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A Fuzzy-Based Risk Assessment Framework for Autonomous Underwater Vehicle Under-Ice Missions

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The use of autonomous underwater vehicles (AUVs) for various scientific, commercial, and military applications has become more common with maturing technology and improved accessibility. One relatively new development lies in the use of AUVs for under-ice marine science research in the Antarctic. The extreme environment, ice cover, and inaccessibility as compared to open-water missions can result in a higher risk of loss. Therefore, having an effective assessment of risks before undertaking any Antarctic under-ice missions is crucial to ensure an AUV's survival. Existing risk assessment approaches predominantly focused on the use of historical fault log data of an AUV and elicitation of experts' opinions for probabilistic quantification. However, an AUV program in its early phases lacks historical data and any assessment of risk may be vague and ambiguous. In this article, a fuzzy-based risk assessment framework is proposed for quantifying the risk of AUV loss under ice. The framework uses the knowledge, prior experience of available subject matter experts, and the widely used semiquantitative risk assessment matrix, albeit in a new form. A well-developed example based on an upcoming mission by an ISE-explorer class AUV is presented to demonstrate the application and effectiveness of the proposed framework. The example demonstrates that the proposed fuzzy-based risk assessment framework is pragmatically useful for future under-ice AUV deployments. Sensitivity analysis demonstrates the validity of the proposed method.

KEY WORDS: Autonomous underwater vehicle; fuzzy set theory; risk assessment; under ice

1. INTRODUCTION

1.1. Autonomous Underwater Vehicle

Autonomous underwater vehicles (AUVs) are best described as self-powered robotic devices that are piloted and overall controlled by onboard computer systems. Sometimes also referred to as an unmanned underwater vehicle (UUV) or named under model aliases, they are untethered and are preprogrammed to perform various underwater data acquisition missions. First developed in the late 1950s by Stan Murphy, Bob Francois, and, later, Terry Ewart from the University of Washington (Dixit, Hazarika, & Davim, 2017), the use of AUVs has grown with maturing technology and improved accessibility. Today, they are the tool of choice for many scientific, commercial, and military applications such as mine clearing operations, feature tracking, cable or pipeline inspection, deep ocean exploration, and even in air crash investigations (Le Hardy & Moore, 2015; Naeem, 2002). AUVs come in different shapes and sizes depending on their built purpose. They can have depth ability of 100 m to more

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than 5,000 m (Bellingham, 2010) and cost anything from a hundred to hundreds of thousands of dollars to construct.

When the first AUV, the Unmanned Arctic Research Submersible (UARS) vehicle, was deployed under the Arctic's ice in 1972 (Francois & Nodland, 1972), it demonstrated not only the feasibility but also the potential of deploying AUVs in the Antarctic for research applications. Concealed under the Antarctic's ice lies one of the more unique ecological, geological, and physical oceanographic ecosystems on the planet (Kunz et al., 2008). It harbors not only valuable information necessary for better understanding of the Earth's climate system and biogeochemical cycles, but also offers insights into other similar extreme environments such as that of Jupiter's moon, Europa (Lorenz et al., 2011).

However, under-ice AUV missions in the Antarctic present a new set of challenges as compared with open-water missions. The extreme environment tests not only the technological limits of the AUV, but it also challenges the onsite AUV team both physiologically and psychologically (Gunderson, 1967). In addition, considerations are needed to account for ice cover, inaccessibility, and emergency abort procedures during missions. It is not surprising, then, that the risk of AUV loss during under-ice missions in the Antarctic is higher when compared with open-water missions (Brito, Griffiths, & Challenor, 2010). The term "AUV loss," usually associated with the complete loss of an AUV, can also represent an AUV being destroyed or damaged beyond economic repair. The risk of AUV loss, therefore, refers to the likelihood that, during a mission, the AUV will be rendered unusable for future missions.

Previous risk analysis on the *Autosub3*, an AUV developed and owned by the National Oceanography Centre, Southampton, UK, showed the median probability of AUV loss for under sea-ice missions to be 4.9 times higher than that of open-water missions. Risk of loss for under-ice shelf missions is even higher, with a median probability 9.4 times higher than open-water missions (Brito et al., 2010). As a result, the loss of AUV in the Antarctic is not without its precedence: one of which was that of *Autosub2*, lost in 2005 under the Fimbulisen ice-shelf with unknown exact cause of loss (Griffiths & Collins, 2006). A subsequent board of inquiry established that the cause of *Autosub2* loss was most likely due to a fault introduced during the manufacturing/assembly phase (Strutt, 2006). *Seaglider SG522*, owned by the University of East Anglia, UK, was lost at the Weddell Sea in the Antarctic in 2012. The subsequent inquiry panel concluded that an erroneous command script placed *Seaglider SG522* in an unsafe state that eventually resulted in its loss (Brito, Smeed, & Griffiths, 2014).

The loss of an AUV is not only financially costly due to the resulting higher insurance premium for all (if it is insured, or loss/rebuild costs if it is not), it can also delay research projects, damage the reputation of the AUV community, cause the loss of valuable research data, and there is a possibility of harming the delicate Antarctic environment (Griffiths & Collins, 2006). As each Antarctic deployment consists of several missions, the risk of loss for individual missions may accumulate beyond the predetermined acceptable risk level for the entire deployment. Therefore, quantifying risk of loss prior to under-ice missions in the Antarctic has important implications for decision making, which may also influence the outcome of insurance coverage. In this article, a fuzzy-based risk assessment framework is proposed.

