. The case study is shown as reference value, as well as the Best Case and the Worst Case. For the Best Case and Worst Case all input node that were not deterministic were set to their best and worst states, respectively. If all input nodes are in their best state, the probability of an "Adequate" HAC is 95.1 %. With the input nodes in their worst states, the probability of "Adequate" HAC drops to 23.4 %. The CPT of HAC limits the best and worst probability of HAC. This is discussed in the discussion Section.

To assess the influence of the individual nodes, they were set individually to the best and worst case. Figure 4 is arranged such that the most influential nodes are on the top and the least influential on the bottom. Figure 3 and Figure 4 shows that Reliability of Autonomous Functions and SA of the Vehicles are the most influential nodes in the case study. In their worst state, they reduce the probability of an "Adequate" HAC by more than 25 %.

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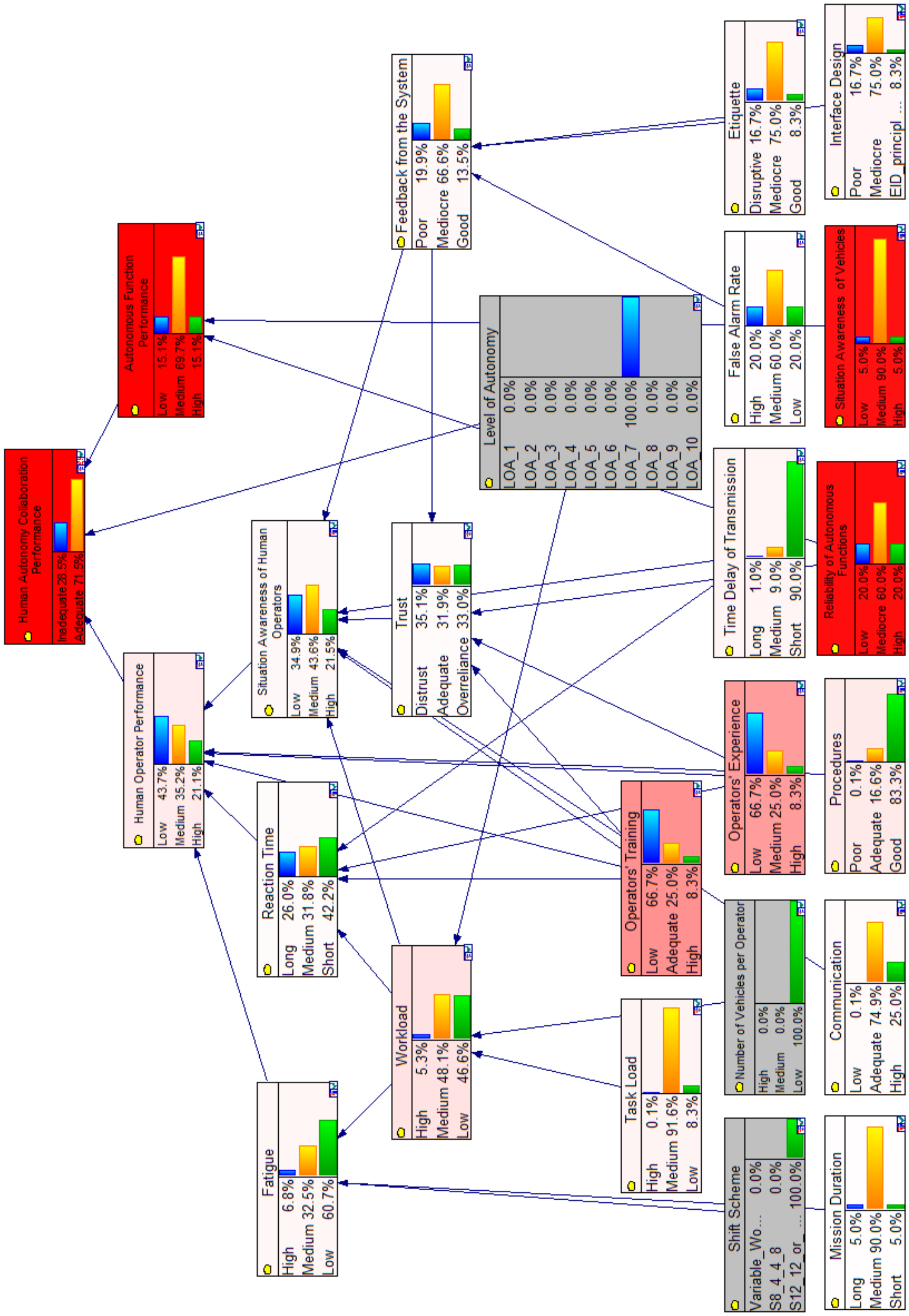

