Towards Building a Safety Case for Marine Unmanned Surface Vehicles: A Bayesian perspective

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ABSTRACT

Marine Unmanned Surface Vehicles (MUSVs) are essential platforms for persistent and adaptable ocean monitoring and sampling. In order to operate these platforms in coastal areas or near oil and gas waters the MUSVs must meet statutorily and industry safety requirements. Given the novelty of these platforms, there is lack of evidence to support the claim that a given safety target can be met without any additional protection. Therefore, for safety critical operations, MUSVs require the implementation of a safety function. The development of a safety function must comply with IEC61508 safety standard, which requires a quantification of the safety integrity level. Compliance to IEC61508 is subject to subjective uncertainty. The nature of the technology in terms of mode of operation and the environment in which operates exacerbates this uncertainty. This paper presents a Bayesian belief network for formalizing the safety arguments underpinning MUSV compliance to IEC 615078 safety standard.

1 INTRODUCTION

Marine Autonomous Surface Vehicles (MASVs) are progressing towards becoming an integral part of marine observation and sampling. Marine autonomous surface vehicles are marine vessels with no humans on board. In the scientific domain, these vessels were originally developed to provide cost effective means to conduct ocean sampling (NOAA, 2010). The current aim is to have these vehicles conducting more sustainable observations, in areas that are more prone to catastrophic risk, such as near coastal areas or close to oil and gas installations (ASV, 2017) (Autonaut, 2017) (Liquid Robotics, 2017).

In order to operate in such areas, the operators must demonstrate that the vehicle operation will not put life in danger or cause disruption to operations. The problem then becomes one of how can we demonstrate that the vehicles are safe for operation? The issue of presenting the safety case for ships is now well understood. Wang (2002) presents a comprehensive analysis of approaches for presenting a safety case for ships, which involves conformance to a number of standards and the use of formal safety assessments. In many ways, MUSVs have the same issues as ships and therefore many processes for the safety case of ships are also applied to MUSVs. However, the consequences of different hazards are significantly different from MUSVs to ships. For example, a fire on board of a MUSV, in open water, is likely to have a lower consequence than a fire on a ferry in the same environment. On the other hand, the consequence of a fire on an MUSV, whilst operating near an oil and gas site or in a high-density marine traffic area, may be critical.

The problem of how to approach a safety case for a MUSV is not clear. If a critical event occurs on a ship, the responsibility for risk mitigation is with the captain. On the other hand, if a hazard event occurs on an MUSVs the responsibility to control the risk is a programmable electronic system (PES). The safety case for a MUSV has to demonstrate the integrity of the PES function tasked with bringing the MUSV to a safe state in light of a hazardous or abnormal event. This PES function is called safety function (IEC 61508, 2000). The (ISO 17894, 2005) standard provides guidelines for developing PES to meet a high level of integrity. However, this standard does not provide means to quantify the system's safety integrity. This is essential for supporting a safety case. IEC61508 (2000) is a functional safety standard that recommends methods for designing a safety function that will bring the main system (denoted as the platform) to a safe state. This standard considers four safety integrity levels, SIL 1 to SIL 4. Each SIL is a probability range for catastrophe failure, where SIL 4 is the lowest probability range. Building a safety case for a PES system is subject to subjective uncertainty and requires the combination of disparate sources of evidence.

In this paper a Bayesian Belief Network model is proposed for injecting transparency in the SIL target allocation process for MUSV. Bayesian Belief Networks are graphical probabilistic models (Pearl, 1998). There is already a body of previous work on the use of BBNs in the analysis of software reliability and integrity (Fenton et al., 1998), (Gran, 2002), (Brito et al., 2006), (Littlewood et al., 2007). However, to the author’s knowledge a BBN has not been proposed for informing the SIL claims of a MUSV. In the author's view, this is needed in order to ensure transparency in the application and conformance to IEC 61508, to assess the rigour of the design and verification methods and to estimate the likelihood of systematic failure. The BBN proposed in this paper is developed from first principles and is the first attempt to articulate the safety arguments that should be presented when building a safety case for an MUSVs.