1.2. Risk Assessment Methodologies

Although debate exists over the precise definition for the term "risk," the most widely adopted definition is that risk is a combination of the severity of an event (or scenario) and the likelihood of that scenario occurring (Kaplan & Garrick, 1981). The systematic process to comprehend the nature of risk and to express the risk, under given circumstances, is often called risk assessment (Glossary—The Society for Risk Analysis, 2015), the intent of which is to enhance the ability of an organization to achieve its objectives. Over years of development, myriad risk assessment methodologies have been proposed in adaptation to different systems, industry, environments, components, or stages of processes. However, there is no single method that suits all needs and multiple methods are often adopted for the assessment of risks. The choice of method has often depended on a variety of factors, such as the purpose of analysis, nature of risk, and the availability and quality of data.

Within the AUV domain, Griffiths and Brito (Brito & Griffiths, 2016; Griffiths & Brito, 2008, 2011; Griffiths, Brito, Robbins, & Moline, 2009) carried out extensive studies that laid the necessary groundwork for structured, quantitative risk assessment of AUV deployment. Probabilistic models such as the Kaplan–Meier estimator, Bayesian belief

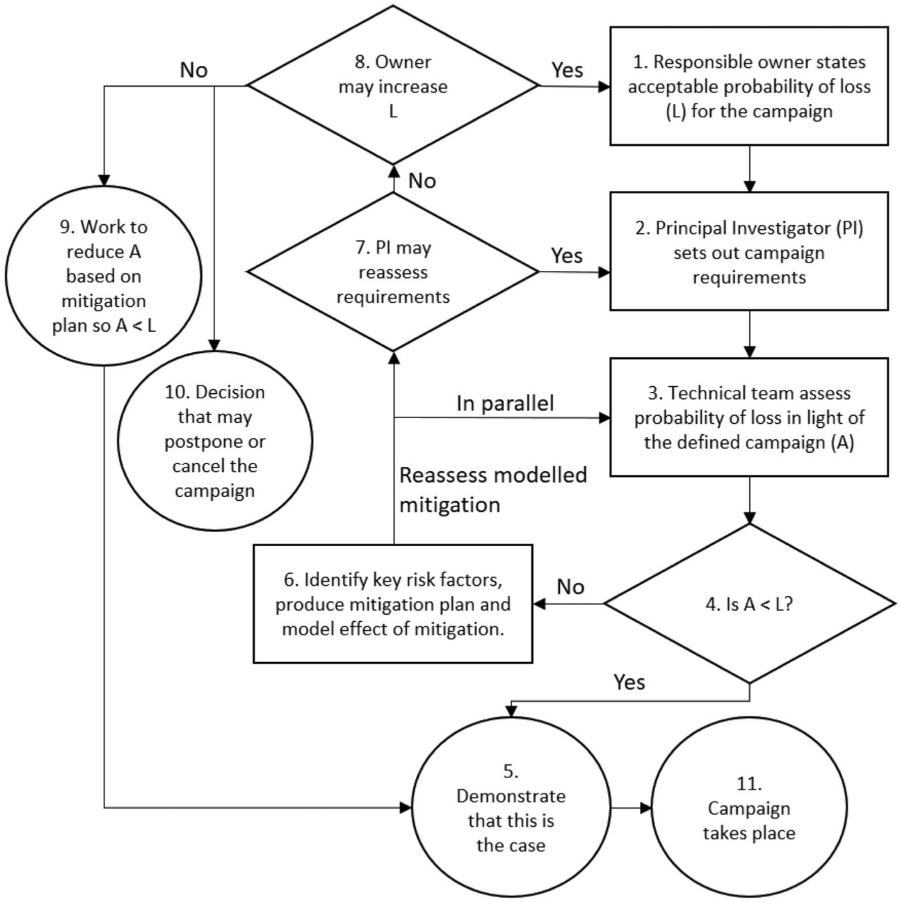

Fig. 1. Risk management process for AUV operations, presented by Griffiths and Trembanis (Griffiths & Collins, 2006) (with permission to reproduce).

network (BBN), and Markov chains were applied on historical failure fault log data of the AUV, and in synthesis with experts' judgments, to predict the probability of AUV loss. Thieme and colleagues (Thieme & Schjølberg, 2015) proposed a risk assessment framework consisting of human reliability analysis, fault tree analysis, and event tree analysis that also depended on professional judgment. Griffiths and Trembanis (Griffiths & Collins, 2006) established a risk management process to support decision making with regard to AUV deployment. The framework starts with the establishment of a risk-acceptance level by the AUV owner and setting of campaign requirements. In the risk assessment step, the probability of AUV loss is derived from independent experts' opinion through prior experience and the track record of the AUV (Fig. 1).

The origin of risk stems from uncertainties (Leveson, 2011), which can be broadly classified into aleatory and epistemic uncertainties. Aleatory uncertainty, also known as irreducible uncertainty, arises from the inherent variability associated with the physical system or the environmental context (Oberkampf, DeLand, Rutherford, Diegert, & Alvin, 2002). For example, despite knowing the mean time between failure (MTBF) for a specific AUV component, the precise moment of component failure is still uncertain. Epistemic uncertainties, also known as reducible uncertainty, exists due to a lack of knowledge, incomplete information, limited data, or ambiguity and vagueness attached to experts' judgment (Oberkampf et al., 2002). An AUV that has yet to be commissioned or relatively new in operation will have a higher level of risk arising from epistemic uncertainties. With the operation of the AUV over time, the inflow of information and gaining of experience will result in a gradual reduction of epistemic uncertainties (Fig. 2).