Figure 3 Sensitivity of the HAC node to input from its parent nodes. Dark red areas indicate a higher influence. Grey nodes are deterministic. The sensitivity from these nodes was not assessed.

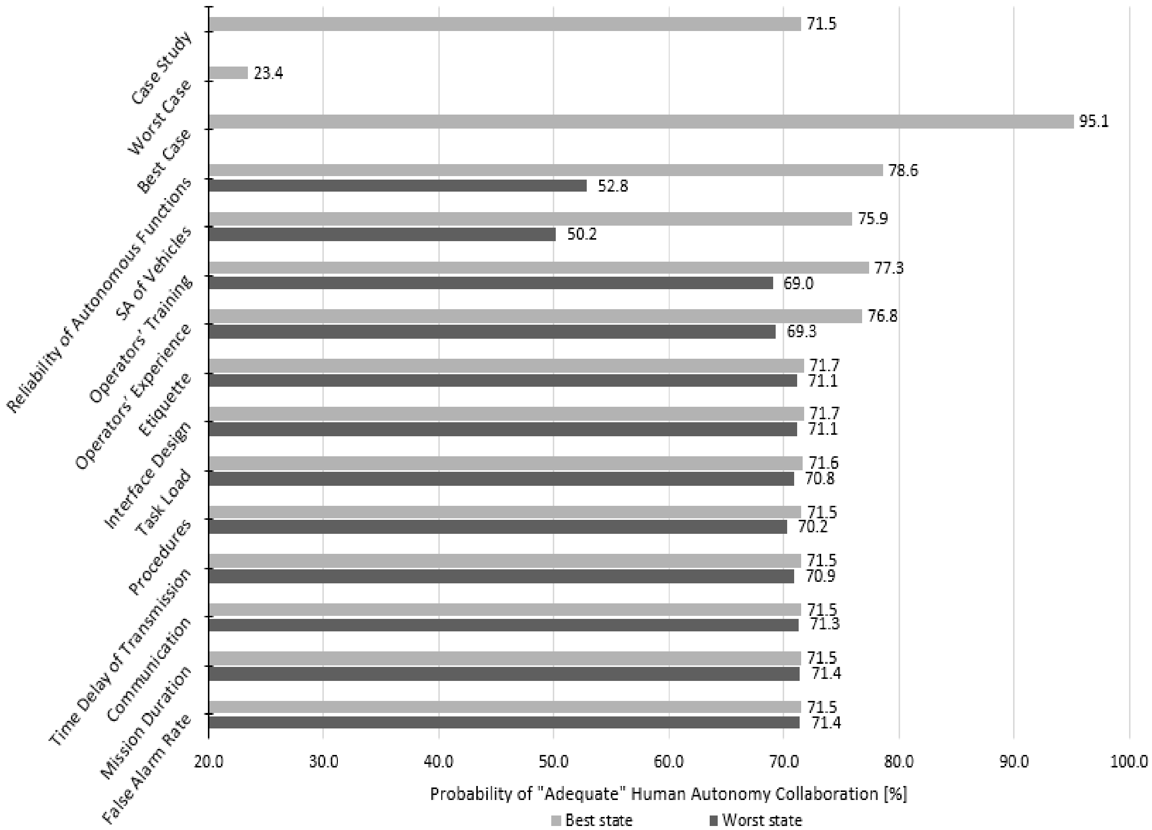

Figure 4 Effect of changing the states of the nodes individually on the probability of "Adequate" Human Autonomy Collaboration Performance. The Worst Case and the Best Case refer to the nodes being set in the worst and best state combined.