2 MARINE AUTONOMOUS SYSTEMS INTEGRITY

Whilst a large number of risk and reliability studies for autonomous underwater systems have been conducted that quantify risks (Brito et al., 2008), (Brito et al., 2010), (Brito et al., 2012), (Podder et al., 2004), (Merckelbach, 2013) (Brito, 2015), to this date there has been no concerted study that focus on the quantification of safety integrity. Studies of safety integrity for buoys, moorings and remotely operated underwater robots is presented (Vedachalam et al., 2016), (Venkatesan et al., 2014), (Venkatesan et al., 2015) but these do not apply to MUSVs. To this date no concerted effort has been proposed which attempts to inject transparency in to the safety integrity claim for a MUSV. The safety integrity of a MUSV is dependent on its risk and reliability as it reflects the level of risk reduction that can be achieved by a safety function. However, previous studies do not focus on the development of safety functions for MUSVs. To ensure that a safety case can be developed the safety function must comply with industry standards. IEC61508 is an international standard that guides the development of the safety function. The first task is to establish the safety integrity level target for the safety function. Assuming that maximum acceptable frequency for a critical risk, for example fatality due to collision with a passenger ship, is 10^{-5} pa (X). Consider also that the reliability analysis of the platform, without the safety function, this is the unprotected system, concluded that the likely failure rate is $3*10^{-3}$ pa (Y). Then the failure on demand of the safety function would need to be Z = X/Y = $3.3*10^{-3}$ pa. Table 1, presents the SIL target for the safety function, as indicated by IEC61508. According to Table 1, the safety function would have to be developed to meet SIL 2.

Following this process, the problem of complying with IEC61508 is quite straightforward. However, the nature of MUSVs and the environments add a significant uncertainty towards defining the SIL target. The next sections of this paper use BBNs to inject transparency into this problem.

Table 1. Safety Integrity Levels (SIL.). High demand rate is for systems that operate in a continuous mode. Low demand rate is for systems that operate in a standby mode.

Safety Integrity Level	**High demand rate (Dangerous failures/hr)**	**Low demand rate (Probability of failure on demand)**
4	$10^{-9} \geq$ to $< 10^{-8}$	$10^{-5} \geq$ to $< 10^{-4}$
3	$10^{-8} \geq$ to $< 10^{-7}$	$10^{-4} \geq$ to $< 10^{-3}$
2	$10^{-7} \geq$ to $< 10^{-6}$	$10^{-3} \geq$ to $< 10^{-2}$
1	$10^{-6} \geq$ to $< 10^{-5}$	$10^{-2} \geq$ to $< 10^{-1}$

3 BBN METHODOLOGY

Bayesian belief networks are graphical probabilistic model that comprise of nodes and arcs. Each node is a variable and arcs are used to capture causation relations between variables (Pearl, 1998). A BBN model will comprise parent and child nodes. Parent nodes have no direct causal dependency from any other variables, that is, they have no inputs. Child nodes have arrows going into them, capturing a causal effect from a parent node. The strength of the causal effect is captured in conditional probability tables. Each BBN model represents a unique probability distribution. Consider a BBN with three parent nodes Y, Z and W and a single child node

X. The joint probability of X, Y, Z and W can be calculated as $P(X,Y,Z,W)=P(X|Y)\times P(X|Z)\times P(X|W)\times P(Y)\times P(Z)\times P(W)$.

BBNs are implemented in commercially available software tools. These implement algorithms for conducting inference on complex models. The tree junction algorithm is an exact method for conducting BBN inference. This algorithm is implemented on Hugin (2017), our tool of choice for implementing the BBN model proposed in this paper, other tools could be used for representing the model. In the next section we present the model developed for injecting transparency into the SIL claim process for MUSVs.

4 PROBABILISTIC ARGUMENTS FOR MUSV INTEGRITY

The Bayesian belief network is presented here to capture the arguments that can be used to make a claim for a given safety integrity level. The graphical structure of the BBN is presented in Figure 1.

There are two key inputs to justify a given SIL claim, first is the design SIL of the safety function and the second is the significance of outstanding errors. The design SIL has four states: {SIL4, SIL3, SIL2, SIL1}. For the purpose of simplification only the possible claimable SILs are considered, the scenario where no SIL can be claimed is not captured as a state. However, realistically another state should be entered to capture the scenario where no SIL claim is put forward. The significance of outstanding errors has the following states: {low, medium, high}. The premise is that a safety function is only effective to meet a given safety target if testing proves it to be so. For example, if a safety function meets a design SIL 3, the next step is to verify the safety function. In a system engineering analogy, the design SIL is the functional specification of the safety function and the verification is the testing (hardware, software testing). If the safety function is not tested, or faults identified during testing are not removed, then this should result in a decrease in the claimable SIL for the safety function. However, different to system engineering, the verification comprises the independent review of the safety function using risk and reliability methods, such as fault trees, historical data statistical analysis, formal expert judgment and others.

