Risk modeling of autonomous underwater vehicle operation focusing on the human operator

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ABSTRACT: Autonomous underwater vehicles (AUVs) are used in scientific, commercial and military organizations to conduct surveys and follow a preprogrammed mission path through the oceans. If a fault or an unexpected deviation from the mission plan should occur, which the autonomous capability of the AUV does not discover as a fault, the operators have to detect these instead and act appropriately. This paper presents a Bayesian Belief Network to assess the probability of monitoring success of an AUV mission. Some of the influences that are incorporated in the model are; Trust in the System, Automation Etiquette, Additional Workload, Time Delay and Loss of Status Messages. It is believed that the model can help improve AUV operations by clarifying relationships between technical, human and organizational factors and their influence on mission risk.

1 INTRODUCTION

Autonomous underwater vehicles (AUVs) are used in scientific, commercial and military surveys in order to map the sea floor, locate objects of interest, and measure properties of the sea water (Yuh et al., 2011). AUVs are mostly cigar shaped untethered vehicles which follow a preprogrammed mission path through the ocean. Future operations of AUVs will be combined with other unmanned systems, such as drones and autonomous surface vessels, e.g., for ice monitoring in arctic areas (Haugen et al., 2011) or environmental impact studies (Niu et al., 2009). For these operations, a high reliability is required to perform satisfactory and deliver the required data without loss of the involved vehicles.

Although the term “autonomous” suggests a high level of independent decisions making, AUV capabilities are quite limited. Autonomy is the capability of a machine to make decisions independently of a human operator. Autonomy is measured in discrete levels, e.g., NFA (2012) applies a six level scale: 1. Human operated, 2. Human assisted, 3. Human delegated, 4. Human Supervised, 5. Mixed Initiative, 6. Fully autonomous. Current automated/ autonomous systems are found in the autonomy levels 2 (human assisted; i.e., the system can perform activities in parallel with human input) and level 3 (human delegated; the system can perform limited control activities on a delegated basis) (NFA, 2012). Hence, the input from the human operator has a high influence on current mission success. For further consideration, AUVs in the third autonomy level will be discussed, but AUVs with higher levels of autonomy might also be relevant.

A mission normally consists of four phases; (1) preparation and mission planning, (2) system test and deployment, (3) mission execution, and (4) AUV retrieval and data download. Manley (2007) states that mission files often contain errors due to typographic, sign or geographic datum errors, and wrong use of the mission programming software, which operators use for mission planning and preparation. Brito and Griffiths (2011) present, along with their Markov model for assessment of critical states of AUV operation, some incident data for the AUTOSUB 3 AUV; nine out of 28 failed or preliminary aborted missions can be attributed to human errors or influences. If the operator introduces errors in the mission plan, the AUV might not detect these errors and follow a path, which is potentially dangerous for the mission or AUV, e.g., passing fishing vessels (Kirkwood, 2009) or heading towards shallow water due to a wrongly implemented waypoint or drift. Hence, the AUV has to be monitored by evaluating its position and status messages about intentions and current actions for the operator to recognize if unplanned behaviors occur. This excludes to detect faults of the system or subsystems, which could lead to loss of the vehicle or mission delay, e.g., loss of thrusters or low battery. Although this information is important with respect to understanding the actions of the AUV, the autonomy functions will allow the

AUV to realize these faults and act accordingly. Utne and Schjølberg (2014) identify among others several human and organizational factors (HOFs) that can act as hazards to the systems. Together with HOFs, technical aspects and environmental conditions that influence the risk are risk-influencing factors (RIFs). Øien (2001 a) defines RIFs as "an aspect (event/ condition) of a system or an activity that affects the risk level of this system/activity".

The objective of this paper is to present a Bayesian Belief Network (BBN) model, which includes the influence of RIFs, in order to find the probability of a successful monitoring by a human operator of an AUV during mission. Risk in this context means the probability not to monitor the AUV correctly. Monitoring implies that the operator observes the status of the AUV via a human machine interface (HMI), understands the status and intentions of the AUV, sets this information into context with the planned mission and responds appropriately, if AUV intentions and the objectives of the planned mission are conflicting.