The best state of Reliability of Autonomous Function and SA of the Vehicles, improves the probability of "Adequate" HAC by 7.1 % and 4.4 % respectively. Operators' Training and Operators' Experience are the most influential human factors in the case study. Their worst states reduce the probability of "Adequate" HAC by 2.5 % and 2.2 %, respectively. The best states improve the probability of "Adequate" HAC by 5.8 % and 5.3 %, respectively. The states with the least influence are Communication, Mission Duration, and False Alarm Rate. Their best states do not improve the probability of "Adequate" HAC. However, the worst states decrease the probability of "Adequate" HAC by 0.2 %, 0.1 %, and 0.1 %, respectively.

3.6 Validation of the model

Six publications form the basis of the validation, i.e., [31, 46, 47, 52, 54, 59]. These publications cover similar models and considerations as the model in this article. It is assumed that face validity is established by the iterative building of the BBN from the literature, i.e., structurally, the model is similar to Riley[52].

Each node in the model presented in this article, except LOA and HAC, has three states. Brito and Griffiths[31] use more states for their nodes, which reflect discretized physical conditions and risk classes. They do not include nodes, which reflect HOFs. This makes a comparison difficult. Groth and Swiler[59] use three and five states. Mazaheri et al.[46] use nodes with mainly two states and few with three states. Content validity is assumed, since the relevant literature, which includes HOF, c.f. [46, 59], uses similar states and discretization as in the BBN presented in this article.

The CPT assessment process was modified from Vinnem et al.[47], with simplified weights and CPT templates. The parametrization process seems valid, since it was adopted from the literature and leads to the expected model behavior. The presented model is a sub-model to find the mission success of AUV operation and it models considerations that are not included in [31]. Hence, there is no convergence. Since this article focuses on AUV operation, it can be compared to the model of [46] with respect to discriminant validity. Their article focuses on ship groundings and includes specific nodes, which are not present in the HAC BBN. Discriminant validity is assumed.

Donmez et al.[54] present results for the performance of operators operating different types of autonomous vehicles. A comparison is not possible, since the case study is based on operation of one AUV and the presented model in this article does not

For Peer Review

assess HAC as a percentage of Score, as[54]. Concurrent validity cannot be established, since there are no suitable reference models.

The model produces expected outputs regarding the overall model behavior in the case study. Setting the input nodes to their best states resulted in a high probability of “Adequate” HAC of 95.1 %. Setting the variable input nodes to the worst case in the case study results in 23.4 % probability of “Adequate” HAC. The presented HAC BBN model is sensitive to the input (Section 3.5). The model reflects, e.g., that the Reliability of Autonomous Functions and the Operators’ Experience and Training are very influential, as was found in the literature [53, 70, 91]. AUV have a high LOA, this is reflected by the fact that the Reliability of Autonomous Functions and SA of the Vehicles modify the probability of “Adequate” HAC most strongly. In addition, human and organizational factors, such as, mission duration, communication, and procedures, influence the probability of “Adequate” HAC only marginal. This is an expected behavior of the model for a high LOA. This gives confidence that the model reflects the real world.

Thieme and Utne [92] analyze, among others, mission and fault logs of nine mission of the REMUS 100 of the AUR Lab. One of these missions had to be aborted due to thruster failure. Unfortunately, no documentation or investigation of the aborted mission and its circumstances exist, which means that it is difficult to use for validation. Incidents and operations need to be better documented in order to derive a sound basis for network validation. Data is missing to establish predictive validity with respect to numerical verification of the outputs.

4 Discussion

For Peer Review

The HAC BBN in this article is developed specifically for AUV operation and merges the findings from the human autonomy interaction literature. The case study shows that the HAC BBN is able to produce meaningful results. The sensitivity analysis shows that HAC in the case study can be improved most significant in two ways; (i) through better training and inclusion of experienced operators, and (ii) through improved Reliability of Autonomous Functions and SA of Vehicles. However, the HAC BBN is only a sub-model of the overall risk model (Figure 1) and its influence on mission success remains to be modelled.

Although the model is sensitive to changes in most of the input nodes, some of them only have a minor influence on the state of HAC. These input nodes are Communication, Etiquette, False Alarm Rate, Interface Design, Mission Duration, Task Load, and Time Delay of Transmission. These nodes are associated with Human Operator Performance. Their low influence can be attributed to the LOA of the AUV, which is high and limits the influence of Human Operator Performance on the HAC node.