The confidence in the design SIL is estimated based on the “effectiveness of the safety function”, the “complexity” of the operations, the “environment” and the “competence” of the development team. The effectiveness of the safety function is a measure of the appropriateness of the safety function. It is possible that more than one safety function is defined. These functions may overlap in terms of coverage of catastrophic events mitigation. A variable denoted as "overlap" is introduced to capture this phenomenon. For example, a safety function may be a system that stops a MUSV in case of a possible collision with a manned vessel. Such a system can be implemented in a PES system or in a combination of PES system with human in the loop.

The "coverage achieved by the safety function" provides an estimate of the proportion of events or critical scenarios mitigated by the safety function. This variable has the following states: {5,4,3,2,1} where state 5, represents the scenario where all hazards are mitigated by the safety function i. A state 1, for the "Coverage achieved by the safety function represents the proportion of hazards mitigated by the safety function. The variable "Power of the safety function" captures the expected SIL level of the safety function, with the following states: {SIL4, SIL3, SIL2, SIL1}. The "Overlap" node captures whether or not the safety functions overlap in terms of mitigating hazards.

The complexity variable aims to capture the difficulty of the tasks that the MUSV is expected to conduct in terms of autonomy and adaptability. The ALFUS autonomy classification framework can be used to inform the complexity of the mission (Huang, 2007). This framework based on the environment, communication and complexity of the mission. Given that the environment is captured separately in the BBN model. Complexity can be defined to measure the level of autonomy and communication. For the purpose of this paper, complexity has the following states: {High, Medium, Low}.

The environment node has three states: {open water, coastal waters, exploration waters}. Open water is defined as away from the coast and traffic lanes. Key failures may be faults that lead to premature mission abort, leading to an expensive recovery; or bad weather (high seat state and wind velocity) that capsizes the vessel or causes the vessel to sink. A safety function may be a system that includes active monitoring of the weather and adaptive mission planning to avoid bad weather. Another possible safety function is a system that carries out condition monitoring of the vessel's internal faults and a fault management system. This safety function can be used regardless of the environment, however what is deemed a safe state would vary from one environment to another.

Coastal environment is defined as waters close to shore and include inland waters. Potential risks are high-density ship traffic comprising, for example, military, commercial, and personal watercraft; engineering structures (e.g. bridges, breakwaters, piers, jetties, groins); fishing gear (e.g. pound nets, lobster/crab pots). Operating close to the seabed can be hazardous, placing reliance on collision avoidance or altitude sensing hardware, algorithms and software (Griffiths and Trembanis, 2007). The type of mission carried out in open and coastal waters are hydrographic surveys.

Exploration waters considers that the vessel is operating to support pipe laying deployment or to support pipe inspection. Explorations waters are deemed to be areas close to oil and gas or sea mining explorations. Here the risks are collision with other vessels or offshore structure leading to human fatalities or disruption in operations. The safety functions mentioned above, such as reliance on collision avoidance and failure mitigation, can be used to bring the vessel to a safe state, however, here, the safety function is expected to meet a higher safety integrity target.

Personnel competence is key for the development and implementation of a safety related function. The Health and Safety Executive, United Kingdom, presents guidelines for managing competence (HSE, 2007). According to these guidelines, for a person to be competent, they need qualifications, experience, and qualities appropriate to their duties – which includes knowledge and understanding, experience and ability to communicate. The "competence of the team" state measures the capability of the team to develop the safety function. This node has the following states: {High, Medium, Low}. For the sake of simplicity, we decided to estimate competence for four variables: "training", "technical knowledge", "technical experience" and "qualifications". Training has the following states: {Yes, No}, Technical knowledge {High, Medium, Low}, Technical Experience {High, Medium, Low} and Qualifications {High, Medium, Low}.

Verification is an essential part of the SIL claim (Kaczor et al., 2016). Several techniques can be applied at this stage. Depending on the technology different techniques are most effective in verifying the SIL level. Kaczor et al. (2016) proposes the use of a combination of block diagrams and Monte Carlo simulation. Day et al. (2008) uses fault trees to demonstrate the SIL of a process plant. Shu and Zhao (2014) propose the use of Markov Chains. Whilst each method may be more suitable to a given problem. The intensity at which the method is applied is very important. The SIL verification process will attempt to find errors, hazards that have been overlooked for example. The greater the significance of these errors the less confidence one will have that a given SIL target can be claimed.

The “significance of outstanding errors” is estimated based on observations for the “quality of the verification”, “complexity of the verification”, “size of the verification team” and “size of the safety function”. In order to simplify the model each of these variables was chosen to have three states: {High, Medium, Low}. With three states it is possible to capture the problem with a sufficient level of granularity.