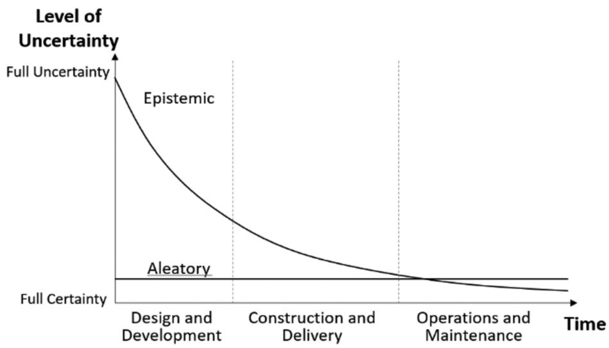

Fig. 2. The level of epistemic and aleatory uncertainties throughout an AUV program life cycle.

Although generic data from other AUVs can be used as a reference to reduce epistemic uncertainties, the difference in specifications, manufacturers, design, and systems can result in inaccurate risk assessment outcomes.

Probabilistic approaches are often applied to assess both aleatory and epistemic uncertainties, typically the relative frequency approach for the former and the subjective probability approach for the latter (Li, Chen, & Feng, 2013). As a result, there are many established probabilistic methodologies such as Monte Carlo simulation or BBNs used for the assessment of risk (Li et al., 2013). For handling the vagueness and ambiguity of risk assessment, a fuzzy-based approach is still the method of choice (Helton, Johnson, Oberkampf, & Sallaberry, 2010; Purba, Sony Tjahyani, Ekariansyah, & Tjahjono, 2015; Unwin, 1986), although the use of interval probabilities may also provide a solution (Fletcher & Davis, 2002).

1.3. Fuzzy Set Theory

The concept of multivalued logic was introduced by Lukasiewicz (Cignoli, 2007). Later, this concept was generalized by Zadeh (1965) with mathematical logic, establishing the fuzzy set theory. One key difference between fuzzy set theory and classical probability theory lies in its ability to account for vagueness and ambiguity by representing a proposition with a degree of ignorance.

Fundamental to the theory are the two main concepts of linguistic variables and fuzzy sets. Linguistic variables are used in day-to-day conversations to represent opinions, which are independent of the measuring system and are easily comprehensible by most listeners. For instance, "Weather Condition" during AUV deployment is a linguistic variable if it is described in linguistic terms of "bad," "average," and "good."

The second fundamental concept is fuzzy sets. In contrast with traditional set theory where an object either belongs to a set or not, every object (in the universe of discourse) belongs to a fuzzy set but with different membership function of 0–1 (Zadeh, 1965). To illustrate this, consider the "five-by-five" risk assessment matrix, which is a commonly used semiquantitative tool for assessing risks. The matrix, with an example from the University of Tasmania shown in Fig. 3, defines risk level by considering the likelihood of occurrence and severity of consequence. It is a practical and simple tool with widespread usage across industries to assess risk and assist management in decision making.

Based on traditional set theory, the risk assessment matrix presents crisp boundaries between risk-level categories, with the term "crisp" referring to

	Severity of Consequence				
Likelihood	Insignificant	Minor	Moderate	Major	Catastrophic
Almost Certain	Mod 11	High 13	Ext 20	Ext 23	Ext 25
Likely	Mod 7	High 12	High 17	Ext 21	Ext 24
Possible	Low 4	Mod 8	High 16	Ext 18	Ext 22
Unlikely	Low 2	Low 5	Mod 9	High 15	Ext 19
Rare	Low 1	Low 3	Mod 6	Mod 10	High 14

Fig. 3. A "five-by-five" risk matrix with the risk level of low, moderate, high, and extreme, represented by risk ratings of 1–25. *Source:* University of Tasmania.

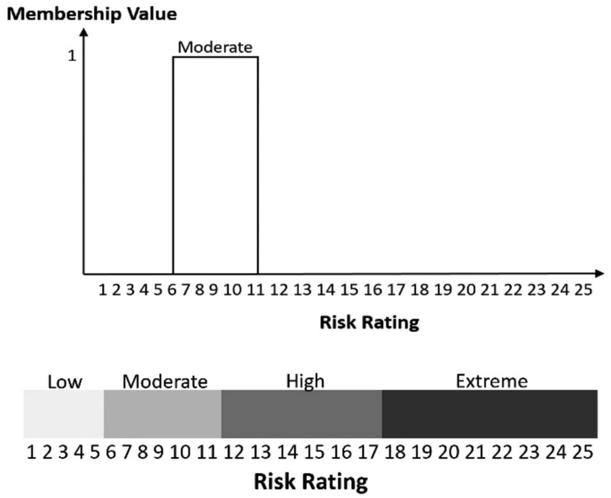

Fig. 4. An example of membership value for "moderate" risk (top) and graphical representation of the risk assessment matrix shown in Fig. 3, illustrating the crisp boundaries between risk-level categories (bottom).