Regarding the case study, the input data was adapted from the literature and complemented with information gathered from the AUR Lab. Especially, Operators' Experience and Training are rated low. The data used was gathered after only 12 missions in the Lab. A separate assessment from the data used for training and experience was not possible. Hence, data from more recent operations may give a better estimate of the state of HAC. The presented results need to be considered with care.

The CPT templates were derived based on approximated and discretized triangular distributions. This is a simplification from the original method, in Vinnem et

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al.[47] This adaptation was necessary, since the original method uses six states. This article only uses three states, due to the lack of data. The influence of the strength the template on the result could not be assessed. More investigation is necessary in order to verify the applicability of the chosen weights and templates. One node for which a refined elicitation process is necessary is Trust, due to the opposing states Distrust and Overreliance. In this case, specially adapted templates might overcome this issue. The weighing between Human Operator Performance and Autonomous Function Performance is assumed linearly dependent on the LOA. Research focuses only on few LOA. No comprehensive data is available to derive these weights. Simulator studies similar to Donmez et al.'s [54] should be carried out in order to validate the quantification of the model and gain an improved model parametrization.

Fatigue related considerations are transferred from Akhtar and Utne[45], who investigate crews of cargo vessels. However, this article adapts their findings. More investigation is necessary in order to validate the applicability of their findings.

Workload is a complex research topic. Each operator will perceive Workload differently.[93] Hence, the Workload node in the HAC BBN depends only on the tasks to be executed. Workload influences Trust, a higher Workload creates "Overreliance".[53, 81] Contrary, if an operator shows "Distrust" towards the autonomous system, the workload is increased due to more frequent and detailed checks.[26] This shows that there is a mutual influence, which is not possible to model with BBN.

Some HOFs mentioned in the literature were excluded, since they were considered not applicable: the operators' fitness for duty and individual personalities[59, 80, 94] are only partially included, e.g., through Fatigue, since little research on this topic in

For Peer Review

relation to human automation interaction and AUV is available. The operators' confidence in their own abilities in relation to the autonomous capabilities[53, 69, 70, 81, 91] are not included explicitly, this is assumed part of Operators' Experience as an adequate confidence develops with experience. The operators' perceived risk associated with the task to execute[53, 69, 70, 81] is excluded, since it is associated with high-risk industries, such as nuclear power plant operation or aviation. It is also connected with the possibility of not using automated functions, which is not possible for AUVs.

Direct influences from the environment have been neglected in the model. Nevertheless, these will inevitable influence the operator if they operate the AUV from a ship. If AUV operation is shore based, the direct influence of weather and sea state is minor to the operator, but may impact the technical system (AUV). The HAC BBN does not address these issues. Firstly, the examined literature does not cover these relations completely. Secondly, the environment, i.e., weather and se state, affects not only the operators and the autonomous function performance, but also the technical performance, and technical factors influencing HAC. Assessment of these factors and interactions requires a holistic system view. This would overextend the scope of this paper.

5 Conclusion and Further Work

This article presents a detailed BBN for human autonomy collaboration performance (HAC) for Autonomous Marine Systems (AMS). The case study and development focus on Autonomous Underwater Vehicle (AUV) operation. The BBN can be used for assessment of mission success of AMS operation, during the planning and preparation phases. The relevant nodes were identified in the literature and their relationships modelled, accordingly. A case study on AUV operation, based on

For Peer Review

information from NTNU's AUR Lab, was used to assess the BBN's applicability. It shows that the HAC BBN is sensitive to input and produces reasonable results. Validity is assumed for the structure, discretization and parametrization. Databased validation is difficult to establish due to limited data, but is assumed, since the models behaves as expected.

The case study shows that the probability of an "Inadequate" HAC is 28.5 % and consequently, 71.5 % for an "Adequate" HAC. A sensitivity analysis shows that Situation Awareness of the Autonomous Vehicles and the Reliability of Autonomous Functions are among the most influential input nodes, which gives confidence that the model reflects the real world. This has implications for the design of autonomous vehicles, which need to ensure efficient cooperation between the operators and potentially other autonomous vehicles. A reliable and self-aware system will promote improved mission performance. In addition, the sensitivity analysis shows that Operators' Experience and Training are highly influential on the state of HAC. The human operator cannot be neglected and is a decisive factor in AUV operation.