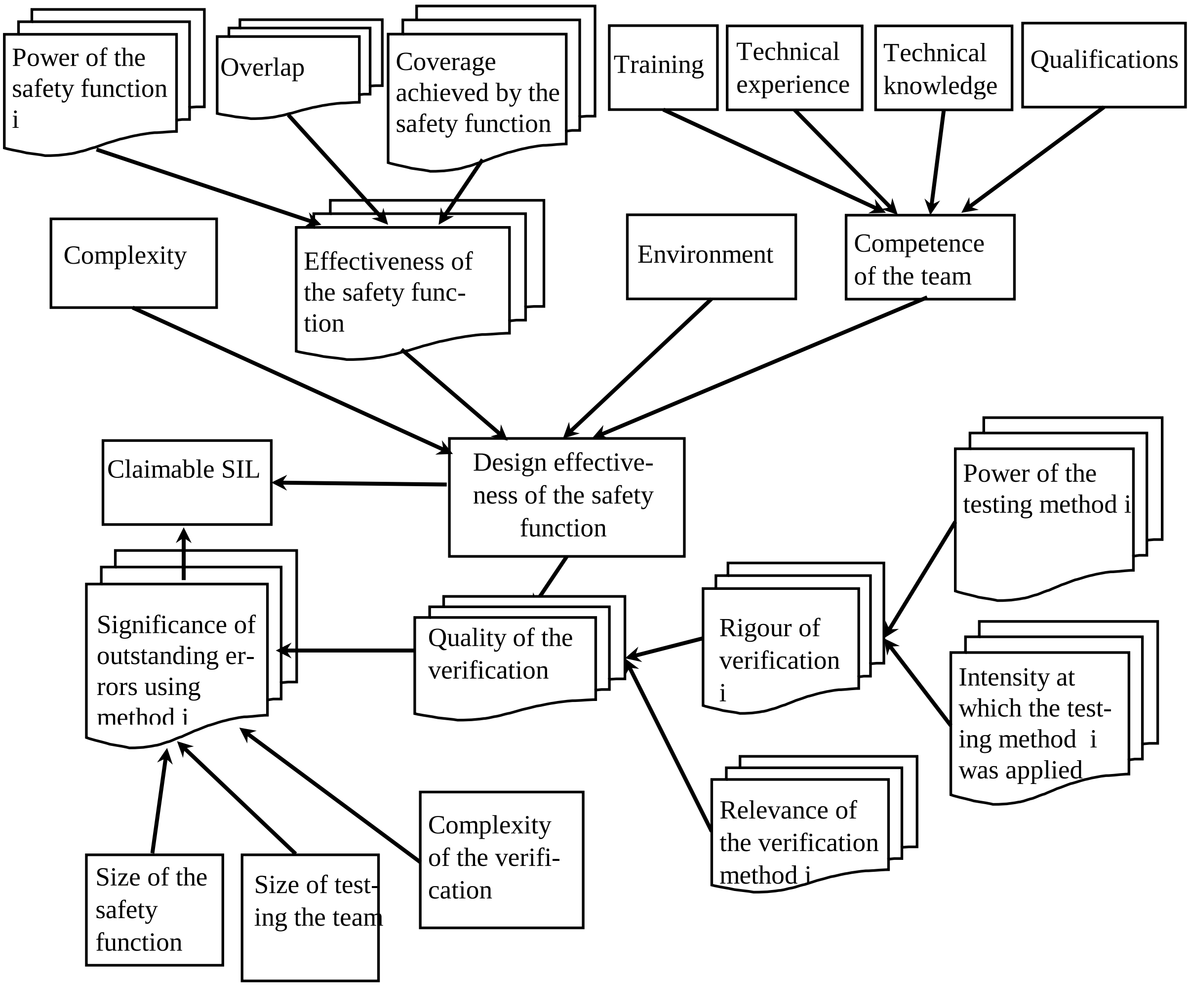

Figure 1. Bayesian belief network for building a safety integrity level argument for Marine Autonomous Systems.

The quantitative relations between variables were captured in the conditional Probability Tables (CPTs). For the "Significance of outstanding errors", the CPT was defined to model the effect that the significance of outstanding errors would be reduced as the quality of the verification increases, that is, the significance of the outstanding errors is monotonically decreasing with with the increase of quality of the verification. The complexity of the verification and the size of the safety function have the opposite relation with the significance of outstanding errors. The significance of outstanding errors is monotonically decreasing with the size of the verification team.

5 BAYESIAN ANALYSIS OF INTEGRITY CLAIM ARGUMENTS

The model proposed in Figure 1 was implemented in Hugin to illustrate how a Bayesian approach can help articulate the arguments for a safety case for a MUSV. Figure 2 presents a screenshot of the model in Hugin, without any hard evidence entered to update the confidence in the SIL claim. The only hypothesis considered is that all input states, for all input nodes, are equally likely. In an assessment of integrity, the assessor will gather evidence to support the belief that one state is more likely than others.