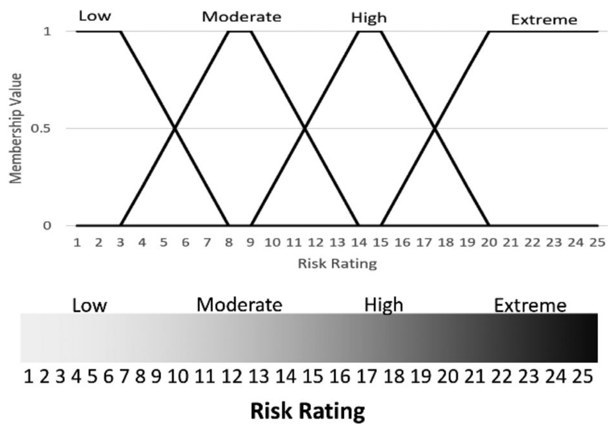

Fig. 5. Graphical representations of the risk assessment matrix (Fig. 3) after application of fuzzy set theory. Membership values (top) and smooth transition between risk-level categories (bottom).

quantitative or countable data (Ross, 2004). In the matrix presented in Fig. 3, each risk rating number from 1 to 25 belongs to a specific category of either "low," "moderate," "high," or "extreme." Adopting this strict interpretation means that two risks with ratings of 11 and 12 will belong to two separate risk levels of "moderate" and "high" despite being only one rating apart. On the contrary, two risks with ratings of 12 and 17 will belong to the same risk level of "high" despite being five ratings apart. The graphical representation in Fig. 4 shows an example of such a crisp boundary. Such an approach cannot represent vague concepts and can be unnatural, as it does not match a human's perception due to the sharply fixed boundaries (Werro, Stormer, & Meier, 2006).

In contrast, fuzzy set theory takes a less rigid view and reflects more naturally each element's association with a particular set. It does so by using membership function $\mu(x)$ that assigns membership values between 0 and 1 to its elements x, defined as:

$$\mu(x) : X \rightarrow [0, 1]. \tag{1}$$

Applying fuzzy set theory to the risk assessment matrix in Fig. 3 resulted in a gradual and smooth transition between risk-level categories as illustrated in Fig. 5. A risk rating of 11 under the new fuzzy risk assessment matrix now belongs to both risk-level categories of "moderate" and "high" with membership function of 0.6 and 0.4, respectively.

The application of fuzzy set theory for risk assessments has garnered attention over the years with application in various domains from nuclear power plants (Rastogi & Gabbar, 2013) through construction (Zhang, Wu, Qin, Skibniewski, & Liu, 2016) to medical fields (Lee & Wang, 2011; Steimann & Adlassnig, 1998). It is also often used in synthesis with other methodologies such as Bayesian network (BN) (Eleye-Datubo, Wall, & Wang, 2008; Zhang et al., 2016), system dynamics (Tessem & Davidsen, 1994), or fault and event tree analyses (Ferdous, Khan, Sadiq, Amyotte, & Veitch, 2011) to improve assessment of risks. In the AUV domain, Bian, Mou, Yan, and Xu (2009) proposed the use of a fuzzy fault tree for technical reliability analysis of AUVs. The incorporation of fuzzy set theory into fault tree analysis copes with the lack of data and accounts for uncertainties in AUVs' subsystem failure. Although the study focused solely on technical reliability and not on deployment risks, it demonstrated the potential for application of fuzzy set theory in risk assessment of AUV deployments. This work aims to present and demonstrate the use of fuzzy set theory in a risk assessment framework for AUV under-ice deployment. In Section 2, the details of the fuzzy-based risk assessment framework are presented. Section 3 demonstrates application of the framework, with a sensitivity analysis. Finally, Section 4 concludes the article with a discussion of the benefits, drawbacks, implications, and potential areas of continuing research.

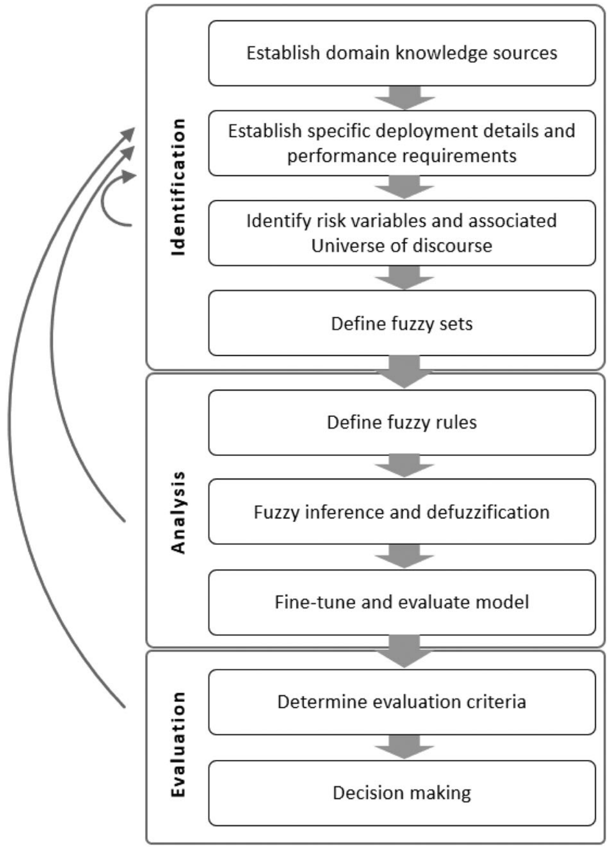

Fig. 6. Overview of the steps involved in the fuzzy-based risk assessment framework. Curved arrows represent the iterative nature of the steps.

2. METHODOLOGY

2.1. Overview

The proposed fuzzy-based risk assessment framework incorporates the generic architecture of a fuzzy expert system (Mendel, 2001) with the risk assessment process presented in widely used international standards such as ISO31000 (Risk Management) (International Standards Organisation, 2009) and ISO45001 (Occupational Health and Safety) (International Standards Organisation, n.d.). Based primarily on experts' judgment, the three-step iterative framework requires extensive discussion with subject matter experts. The overview of the framework is presented in Fig. 6.

2.2. Scenario Identification

Adopting and referencing international standards (International Standards Organisation, 2009; International Standards Organisation, n.d.), the scenario identification phase lays the foundation for risk assessment by finding, recognizing, and describing sources of risk. It consists of several tasks and should be executed iteratively to ensure that objectives of the risk assessment are met.