Nodes included in this model, which were not mentioned previously in the literature in connection with operation of AUV and human autonomy interaction, are Human Fatigue, Shift Scheme, and SA of Vehicles. The BBN was developed based on an extensive literature study. Work similar to Donmez et al.[54], which assess the influence of certain factors on the mission outcome, can aid in validating and improving the model. AUV simulators are a useful tool for these kind of assessments, which should be carried out in the future. In addition, investigation of incidents and their documentation can help in this validation process.

For Peer Review

The BBN is adaptable to other autonomous marine systems, such as underwater gliders or autonomous surface vehicles. The tasks and modes associated with operation of these type of autonomous marine systems is similar to the operation of AUV. They are remotely supervised and intervention is necessary only in few cases. Some of the nodes' states might need adaption to the specific cases of these other systems. Necessary adaptions to other systems need to be further investigated in the future.

The HAC BBN presented in this article could be part of a larger overall risk model for the assessment of the probability of mission success. Further work is necessary to integrate it completely with the other model considerations: environmental interactions, technical system performance, societal expectations, and regulatory and customer requirements. The BBN modelling technique and the chosen quantification method are useful tools for implementation of these aspects.

Acknowledgements

The authors wish to thank two anonymous reviewers, who contributed with valuable comments, suggestions and questions on the first version of this article. The authors wish to acknowledge Professor Ingrid Schjølberg for her comments on an earlier version of this article. This work was supported by the Research Council of Norway through the Centres of Excellence funding scheme, Project number 223254 – AMOS.

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For Peer Review

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Appendix 1: Assessment of influence of strength for CPT building

This Section summarizes the considerations underlying the CPT assessment. For each child node, except for Autonomous Function Performance and HAC, which are in the main body of this article, the parent nodes, their influence and associated considerations are presented in the following tables. The assessment was conducted by

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the authors and supported with input from the literature, as indicated. The assessment was conducted for AUV specific operation.

Table 8 Strength rating and associated reasoning for the CPT Fatigue, these considerations are supported by results of Akhtar and Utne[45]

Parent state	Strength	Reasoning
Mission Duration	Low	The mission duration has a low influence on fatigue, since the operators will still have to fulfil their shift lengths. Shorter missions will give more room for short breaks and hence, only have little effect.
Shift Scheme	High	Insufficient length of rest and sleep can lead to strong effects of fatigue.
Workload	High	Workload influences fatigue strongly, since it represents the cognitive work and the exhaustion of these capabilities.

Table 9 Strength rating and associated reasoning for the CPT Feedback from the System

Parent state	Strength	Reasoning
Etiquette	High	Research shows that the way information is presented has a significant influence on the operator.[69]
False Alarm Rate	Low	In comparison to Etiquette and information presentation, the False Alarm Rate, has only a marginal influence on the operator.[69]
Interface Design	High	The quality of interfaces, both physical and virtual, highly influences the way information is perceived.[70]

Table 10 Strength rating and associated reasoning for the CPT Human Operator Performance

Parent state	Strength	Reasoning
Fatigue	Low	Fatigues is seen as a contributing factor to the performance of operators, not as a decisive factor. A fatigued operator can still perform adequately. Additionally, the role of fatigue in AUV operation and human autonomy collaboration is not well analysed, and the role of fatigue shall not be overemphasized.
Operators' Experience	High	Operators' Experience is highly important, in order to perform their tasks. It enables them to operate the system efficiently.
Operators' Training	High	Operators' Training is highly important, in order to perform their tasks. It enables them to take the right actions.
Procedures	Low	It is believed that they have a low influence, in order to reflect that for normal operation they are important, but have limited influence in critical situations.
Reaction Time	Low	The Reaction Time is of low influence. AUVs are rather slow and most situations leave a sufficient long time to react.
SA of Human Operators	High	SA of Human Operators is highly influential, since it determines the operators' operational picture of the AUV mission. This is a decisive factor, for the operators to know what to do.