Let us now consider that the assessor believes that the power of the safety function meets SIL 3 and in a scale of 1 to 5 the coverage achieved by the safety function is 4. Here we consider that only one safety function is used. Based on this assessment, the effectiveness of the safety function has the following distribution: {SIL 4 = 0, SIL 3 = 80, SIL 2 = 20, SIL 1 = 0}. That is, there is 80% confidence that the safety function meets SIL 3 and there is 20% confidence that the safety function meets SIL 2. The complexity of the safety function is deemed medium, with 100% confidence. The environment of operation is coastal waters and the competence of the team is high with 100% confidence. Note that the distribution for this node is calculated based on the instantiations for training (100% Yes), Technical experience (100% yes), Technical knowledge (100% High) and Qualifications (100% Yes). In this scenario, we consider that the verification process is good. More specifically, the power of the verification is high, with 100% confidence, the intensity at which the verification method was applied is high with 100% confidence. In addition, the relevance of the verification method is high with 100% confidence. This scenario is presented in Figure 3. Consequently, the following distribution is obtained for the significance of outstanding errors: {High = 0, Medium = 0.3, Low = 0.7}. Therefore, there is 53% confidence that the safety function meets SIL 3.

The key argument here, is that the effect of the SIL target is primarily influenced by the coverage achieved by the safety function and the complexity, provided that a good verification process is put in place. A good verification process cannot increase the SIL target, indeed, it only verifies that the target SIL claim can be achieved. It is possible that a verification process finds important limitations in the design. If these limitations are addressed, it can possibly result in an increase in the coverage of the SIL function.