The first task aims to establish the available sources of knowledge. In the early stages of an AUV program, expert knowledge is often the only source of information, and this can come from AUV engineers and AUV program owners, as well as manufacturer or contractors. Additional information can also be sought indirectly from experts in the form of documentation such as technical specifications of the AUV, safe work procedures, fault logs, risk assessment records, program schedules, budget plans, previous audit findings, online articles or publications, organization charts, or incident reports. For instance, examining a budget plan can reveal budget priorities and the AUV program's financial condition. This may be relevant to the risk assessment in terms of infrastructure investment, human resources, and technical maintenance. In addition, specific deployment plans and expected performance requirements can also hold important information about possible risk variables influencing the risk of AUV loss.

The second task involves the identification of risk variables in the form of linguistic variables and the universe of discourse. The universe of discourse is the numerical range of possible values associated with the risk variable. There are two ways to accomplish this task:

(1) Through semistructured interviews and discussion with subject matter experts.
(2) Through the extraction of information from texts in documentation.

Important considerations for interviews are the choice and number of experts necessary to capture both spatial and temporal risk variables of interest. Although there is no formal guidance tailored specifically to risk assessment of AUV operations, guidance can be taken from the recommended selection criteria published by Pulkkinen and Simola (2000) and Kotra, Lee, and Dewispelare (1996). The number of experts to interview lies between 6 and 12 as recommended by Cooke and Probst (2006). The eventual outcome of this task is a comprehensive list of risk variables relevant to the AUV under assessment. Using published risk studies, some risk variables influencing the risk of AUV loss during under-ice

Table I. An Example of Risk Variables and Their Associated Universe of Discourse

Risk Variable	Reference(s)	Possible Universe of Discourse (Units)
Situation Awareness	Ho, Pavlovic, and Arrabito (2011); Wu, Stuck, Rekleitis, and Beer (2015); Parasuraman, Sheridan, and Wickens (2008)	1–3 (dimensionless, level) (Endsley, 1995)
Annual Insurance Premium	Griffiths, Bose, Ferguson, and Blidberg (2010)	0–12 (dimensionless, % capital cost)
Trust in the AUV	Ho et al. (2011); Wu et al. (2015); Johnson, Patron, and Lane (2007); Parasuraman (1997)	Arbitrary, 0–10 (dimensionless)
Distance of Mission	Brito et al. (2010)	0–400 (km)
Maximum Depth of Mission	Brito (2015)	0–5,000 (m)
Weather Condition	Bolstad, Cuevas, Gonzalez, and Schneider (2005); Brito and Griffiths (2016)	Arbitrary, 0–10 (dimensionless)
Average Experience of AUV Team with Under-Ice Missions	Utne and Schjolberg (2014)	0–30 (years)
Operator Stress and Fatigue Level	Bolstad et al. (2005); Palinkas (1992)	Arbitrary, 0–10 (dimensionless)
Level of Interactions Within AUV Team	Bolstad et al. (2005)	Arbitrary, 0–10 (dimensionless)
Technical Reliability	Ruff, Narayanan, and Draper (2002); Brito (2015); Griffiths, Millard, McPhail, Stevenson, and Challenor (2003)	0–20 (MTBF, years)
Level of Automation	Ruff et al. (2002)	0–10 (automation level) (Endsley & Kaber, 1999)
Mental Workload	Ho et al. (2011); Wu et al. (2015); Parasuraman (1997)	Arbitrary, 0–10 (dimensionless)
Operator Complacency Level	Endsley and Kiris (1995)	Arbitrary, 0–10 (dimensionless)
Time Duration Under Ice	Brito, Griffiths, and Trembranis (2008)	0–48 (hours)

Table II. Example of Risk Variables and Their Associated Fuzzy Sets

Risk Variable	Fuzzy Set
Situation Awareness	Poor, normal, good
Distance of Mission	Short, average, long
Maximum Depth of Mission	Shallow, intermediate, deep
Weather Condition	Good, average, bad, severe
Average Experience of AUV Team with Under-Ice Missions	Inexperienced, average, experienced
Operator Stress and Fatigue Level	Low, average, high, extreme
Time Duration Under Ice	Short, medium, long

mission in the Antarctic and their possible associated universe of discourse are presented in Table I.

The next task involves the definition of fuzzy sets and membership functions using the same sources of information as in the previous task. To ascertain the fuzzy set, a list of typical adjectives associated with each risk variable is identified. Using some of the risk variables from Table I as an example, this task will result in an output similar to one shown in Table II.

To define the membership functions, experts' opinion can be elicited using matrices, which are dependent on the adopted distribution shapes, for instance, bell shaped, Gaussian, triangular, or trapezoidal (Jang, Sun, & Mizutani, 1997). The choice of distribution shape is problem dependent and reflects how experts relate the range of possible values to the fuzzy set. However, both triangular and trapezoidal shapes are most commonly used because of their effectiveness in capturing subjective and imprecise information, as well as being simple to compute (Barua, Mudunuri, & Kosheleva, 2014; Chang, Yeh, & Wang, 2007; Kannan, De Sousa Jabbour, & Jabbour, 2014). A triangular membership function is defined by a lower limit a, an upper limit c, and a most likely value b, as shown in Fig. 7(a). A trapezoidal membership function is defined by a lower support margin a, a lower core margin b, an upper core margin c, and an upper support margin d, as shown in Fig. 7(b). Table III shows an example of a matrix to define membership function for the risk variable "Maximum Depth of Mission," with the graphical representation shown in Fig. 8.