For Peer Review

Table 11 Strength rating and associated reasoning for the CPT Reaction Time

Parent state	Strength	Reasoning
Operators' Experience	High	Experience improves reaction time.
Operators' Training	Low	The influence of training was assumed low, since it implies to implement the right actions timely. However, training, in the sense of course and workshops only addresses this issue in a limited way.
Time Delay of Transmission	High	Status messages and commands travel relative slowly through water. Hence, the Reaction Time is highly dependent on the delay of important commands send to the AUVs or messages received from the AUVs.
Workload	High	Occupation with other tasks, especially complex ones, has proven to increase the operators time to switch to another task that needs attention, c.f., [72].

Table 12 Strength rating and associated reasoning for the CPT SA of Human Operators

Parent state	Strength	Reasoning
Communication	Low	Information is mainly communicated through interface of the system. Hence, the influence is assumed low.
Feedback from the System	High	Feedback from the System is highly important for the operators[69].
Operators' Training	High	Training of the operators is highly important for the operators to create an operational picture of the current operation.
Time Delay of Transmission	Low	The delay of information updating, reduces the knowledge about the current state of a mission. Since, no video streams or direct control are possible in current AUV operation[26], it was assumed low.
Trust	High	Inadequate Trust in a system is decisive for SA of Human Operators.[53]
Workload	High	A high Workload of the operators has been shown to reduce SA of Human Operators significantly, e.g., [67].

Table 13 Strength rating and associated reasoning for the CPT Trust

Parent state	Strength	Reasoning
Feedback from the System	High	The way a system presents information is highly important for building an adequate level of trust.[69, 70]
Operators' Experience	High	Experience with a system builds Trust.[81] Hence, a high influence is assumed.
Operators' Training	Low	Training can give understanding for the system, guidance in usage and handling of systems. However, training will only make a system more trustable.[81] Hence, it is assumed to have a low influence.
Reliability of Autonomous Functions	High	The influence of Reliability of Autonomous Functions is high. People tend to project emotions on systems. Reliable systems are easily trusted.[81]

For Peer Review

Table 14 Strength rating and associated reasoning for the CPT Workload

Parent state	Strength	Reasoning
LOA	Low	The LOA has only a marginal influence on the operator Workload.[66]it is believed that the same is true for AUV operation.
Task Load	High	Carrying out tasks concurrently will increase the workload highly.
Number of Vehicles per Operator	High	The number of vehicles effectively increases the number of tasks, c.f., e.g., [55].