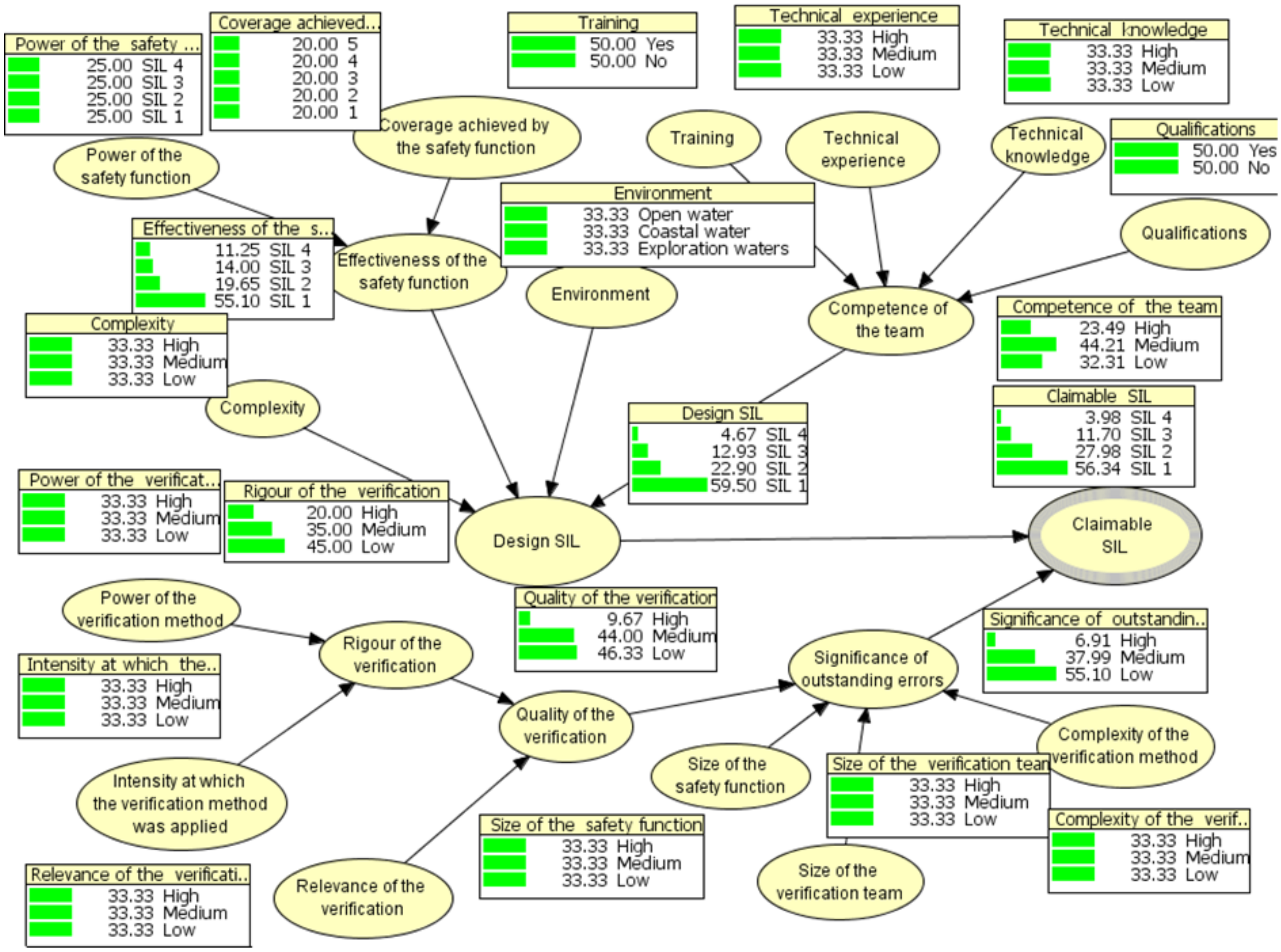

Figure 2. Hugin screenshot of the BBN model of a MUSV safety case

This causal relation is not captured in the model. The principle here is that the rational decision maker would first assess the benefits of increasing the coverage of the safety function. IEC 61508 captures this as the as low as reasonably practicable (ALARP) approach (IEC 61508, 2000). If the benefits outweigh the costs, then an increase of the coverage may be decided. This increase in coverage can be achieved by improving the safety function or by adding a new safety function that mitigates the hazards not covered by the first safety function.

A scenario where a poor review process is put in place is presented in Figure 4. The design SIL claim is the same as in the previous scenario {SIL 4= 0, SIL 3 = 0.56, SIL 2 = 0.41, SIL 1 = 0.3}. However, the claimable SIL is now {SIL 4 = 0, SIL 3 = 0.535, SIL 2 = 0.421, SIL 1 = 0.044}. The confidence in the claimable SIL reduced from 53% to 35%. This relation between the verification process and the claimable SIL is not explicitly captured in any standard.

The inference mechanism used by BBNs allows us to estimate the states of variables of interest based on new evidence for observable variables. For example, Figure 5 presents the estimates for the confidence of SIL 3 claim for nine different scenarios that can be categorized in 3 groups. The first group of scenarios assess the impact of the relevance of the verification method. The state of the "relevance of the verification method" is increased from low to high. The second group considers the effect of the environment. The state of the environment is changed from exploration waters, to coastal water to open water. The third group assesses the impact of coverage of the safety function. The state for the node "coverage of the safety function" is increased from 1 to 3 to 5. All remaining variables were instantiated as presented in Figure 3.