The BBN model in this paper is the first step towards the development of a larger risk model addressing mission outcomes of operations with multiple AUVs, unmanned surface and aerial vehicles, and other unmanned underwater vehicles. The model can be used to analyze risk before a mission, to identify shortcomings of the mission plan and the conduction of operation. This is necessary to be aware of and counteract any shortcomings before the mission is executed.

The model in this paper is limited to the operation of AUVs. Other types of autonomous vehicles will not be covered explicitly. The model presented is applicable to operation of multiple AUVs simultaneously even though the description in this paper refers to one AUV, only. The analysis is focused on the assessment of monitoring success during a mission.

2 RELATED WORK

Several attempts to analyze the reliability and risk in AUV operation have been made, focusing on the technical aspects and faults of AUV systems. The AUTOSUB AUVs of the National Oceanography Centre, Southampton have been analyzed with respect to reliability and risk associated to under ice operation (Griffiths et al., 2003, Griffiths and Brito, 2008, Brito and Griffiths, 2009). The reliability was derived by expert judgement based on the fault logs of the vehicle. Brito and Griffiths (2011) used a Markov model to assess the reliability of the AUTOSUB 3. The aim was to identify the probability of critical states that might lead to loss of the vehicle. The transition rates were based on the aforementioned literature.

Using expert judgment on the fault logs of a REMUS 100 AUV, Griffiths et al. (2009) analyzed the probability of successful missions for these kind of AUVs in different scenarios. Thieme et al. (2015) develop a risk management framework incorporating HOFs, including a case study focusing on the operation of a REMUS 100 AUV. They rely mainly on the SPAR-H human reliability assessment (HRA) method. Two events from Thieme et al. (2015) refer to monitoring of the AUV during a mission; "Crew insufficiently monitors AUV during mission" and "Crew does not detect unexpected behavior".

Different applications of BBN are described in the literature. This paper refers to those in the marine and maritime environment, e.g., collision (Martins and Maturana, 2009), grounding risk (Akhtar and Utne, 2014), and offshore maintenance work (Vinnem et al., 2012). Mkrtchyan et al. (2015) give a wider overview of applications of BBN in HRA.

3 MODELLING

3.1 *Bayesian Belief Network*

A BBN is an acyclic directed graph and consists of nodes and arcs. Each node is associated with a set of variables, representing the state of the node. An arc connects a parent node with a child node and is associated with a conditional probability table (CPT) that determines the probability distribution of the child node based on the parent nodes. The Bayesian reasoning law may be applied to these nodes to find, based on the child nodes, the state of the parent nodes (Jensen and Nielsen, 2009).

Figure 1 shows the resulting model for Monitoring Success. The nodes in Figure 1 are categorized in outcome, i.e., mission success (orange), RIFs associated with the human operator (blue), design and technical RIFs (yellow), organizational RIFs (grey), and environmental RIFs (green). The model in this paper was created with the computer program GeNIe (Decision Systems Laboratory of the University of Pittsburgh, 2013).

Monitoring success related to AUV operation includes detecting the need for an action, identification of actions, and execution of the right actions. The need for action might arise if there is an unforeseen change in the operational conditions (weather, sea state), the vehicle follows a different path than planned or expected, other vessels (especially fishing vessels) approaching the AUV, or bad vehicle performance (slow, wide turning radii, few messages received) (Stokey et al., 1999, Manley, 2007, Kirkwood, 2009). The vehicle provides status messages regarding incidents that may occur during mission, especially problems with navigation, excessive energy consumption, mission abort due to a fault or excess of a set limit. Despite these messages, the operator has to be aware of current intentions and actions of the AUV.

3.2 *Model description*

Ho et al. (2011) highlight Situational Awareness (SA) as a problem for AUV supervision. Ho et al. (2011) state that the influences on SA are Time Delays, Loss of Status Messages, Trust in the System and Additional Workload (AW) during the task. Only intermittent status messages are sent with limited information, due to low data transfer rates. On the one hand, this makes continuous monitoring obsolete, but if an unforeseen event should occur, it is even more difficult for the operator to identify the correct actions to take. SA research in the context of AUV is limited in the scientific literature. The developed model in this paper includes two main RIFs on SA, namely the state of the Human Operator and the Quality of HMI. Table 1 describes the factors identified for the BBN model and associated sources. The most important ones are detailed below.