For Peer Review

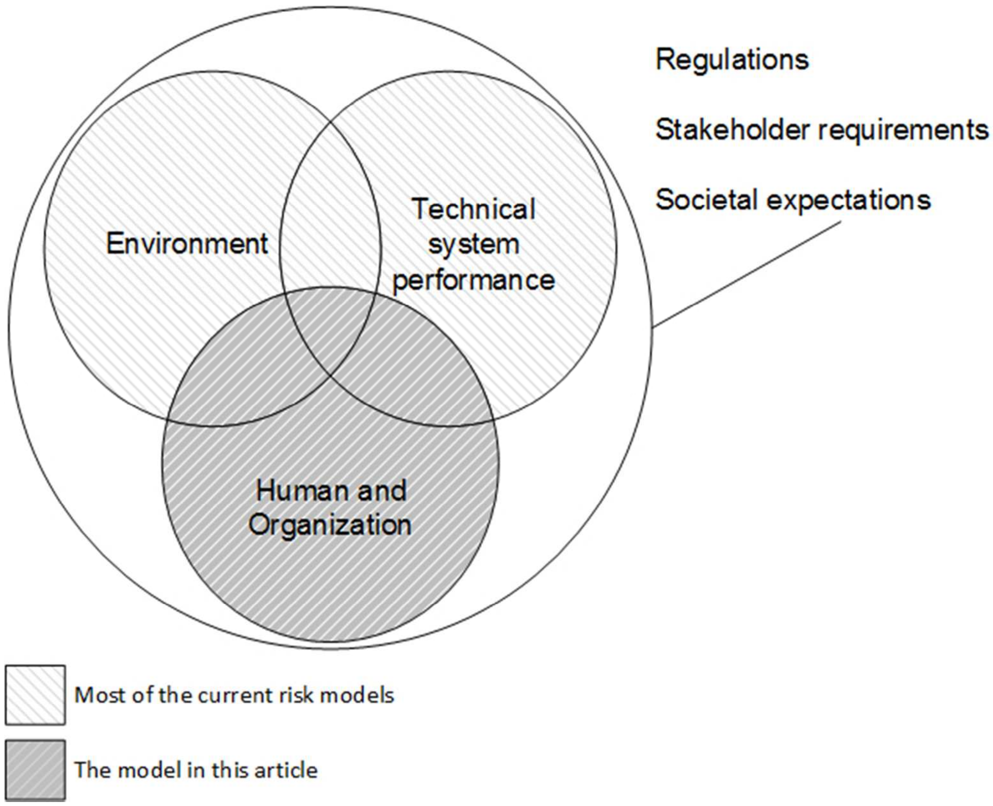

Figure 1 The main aspects to include in an overall risk model for AUV operation. The human autonomy collaboration (HAC) model focuses on the human and organizational part.
Figure 1
169x134mm (96 x 96 DPI)

view

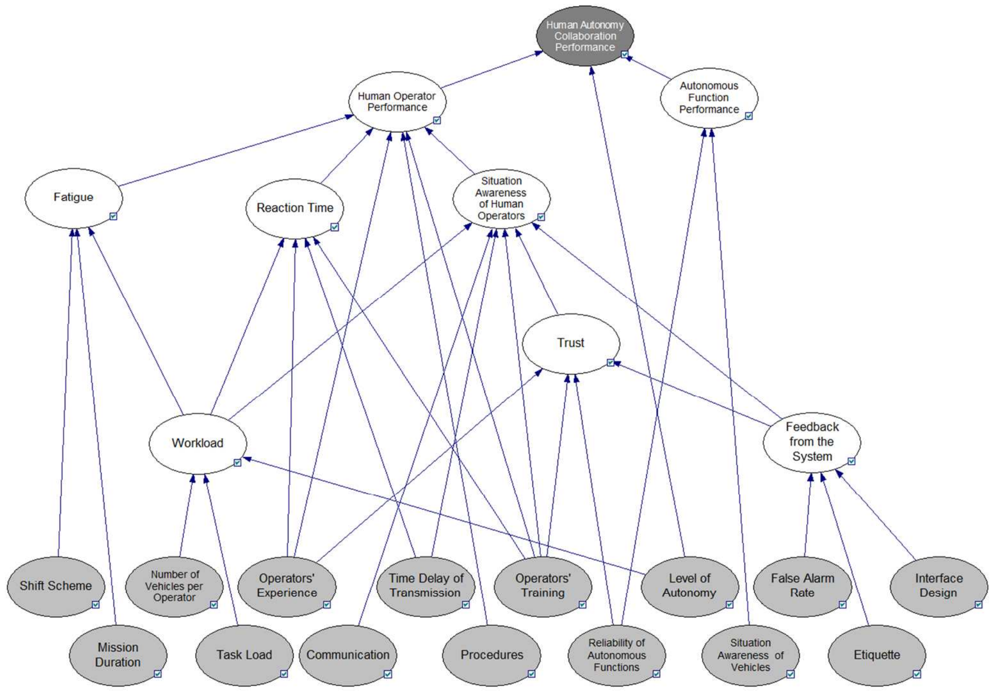

Figure 2 BBN for Human Autonomy Collaboration Performance.
Node color-coding: Light grey – Input nodes, White – Intermediate nodes, Dark grey – HAC node.
Figure 2
358x246mm (96 x 96 DPI)