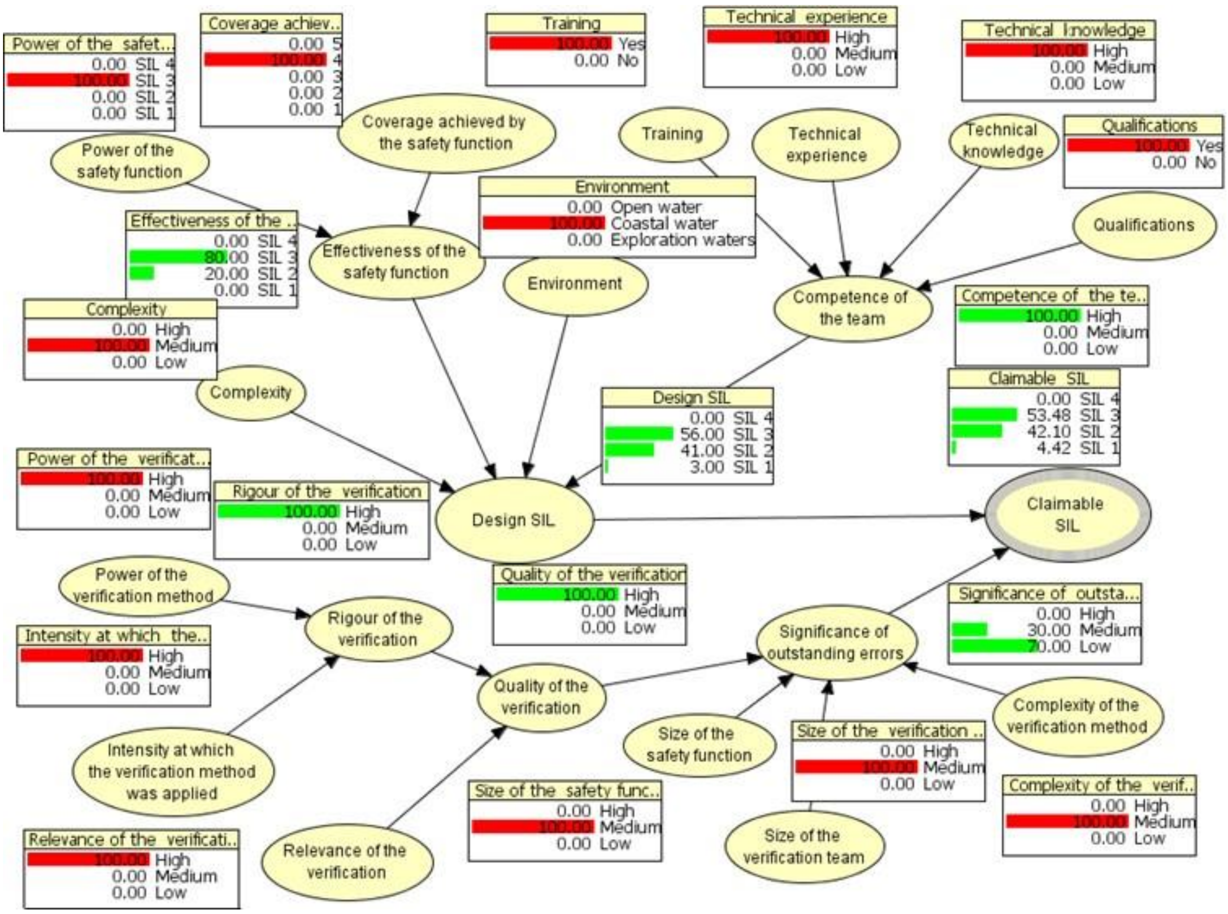

Figure 3. SIL 3 case with good verification process.