Parasuraman and Miller (2004) investigate Trust in automated/autonomous systems. RIFs on Trust were modeled, accordingly; namely Automation Etiquette and AW. Sheridan and Parasuraman (2005) identify influences affecting performance in human machine interaction. One influence highlighted and hence integrated in the present model (as a node) is Automation Etiquette. It describes the way a system presents information and status messages to the human operator. This both influences Trust in the System, because a disruptive system is less likely to be trusted and relied upon, and the Quality of HMI. The Quality of HMI summarizes the design properties of the human-machine interface, Loss of Status Messages and, aforementioned, Automation Etiquette.

Environmental Conditions is not directly connected to SA, although it is important to monitor the environment. Environmental Conditions affects the state of the Human Operator and partly the Quality of HMI. The reasons are that motion induced by waves and wind will influence operator performance in some way, as well as the usability of the equipment. This is of course highly dependent on the vessel the operation takes place on.

Other models, e.g., Davoudian et al. (1994), Aven et al. (2006), Aas (2008), Vinnem et al. (2012), Groth and Swiler (2013), Akhtar and Utne (2014) give input to inclusion of more generic HOF, such as Communication, Training of Operators, Procedures, Human Fatigue and Weather.

The literature does not directly mention the RIFs Human Operator, Quality of HMI and Environmental Conditions; these nodes were introduced in the present model to facilitate a future elicitation process by reducing the number of parent nodes on the node SA (cf. next Section). The last node without references in Table 1 (Sea state) was added to highlight the underlying influences, as described above.

3.3 *Suggested states for the nodes*

Table 2 summarizes the proposed states for the nodes described in Table 1. The states represent a suggestion for a reasonable discretization of the variables. For some nodes, the states are obvious, for the less obvious, the states will be described below.

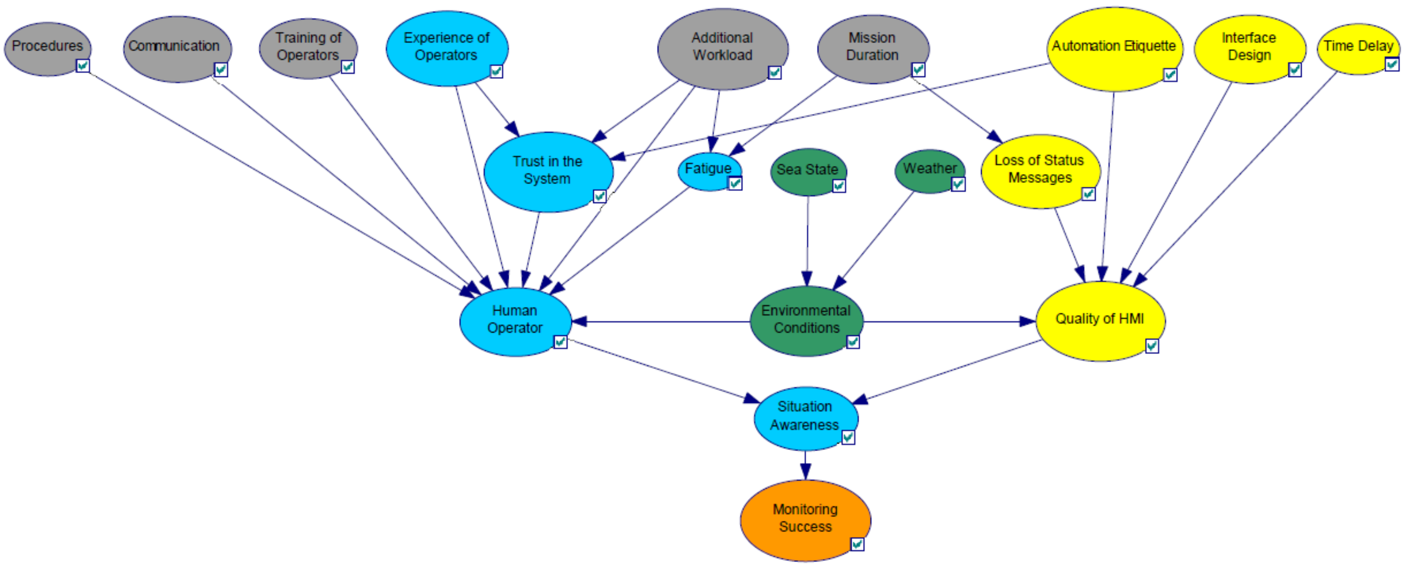

Figure 1 BBN model for monitoring success
Colors: Orange – outcome, blue – RIFs associated with the human operator, yellow – design and technical RIFs, grey – organizational RIFs, green – environmental RIFs