Finally, if more than one expert is elicited in the earlier described tasks, aggregation of different opinions will be required. Several aggregation methods have been proposed in the literature, a summary of which are described below:

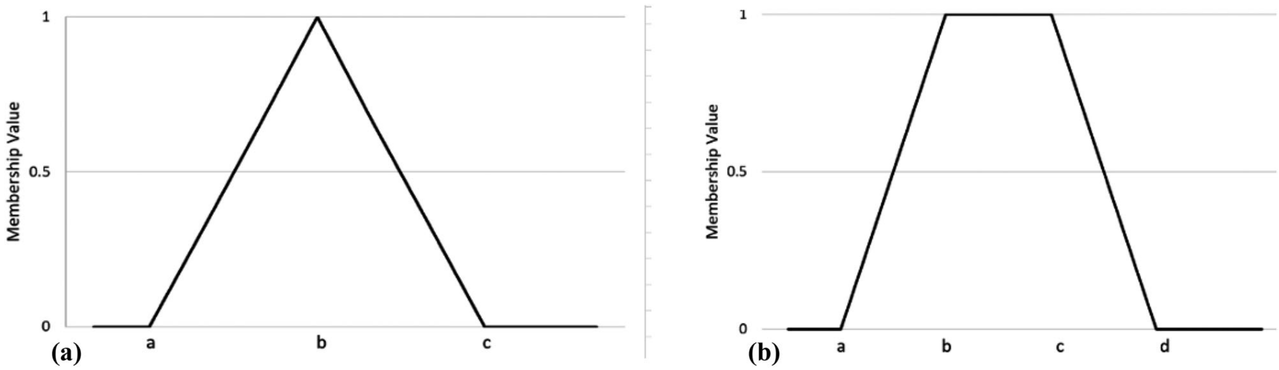

Fig. 7. Types of membership functions (a) Triangular membership function. (b) Trapezoidal membership function.

Table III. Matrix to Elicit Experts' Opinion for Risk Variable "Maximum Depth of Mission"

Maximum Depth of Mission (0–5,000 m)			
	Membership Functions		
Fuzzy Sets	Min (m)	Most Likely (m)	Max (m)
Shallow	0	500	750
Intermediate	250	750	1,500
Deep	750	1,500	5,000

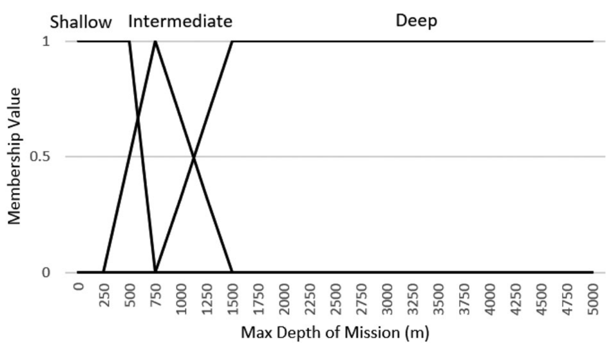

Fig. 8. Membership function for the risk variable "Maximum Depth of Mission."

(1) For each fuzzy set, use the lowest and greatest value provided by experts as the lower bound and upper bound. The average value is then used as the modal value (Tadic, Milanovic, Misita, & Tadic, 2011).
(2) The similarity aggregation method (SAM) (Hsu & Chen, 1996), which uses a similarity index to measure the consistency of each opinion from others. Other aggregation methods based on SAM can also be used, such as the consistency aggregation method (CAM; Lu, Lan, & Wang, 2006) and the optimal aggregation method (OAM; Lee, 2002).
(3) The Delphi method (Rowe & Wright, 1999) where opinions of experts are made to converge through iteration until it meets predefined criteria. The fuzzy Delphi method (FDM) draws ideas from fuzzy theory in synthesis with the original Delphi method. It uses a similarity function to assess the level of consistency between experts. The similarity coefficient is then used to derive the fuzzy evaluation value of all experts. (Ishikawa et al., 1993).

2.3. Analysis

The analysis step aims to understand the nature, effects, and relationships of risk variables by eliciting and constructing fuzzy rules. A fuzzy rule infers information using linguistic variables and fuzzy sets to derive an output. Although there are several forms of fuzzy rules, one of the simplest representations uses IF–THEN rule statements in the form of:

IF Risk Variable is *x THEN* Risk of Loss is *y*,

where *x* and *y* are adjectives associated with the risk variable and risk of loss, respectively. The fuzzy rule can also be in the form of AND and OR statements, such as:

IF weather condition is *bad*, AND the AUV team is *inexperienced*,

THEN risk of AUV loss is *high*.

For intuitive elicitation of a fuzzy rules base, a hypercube matrix can be used. A hypercube is a geometric shape of *n*-dimensions, determined by the number of input risk variables (McNeil & Thro, 1994). For instance, a four-dimensional hypercube can be used for a fuzzy system consisting of four input risk variables and a three-dimensional (3D) hypercube for a three-input risk variable fuzzy system. Although fuzzy rules can be established using the same sources of information as earlier steps in the risk assessment framework, the process can become increasingly complex with the number of identified risk variables. This phenomenon, where the number of fuzzy rules increases exponentially with the number of inputs, is known as the "curse of dimensionality" (Kosko & Isaka, 1993). One common method to overcome the curse of dimensionality is to implement the use of a hierarchical fuzzy system (Raju, Zhou, & Kisner, 1991). The idea is to decompose a large fuzzy logic unit (Fig. 9(a)) into several smaller, related fuzzy logic units that are then interconnected according to a given topology (Raju et al., 1991) (Figs. 9(b) and (c)). Each single fuzzy logic unit consists of a fuzzifier, membership functions, a fuzzy rule base, an inference engine, and a defuzzifier (Ross, 2004). Adopting a hierarchical fuzzy system reduces the total number of fuzzy rules that consequently reduces computational time and increases the efficiency of the system (Raju et al., 1991). As an example, an aggregated hierarchical fuzzy system is presented in Fig. 10 using some risk variables from Table I.