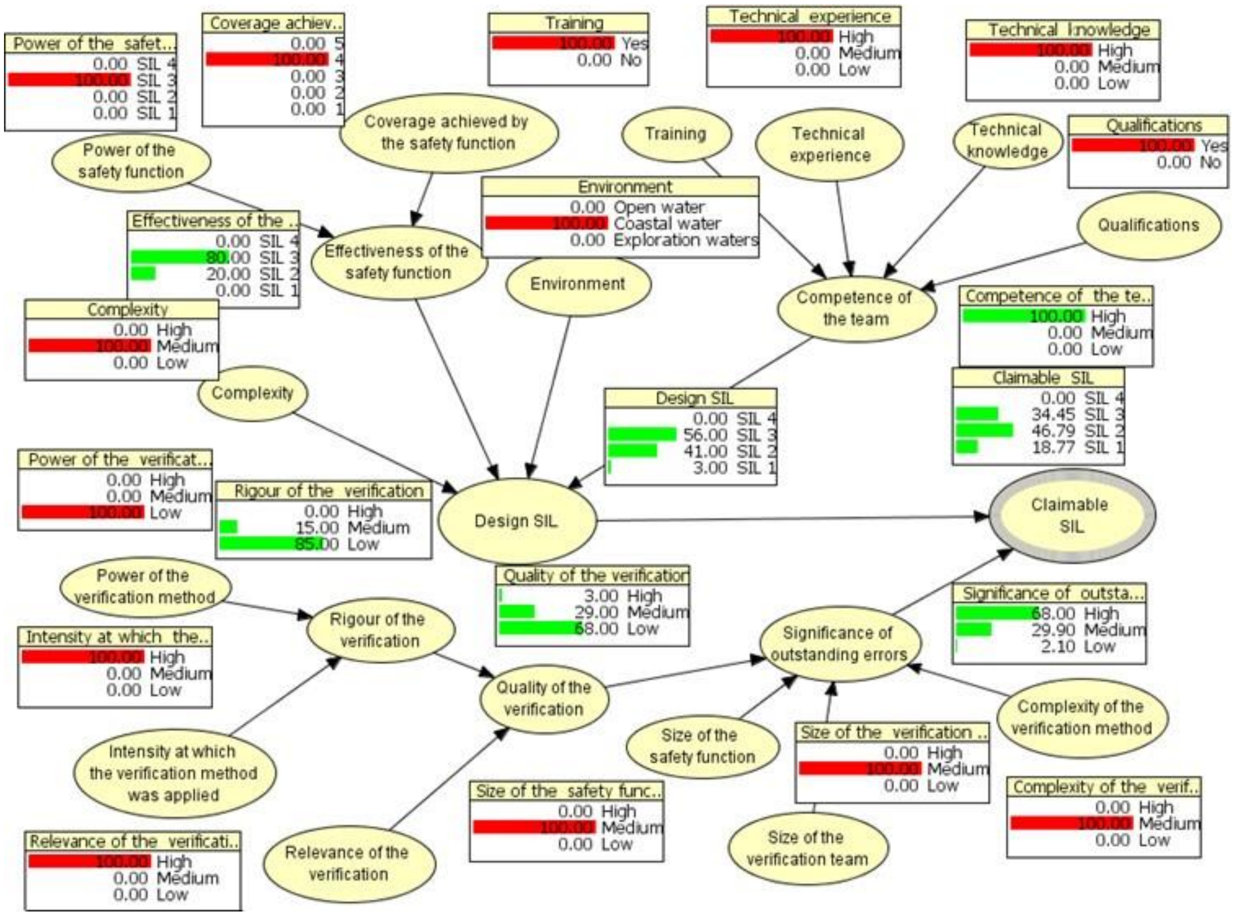

Figure 4. SIL 3 case with a poor verification process.

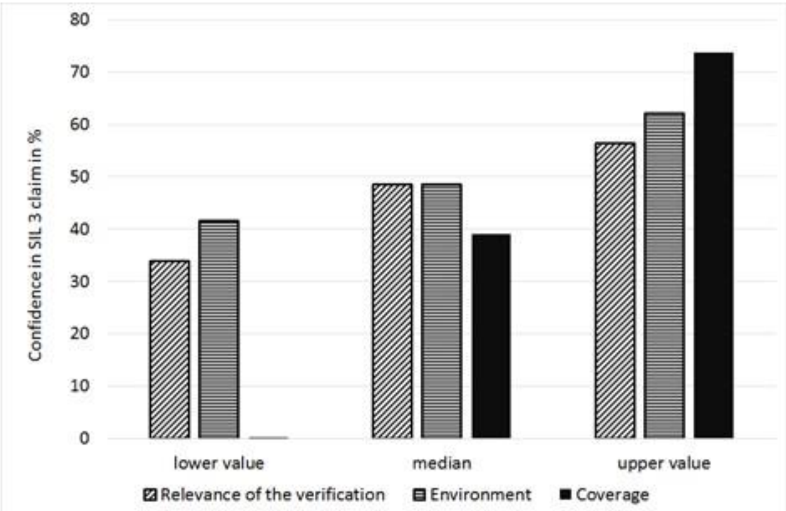

Figure 5. Variation in the claimable SIL, for SIL 3 state based on the upper, lower and medium value for relevance of the verification, environment and coverage.

6 CONCLUSIONS

Marine Unmanned Surface Vehicles (MUSVs) are expected to operate in coastal areas and exploration areas, where the consequence of failure can lead to catastrophic events, such as loss of life, significant environmental impact or loss of production. Reliability studies conducted on these vehicles have indicated that safety systems have to be put in place to reduce the risk to tolerable levels. In order to build a safety case for an MUSV safety system it is imperative to demonstrate compliance to IEC61508 safety standard. IEC61508 is a safety standard that requires the quantification of the safety integrity level. Adhering to the recommendations made in the standard should support the claim that a target SIL level is met. However, given the novelty of these vehicles, and their typical operating environment, the process of compliance to the standard is subject to subjective uncertainty. It is important to present the underlying framework for safety argumentation.

In this paper, a BBN approach is proposed for capturing the arguments underlying MUSV safety system compliance to the IEC 61508 safety standard. The literature shows that there is a causal effect between the power of the techniques used, the complexity of the environment, the complexity of the mission, and the techniques used for verification on the SIL claim. The BBN proposed in this paper captures this causality and demonstrates that probabilistic reasoning is a sound method to present safety arguments. This means that a BBN can be used for estimating MUSV reliability based on this safety standard.

There are however a number of limitations with this approach. The variables in the BBN must be defined so that they are meaningful to experts. In addition, each variable must have a level of granularity that allows experts to provide assessments with a good degree of confidence. It is clear that the greater the number of states for a variable the larger the conditional probability tables (CPTs). This can present challenges in terms of BBN verification. Recent research has shown that graphical methods can be used to support the verification of large CPTs (Brito and Griffiths, 2016).

The BBN presented in this paper is a first attempt at formalizing the safety arguments for MUSVs. Further work is required in order to develop a mature network. Namely, the complexity node must be revisited to capture the level of autonomy and communication with the human operators (who may be in standby during operations). The CPTs must be elicited from experts involved in measuring compliance with IEC61508. Finally, a more intensive sensitivity study has to be conducted.

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