Table 1 Description of factors in the BBN with the top node "monitoring success"

Node	Description	Source
Additional Work-load	Proportion of other tasks that have to be executed additional to monitoring, e.g., preparation of equipment or evaluating data from a previous mission.	Parasuraman and Miller (2004), Ho et al. (2011), Fouse et al. (2012)
Communication	Quality and level of communication among operators and other crewmembers to relay information during operation.	Included in other models[1]
Environmental Conditions	Summary node for all the RIF from the environment.	
Experience of Operators	Level of experience of the operators with the AUV system and its operation.	Manley (2007), Included in other models
Human Fatigue	Fatigue is defined by Gander et al. (2011) as: *Inability to function at the desired level due to incomplete recovery from the demands of prior work and other waking activities.*	Akhtar and Utne (2014)
Human Operator	Summary node for all the RIF influencing the operator and representing the operator's ability to be aware of the ongoing mission.	
Interface Design	The adequacy of the physical interface, which is used to monitor the system, e.g., computer terminal in control room, or use of ergonomic design principles.	Garcia et al. (2010)
Loss of Status Messages	The proportion of messages that are not received by the transponder and lost.	Ho et al. (2011)
Mission Duration	The amount of time the operator(s) have to monitor the AUV.	Time (e.g., work scheme) Included in other models
Monitoring Success	Probability to successful monitor the AUV and detect faults, deteriorating operational conditions or deviations that are not detected by autonomous functions.	
Procedures	Documentation that describes operation and provides guidance for the operator.	Giese et al. (2013), Included in other models
Quality of HMI	Summary node for the overall quality of the human machine Interface (HMI), used to obtain an overview of operation.	Ho et al. (2011)
Sea State	Expected wave height during a mission.	
Situational Awareness	Ability to monitor the system, comprehend the information and take the right decisions.	Baxter and Bass (1998), Ho et al. (2011), Johnson and Lane (2011)
Automation Etiquette	The way information is presented to the operators and important information is highlighted.	Parasuraman and Miller (2004), Garcia et al. (2010), Ho et al. (2011)
Time Delay	The delay of time between a message being sent from the AUV and being received by the operator. This delay is proportional to the distance between AUV and transponder on the monitoring vessel.	Ho et al. (2011)
Training of Operators	The amount of training Operators received to monitor the AUV and decision making in abnormal cases.	Included in other models
Trust in the System	Reflects the operator's belief in the autonomous capabilities of the AUV.	Parasuraman and Miller (2004), Johnson et al. (2007), Ho et al. (2011)
Weather	Condition of the atmospherically weather during operation, in this case wind is assumingly the main influence.	Partly included in other models

[1] These factors were found partly in other frameworks or models and seem applicable here, such as Davoudian et al. (1994), Aven et al. (2006), Aas (2008), Vinnem et al. (2012), Groth and Swiler (2013), Akhtar and Utne (2014)

Human operator refers to the overall state of the operator, so "none" means, in this case, that the operator/s are not prepared, enabled and/ or qualified for the monitoring task under the given circumstances. A "low" state of a human operator implies that the operator is prepared/ enabled for the task of monitoring the AUV, but not sufficiently. A "high" human operator is accordingly in a very good state for the monitoring task. An "adequate" human operator is in a state, such that she or he is able to handle the monitoring task adequately.

AW has four states; none, low, adequate, high. "None" or "low" AW means that no other or only few other tasks are executed besides monitoring the

AUV. This might lead to Human fatigue in terms of monotony. A “high” AW may lead to negligence of the monitoring task. An “adequate” AW is a state where other tasks keep the operator busy so he/she is not bored, but on the other hand not to too occupied to neglect her/ his monitoring task.