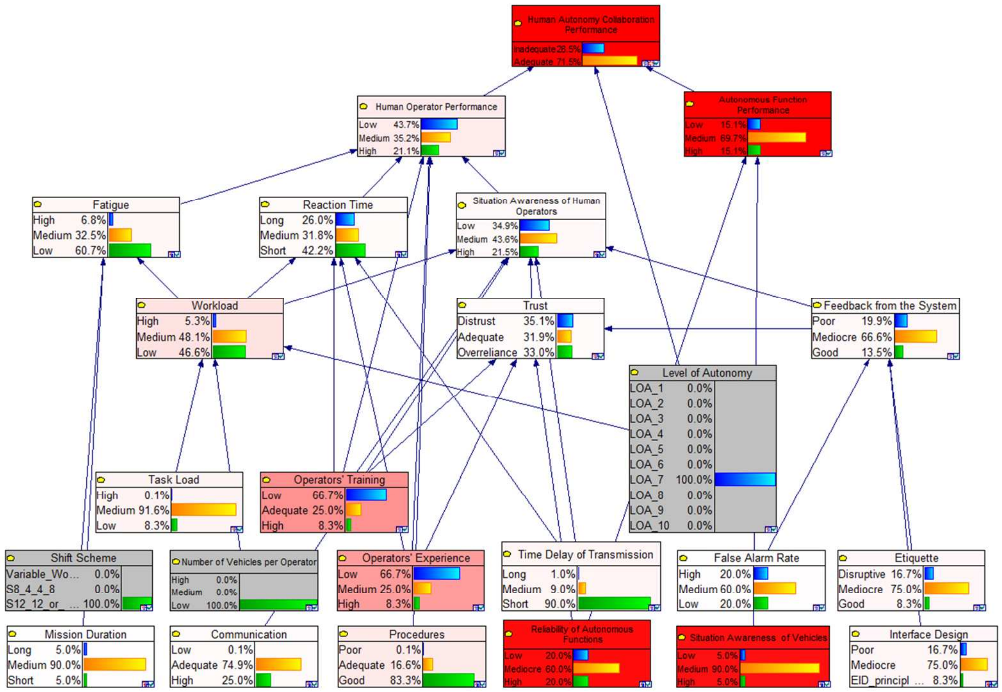

Figure 3 Sensitivity of the HAC node to input from its parent nodes. Dark red areas indicate a higher influence. Grey nodes are deterministic. The sensitivity from these nodes was not assessed.
Figure 3
313x215mm (96 x 96 DPI)

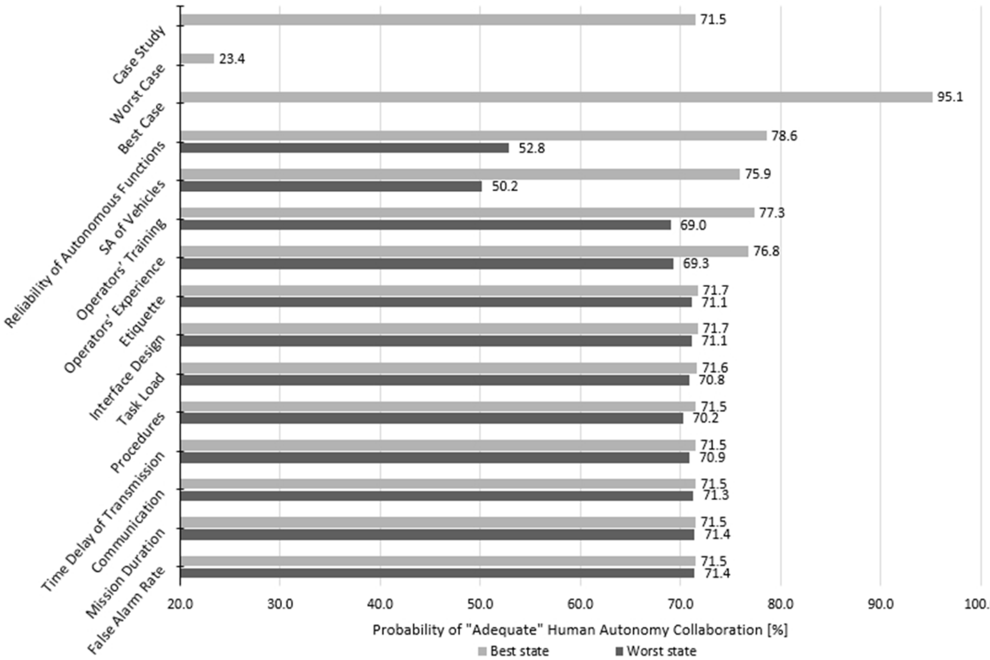

Figure 4 Effect of changing the states of the nodes individually on the probability of "Adequate" Human Autonomy Collaboration Performance. The Worst Case and the Best Case refer to the nodes being set in the worst and best state combined.
Figure 4
215x143mm (96 x 96 DPI)