In the process of establishing of fuzzy rules, experts may provide differing opinions, resulting in redundant, inconsistent, or conflicting rules. This can affect the risk assessment outcome and interpretability of the model (Alcalá, Casillas, Cordón, González, & Herrera, 2005). Several methods have been proposed in the literature to overcome this, such as complexity reduction with fuzzy clustering techniques, rule reduction by orthogonal transformation methods, algorithms based on similarity measures, and genetic optimization (Roubos & Setnes, 2000).

Upon establishment of fuzzy rules, the next task is to formulate the mapping from inputs to output in a process called fuzzy inference. Two most commonly used fuzzy inference methods are the Mamdani (Mamdani & Assilian, 1975) and Sugeno (Sugeno, 1985) inferences. The fundamental difference between these two methods lies in the way outputs are represented and determined (Kaur & Kaur, 2012; Ying, Ding, Li, & Shao, 1999). Mamdani inference uses defuzzification of a fuzzy output to generate a crisp output while Sugeno inference uses a weighted average to compute the crisp output (Mamdani & Assilian, 1975; Sugeno, 1985). The Mamdani method is widely accepted for capturing expert knowledge and is more intuitive, while the Sugeno method works well with optimization and adaptive techniques, particularly for dynamic nonlinear systems (Kaur & Kaur, 2012; Ying et al., 1999). An example of the fuzzy inference process is presented in Section 3.3. Defuzzification is the process of deriving a quantifiable output from the fuzzy system. Consider the following rule:

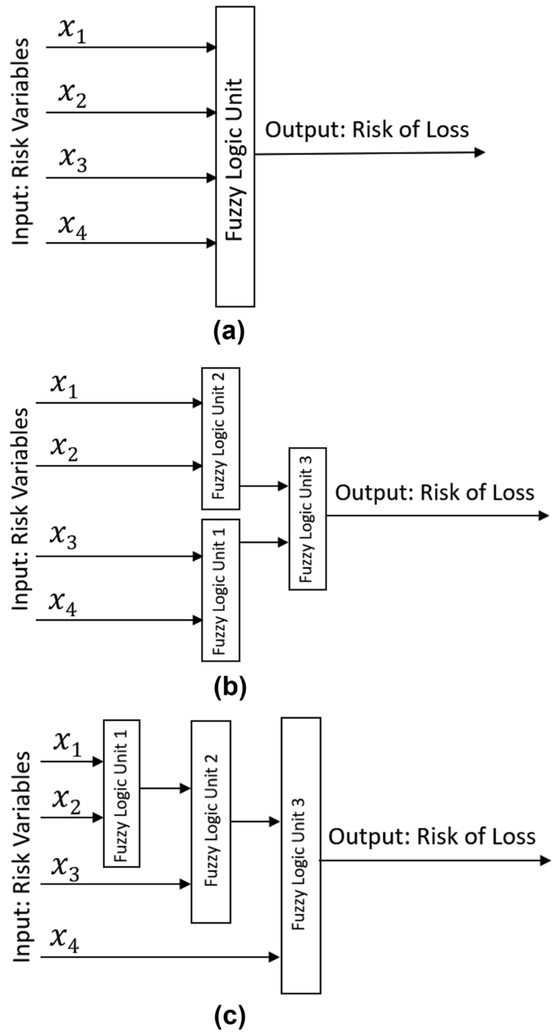

Fig. 9. (a) A single-layer fuzzy system consisting of four risk variables as input and risk of loss as output. (b) An aggregated hierarchical fuzzy system based on (a). (c) An incremental hierarchical fuzzy system based on (a).

IF weather condition is *bad*, THEN risk of AUV loss is *high*.

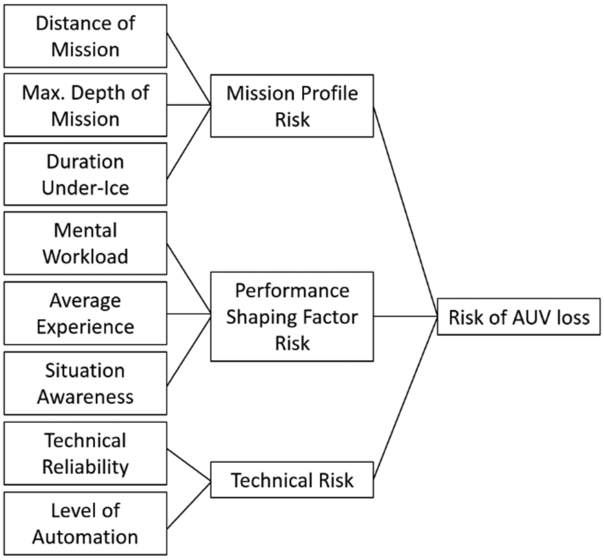

Fig. 10. Example of an aggregated hierarchical fuzzy system.