Table 2 Proposed states for each node

Node	Proposed states
Additional Workload	None, Low, Adequate, High
Communication	None, Bad, Adequate, Good
Environmental Conditions	Beyond operational conditions, Close to operational limit, Medium, Good
Experience of Operators	None, Low, Nominal, High (e.g., less than a half year, one half to one years, two to five years, more than five years)
Human Fatigue	High, Nominal, Low
Human Operator	None, Low, Adequate, High
Interface Design	Inadequate, Low, Adequate, Good
Loss of Status Messages	Low, Medium, High
Mission Duration	Short (Less than 2 hours), Medium, Long (more than 8 hours, longer than one shift)
Monitoring Success	Success, Failure
Procedures	None available, Less than Adequate, Adequate, Good
Quality of HMI	Inadequate, Low, Adequate, High
Sea State	Smooth, Small Waves, Operational limit
Situational Awareness	None, Low, Adequate, High
Automation Etiquette	Disruptive, Adequate, Helpful
Time Delay	Short, Medium, Long
Training of Operators	None, Low, Adequate, High
Trust in the System	Distrust, Adequate, Overreliance
Weather	Calm, Windy, Storm

The states of Automation Etiquette reflect the way system informs the operator about events, e.g., status updates. A “Disruptive” etiquette, for example, pushes new information to the foreground of the interface, although the operator is occupied with another task and is interrupted by this message. A “Helpful” Automation Etiquette will prompt status updates if necessary, in a way that the operator can finish his/her current task without interruption. These states are based on research by Parasuraman and Miller (2004)

Trust in the system includes two opposing states. “Distrust” expresses that the operator will be skeptical towards the information given and might be reluctant to react to some information, until it is confirmed by several status updates. “Overreliance” expresses the state when an operator assumes that the AUV status messages and monitoring system will inform her or him if an important event should occur, disregarding possible failures to do so.

Weather only includes states that refer to wind, since this influences vessel motion, while rain and temperature have a minor influence on the operators. However, the states depend on the area of operation and the vessel/ operation control room.

3.4 *Utilization of the BNN*

The following example demonstrates the application of the BBN model. Two experienced operators conduct a subsea pipeline inspection with an AUV. Operation takes place under good weather conditions. The current shift uploaded the mission plan and started it. As additional work, the operators have to evaluate mission data collected during a prior mission. The shift is going to be relieved soon and the risk level during the next shift is assessed. During the next shift, a storm is expected. The operators in the next shift have been working with this particular AUV system only for a short time and they did not spent much time working together. This implies a low experience, low communication, and operational conditions close to the operational limits. A decrease of monitoring success probability from the first shift to the second shift is expected. This decreased success probability and associated lower situational awareness can be counteracted by, e.g., decreasing additional workload or changing the settings for status update prompting, so the operators are better informed and focus more on monitoring, if the operational conditions require this.

3.5 *Conditional probability tables*

The quantitative relationship between parent nodes and children nodes can be determined by conditional probability tables CPT (Jensen and Nielsen, 2009). Elicitation of CPT can be resource demanding. Currently, a data driven approach to derive the CPT is not applicable, since only few incident reports have been published regarding operation of AUVs and monitoring success. Including expert judgments for development of the CPT is possible, and is subject to further work.

An option could be to weight the influence of the parent nodes on the child node with the analytical hierarchy process (AHP) (Saaty and Vargas, 2012). To find the state of the child, the ratings must be transformed from the verbal scale to a numerical scale. The weighted sum of the states can be used to find the mean rating of the child node, around which the probabilities for the child’s states are distributed with, e.g., the triangular distribution or the beta-distribution (Vinnem et al., 2012). Further investigation is necessary to determine adequate distributions for this case.

3.6 *Quantification of the model*

The overall aim of the BBN model is to find the probability of a successful mission. Only part of the model, focusing on Monitoring Success, is presented in this paper. The CPT and the initial states of the input nodes determine this probability. Input nodes are only parent nodes. Some of these states, e.g., Mission Duration, Sea State or Weather, can be predicted quite reliably. For the initial states of the human and organizational RIF (e.g., Training of operators, Communication, Experience, Procedures, Automation Etiquette) questionnaire surveys or interviews among operators can be used. The initial states could be distributed accordingly around the mean rating of operators.

For some of the RIF organizational risk indicators could be used, e.g., procedures (how often are procedures violated, procedures and documentation available per task) or experience (mean experience of operators). Further examples are given by, e.g., (Øien, 2001 b).

4 DISCUSSION

4.1 *BBN model*

The qualitative model developed in this paper represents the relationships between the nodes described in Table 1 and Table 2 without creating a too complex network.

One RIF that has been excluded from the model is the individual personality of an operator. Individual personality includes the mindset of an operator, her/ his mood, attitudes, personal problems (Alcohol, Drug abuse), etc. This RIF is difficult to assess and would exceed the scope of this paper.

Situational awareness includes perception and comprehension of a situation, decision-making and execution and implementation of a decision. These processes are not modelled separately, but as a combined influence on monitoring success. It is believed that a separate modelling would increase the model size and complexity without adding new insights into operation. Another RIF, which is not explicitly included, is task complexity, included in e.g., Groth and Swiler (2013). This is assumed part of the node AW, since a higher workload will increase task complexity and vice versa. Operators are, in most cases, involved in mission planning, which reduces task complexity from the operators point of view, since she/ he is more familiar with the mission.

The node AW itself is quite undeveloped. It comprises several RIFs and might have to be further analyzed to identify underlying RIFs. The literature related to this RIF focuses mostly on the relationship between performance and AW, e.g., Fouse et al. (2012).

Human Fatigue and underlying influences is a research topic on its own. In the BBN, it is included as solely dependent on AW and Mission Duration, which is a limitation. As mentioned, individual personality is not included, which may influence Human Fatigue. Mission Duration and its influence is included, although mission planning errors or setup errors in most cases manifest themselves in the early stages of a mission. Some planning errors might manifest itself quite late, e.g., a coordinate error for one of the last waypoints.

Three summarizing nodes, Human Operator, Quality of HMI and Environmental Conditions, are added in the model. These nodes have two advantages: Firstly, the deduction process of the CPT for SA is reduced. Secondly, modelling of synergies and negating effects can be included in the CPTs. An example is that good experience could negate the effect of low quality procedures.

Concerning the RIF from other models and frameworks, each of the publications included in Table 1 presents a variety of RIFs, but only the relevant and applicable ones were included in the present model. For Example, higher management decisions were not included, in contrast to, e.g., Vinnem et al. (2012).

4.2 *States and Quantification*

A general point for discussion is the choice of states for the nodes. The literature ranges from two states per node (Akhtar and Utne, 2014) to six states per node (Vinnem et al., 2012). Few states simplify the process of CPT elicitation, but might not reflect sufficiently the possible states a RIF may have in reality. A high number of states per node will lead to better resolution, but increases the number of necessary elicitations exponentially. Three states for each seem adequate in the presented case.

Finding the probability of monitoring success needs input from operators. They need to assess the current state of the input nodes affecting the human operator and on HMI design. Quantification could also be achieved by using organizational risk indicators, which require a continuous collection of data for a certain operating period in order to be significant and representable. The assessment of states may also give input to the improvement of operation, by highlighting weaknesses and influence on risk. A sensitivity analysis may point out the factors that need most attention, but also those factors that have to be assessed with care, because of their high influence on the model outcome.

CONCLUSION AND FURTHER WORK

This paper presents a Bayesian Belief Network (BBN) to determine the monitoring success of an

Autonomous Underwater Vehicle (AUV) mission. Risk Influencing factors (RIF) for the BBN were found in the literature and influences were modeled, accordingly. Very limited work has been done previously to model these interactions for AUV with a BBN. It is believed that the risk model is not only applicable to AUV operation, but also to unmanned aerial and unmanned surface vehicles. For these operations, however, modifications to the BBN might be necessary.

According to the literature; Trust in the System, Automation Etiquette, Additional Workload, Time Delay and Loss of Status Messages are the main influences on Situational Awareness and, accordingly, on Monitoring Success of the AUV. RIF that were included, but so far are not mentioned in the literature in connection with monitoring of AUV operations are Human Fatigue and Environmental Conditions (including Weather and Sea state). The aspects in the model should be considered in future AUV operations and in the design of new AUV and interfaces. Even though the BBN model has not been quantified yet, it is believed that the model will help improve operations by clarifying the strength of relationships between risk and HOF, and highlighting any challenging areas.

Future work is to quantify the relationships and evaluate the model quantitatively. The model presented in this paper is part of a larger model, which is currently under development. The total model will assess mission performance of multiple unmanned and autonomous vehicles in marine environments and associated risks, prior to the mission.

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REFERENCES

AAS, A. L. (2008) The human factors assessment and classification system (HFACS) for the oil gas industry. International Petroleum Technology Conference, IPTC 2008, December 3, 2008 - December 5, 2008. Kuala Lumpur, Malaysia, Society of Petroleum Engineers.

AKHTAR, M. J. & UTNE, I. B. (2014) Human fatigue's effect on the risk of maritime groundings – A Bayesian Network modeling approach. Safety Science, 62, 427-440.

AVEN, T., SKLET, S. & VINNEM, J. E. (2006) Barrier and operational risk analysis of hydrocarbon releases (BORA-Release). Part I. Method description. Journal of Hazardous Materials, 137, 681-691.

BAXTER, G. D. & BASS, E. J. (1998) Human error revisited: some lessons for situation awareness. Human Interaction with Complex Systems, 1998. Proceedings., Fourth Annual Symposium on.

BRITO, M. P. & GRIFFITHS, G. (2009) Results of expert judgments on the faults and risks with Autosub3 and an analysis of its campaign to Pine Island Bay, Antarctica, 2009. Proceedings of the International Symposium on Unmanned Untethered Submersible Technology (UUST 2009), Durham, New Hampshire, 23-26 August 2009. Autonomous Undersea Systems Institute (AUSI).

BRITO, M. P. & GRIFFITHS, G. (2011) A Markov Chain State Transition Approach to Establishing Critical Phases for AUV Reliability. Ieee Journal of Oceanic Engineering, 36, 139-149.

DAVOUDIAN, K., WU, J.-S. & APOSTOLAKIS, G. (1994) Incorporating organizational factors into risk assessment through the analysis of work processes. Reliability Engineering and System Safety, 45, 85-105.

DECISION SYSTEMS LABORATORY OF THE UNIVERSITY OF PITTSBURGH (2013) GeNIe modeling environment GeNIe 2.0 ed., University of Pittsburgh.

FOUSE, S., CHAMPION, M. & COOKE, N. J. (2012) The effects of vehicle number and function on performance and workload in human-robot teaming. Proceedings of the Human Factors and Ergonomics Society.

GANDER, P., HARTLEY, L., POWELL, D., CABON, P., HITCHCOCK, E., MILLS, A. & POPKIN, S. (2011) Fatigue risk management: Organizational factors at the regulatory and industry/company level. Accident Analysis & Prevention, 43, 573-590.

GARCIA, J. C., FERNANDEZ, J. J., SANZ, P. J. & MARIN, R. (2010) Increasing autonomy within underwater intervention scenarios: The user interface approach. Systems Conference, 2010 4th Annual IEEE.

GIESE, S., CARR, D. & CHAHL, J. (2013) Implications for unmanned systems research of military UAV mishap statistics. IEEE Intelligent Vehicles Symposium, Proceedings.

GRIFFITHS, G. & BRITO, M. (2008) Predicting risk in missions under sea ice with Autonomous Underwater Vehicles. Autonomous Underwater Vehicles, 2008. AUV 2008. IEEE/OES.

GRIFFITHS, G., BRITO, M., ROBBINS, I. & MOLINE, M. (2009) Reliability of two REMUS-100 AUVs based on fault log analysis and elicited expert judgment. Proceedings of the International Symposium on Unmanned Untethered Submersible Technology (UUST 2009), Durham, New Hampshire, 23-26 August 2009. Durham NH, USA, Autonomous Undersea Systems Institute (AUSI).

GRIFFITHS, G., MILLARD, N. W., MCPHAIL, S. D., STEVENSON, P. & CHALLENOR, P. G. (2003) On the reliability of the Autosub autonomous underwater vehicle. Underwater Technology, 25, 175-184.

GROTH, K. M. & SWILER, L. P. (2013) Bridging the gap between HRA research and HRA practice: A Bayesian network version of SPAR-H. Reliability Engineering & System Safety, 115, 33-42.

HAUGEN, J., IMSLAND, L., LØSET, S. & SKJETNE, R. (2011) Ice observer system for ice management operations. Proc. 21st Int. Offshore (Ocean) and Polar Eng. Conf., Maui, Hawaii, USA.

HO, G., PAVLOVIC, N. & ARRABITO, R. (2011) Human Factors Issues with Operating Unmanned Underwater Vehicles. Proceedings of the Human Factors and Ergonomics Society Annual Meeting, 55, 429-433.

JENSEN, F. V. & NIELSEN, T. D. (2009) Bayesian networks and decision graphs, New York, NY 10013, USA, Springer Science & Business Media.

JOHNSON, N., PATRON, P. & LANE, D. (2007) The importance of trust between operator and AUV: Crossing the human/computer language barrier. OCEANS 2007 - Europe.

JOHNSON, N. A. R. & LANE, D. M. (2011) Narrative monologue as a first step towards advanced mission debrief for

AUV operator situational awareness. IEEE 15th International Conference on Advanced Robotics: New Boundaries for Robotics, ICAR 2011, June 20, 2011 - June 23, 2011. Tallinn, Estonia, IEEE Computer Society.

KIRKWOOD, W. J. (2009) AUV incidents and outcomes. OCEANS 2009, MTS/IEEE Biloxi - Marine Technology for Our Future: Global and Local Challenges.

MANLEY, J. E. (2007) The Role of Risk in AUV Development and Deployment. OCEANS 2007 - Europe.

MARTINS, M. R. & MATURANA, M. C. (2009) The Application of the Bayesian Networks in the Human Reliability Analysis. ASME 2009 International Mechanical Engineering Congress and Exposition. Lake Buena Vista, Florida, USA, ASME.

MKRTCHYAN, L., PODOFILLINI, L. & DANG, V. N. (2015) A survey of Bayesian Belief Network Applications in Human Reliability Analysis. Safety and Reliability: Methodology and Applications - Proceedings of the European Safety and Reliability Conference, ESREL 2014.

NFA (2012) Autonomous Systems: Opportunities and Challenges for the Oil & Gas industry. Norwegian Society of Automatic Control.

NIU, H., ADAMS, S., LEE, K., HUSAIN, T. & BOSE, N. (2009) Applications of Autonomous Underwater Vehicles in Offshore Petroleum Industry Environmental Effects Monitoring.

PARASURAMAN, R. & MILLER, C. A. (2004) Trust and etiquette in high-criticality automated systems. Communications of the Acm, 47, 51-55.

SAATY, T. L. & VARGAS, L. G. (2012) Models, Methods, Concepts & Applications of the Analytic Hierarchy Process, Boston, MA, Springer US.

SHERIDAN, T. B. & PARASURAMAN, R. (2005) Human-Automation Interaction. Reviews of Human Factors and Ergonomics, 1, 89-129.

STOKEY, R., AUSTIN, T., VON ALT, C., PURCELL, M., GOLDSBOROUGH, R., FORRESTER, N. & ALLEN, B. (1999) AUV Bloopers or Why Murphy Must have been an Optimist: A Practical Look at Achieving Mission Level Reliability in an Autonomous Underwater Vehicle. Proceedings of the International Symposium on Unmanned Untethered Submersible Technology. New Hampshire.

THIEME, C. A., UTNE, I. B. & SCHJØLBERG, I. (2015) A Risk Management Framework For Unmanned Underwater Vehicles Focusing On Human And Organizational Factors Proceedings of the ASME 2015 34th International Conference on Ocean, Offshore and Arctic Engineering OMAE2015. St. John’s, NL, Canada, ASME, accepted for publication.

UTNE, I. B. & SCHJØLBERG, I. (2014) A Systematic Approach To Risk Assessment - Focusing On Autonomous Underwater Vehicles And Operations In Arctic Areas. Proceedings of the ASME 2014 33rd International Conference on Ocean, Offshore and Arctic Engineering. San Francisco, California, USA.

VINNEM, J. E., BYE, R., GRAN, B. A., KONGSVIK, T., NYHEIM, O. M., OKSTAD, E. H., SELJELID, J. & VATN, J. (2012) Risk modelling of maintenance work on major process equipment on offshore petroleum installations. Journal of Loss Prevention in the Process Industries, 25, 274-292.

YUH, J., MARANI, G. & BLIDBERG, D. R. (2011) Applications of marine robotic vehicles. Intelligent Service Robotics, 4, 221-231.

ØIEN, K. (2001 a) Risk indicators as a tool for risk control. Reliability Engineering & System Safety, 74, 129 - 145.

ØIEN, K. (2001 b) A framework for the establishment of organizational risk indicators. Reliability Engineering & System Safety, 74, 147-167.