Defuzzification translates "high" into a quantifiable risk level, such as a risk rating value based on the organizational risk matrix (Fig. 3.). There are several defuzzification methods, such as the centroid method, weighted average method, center of sums, center of largest area, mean-max membership, and max-membership principal (Leekwijck & Kerre, 1999; Zhao & Govind, 1991). Each method has its advantages and disadvantages, and the appropriate defuzzification method should be chosen based on nature of the problem, the number of input and output variables, and sensitivity of the method (Chmielowski, 2015).

The final task of the risk analysis step is to evaluate and fine-tune the system. Despite being a time-consuming process, proper execution of this task improves reliability of the risk assessment and ensures that original objectives are met. Carried out in close consultation with experts and decisionmakers, this task involves one or more adjustments of fuzzy rules and fuzzy sets (Table IV).

Table IV. List of Fine-Tuning Actions

Fuzzy Rules Adjustment

(1) Add, reduce, or optimize fuzzy rules.
(2) Add hedge operators by using adverbs such as "very," "somewhat," or "indeed."
(3) Adjust rule execution weights to increase or reduce the force of any fuzzy rules.

Fuzzy Sets Adjustment

(1) Add fuzzy sets.
(2) Widen or narrow existing sets by reviewing membership functions.
(3) Shift existing fuzzy sets to ensure sufficient overlaps.
(4) Review and adjust the shape of existing fuzzy sets.

2.4. Evaluation

The objective of the risk evaluation step is to support decision making through significance of the results derived from the risk analysis step, the significance of which is based on its acceptability in relation to predetermined evaluation criteria set by the AUV owner, higher management of the organization, or external groups. External groups that may exhibit interest in the results of the risk assessment may include insurance companies and the regulators. An acceptable probability of AUV loss based on the capital and operating cost of the AUV (Griffiths & Collins, 2006) is an example of evaluation criteria. However, for an AUV program in its early phases, the evaluation criteria may be uncertain and yet to be established. In such circumstances, the organizational safety and health standard can be used as a good starting reference for criteria setting.

At the fundamental level, the risk of AUV loss will be either acceptable or unacceptable, as decided by the AUV owner. If deemed acceptable, the Antarctic under-ice mission can proceed under close monitoring and regular review to ensure that risk remains acceptable. If unacceptable, the AUV owner has to make decisions taking into consideration available resources and time constraints, which may include:

(1) Whether the deployment should proceed by accepting a higher risk of loss.
(2) Whether treatments are required, taking into consideration the adequacy of existing control measures.
(3) The priorities for risk treatment.

Although risk evaluation is the last step of the proposed risk assessment framework (Fig. 6), analysis of new information and filling of data gaps needs to be performed on a regular basis. This iterative process helps ensure relevancy and effectiveness of the risk assessment.

3. EXAMPLE OF APPLICATION

3.1. Description

To demonstrate application of the fuzzy-based risk assessment framework, an example based on the *nupiri muka* AUV program is presented. The program was funded by the Antarctic Gateway Partnership, an Australian government initiative to build further polar research capability in Tasmania. The explorer-class AUV was named *nupiri muka*, which means "Eye of the Sea" in *palawa kani*, the language of Tasmanian Aborigines (UTAS, 2017). The program aims to acquire high-resolution data under sea ice and ice shelves in Antarctic regions. Capable of exploring depths of up to 5,000 m and with a present cruising range of 140 km, the AUV is able to conduct long-range under-ice operations with its diverse scientific payload. Delivered in May 2017, the AUV was relatively new at the time of writing and has very limited historical failure fault log data. Initial semiquantitative risk assessment was performed in accordance to the Work Health and Safety Policy stipulated by the University of Tasmania (Work Health and Safety Policy—University of Tasmania, 2013) and leveraging on prior experience of the AUV team.

To apply the proposed fuzzy-based risk assessment framework, the risk assessment matrix recommended under the University of Tasmania's Work Health and Safety Policy (Fig. 3) was converted to a fuzzy risk assessment matrix (Fig. 5) as the output of the risk model. Assessment on risk of AUV loss was carried out on a planned deployment to the Sørsdal Glacier in Antarctica (Fig. 11), expected to take place between December 2018 and February 2019. Although the exact details of the marine scientific research missions have yet to be decided at the time of writing, there will likely be five to six missions comprising both open-water and under-ice operation. One of the proposed missions requires the *nupiri muka* to travel approximately 100 km from launch to recovery, with six hours under an ice shelf at a maximum depth of around 800 m. Likely the longest mission for this deployment in terms of both distance and time duration, the fuzzy-based risk assessment framework was applied to determine the risk level of this mission.

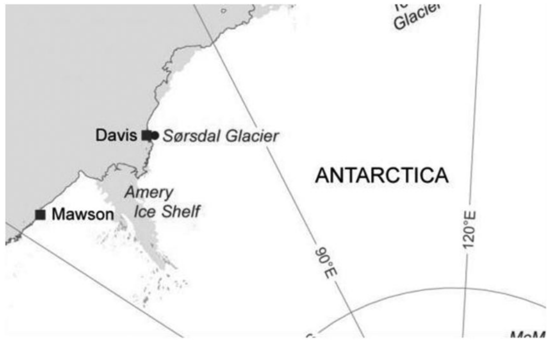

Fig. 11. Map showing location of the Sørsdal Glacier in the Antarctic (photo: AADC).

3.2. Scenario Identification

In this initial step, five risk variables, their associated universe of discourse, and fuzzy sets were identified (Table V). These were based on best available deployment information at the time of writing, as well as through available sources of knowledge and information, which included in-house AUV engineers, technical specifications of the AUV, safe work procedures, risk assessment records, and literature.

To define membership functions, a mixture of triangular and trapezoidal membership functions was used for elicitation after considering their advantages (Section 2.2). The resultant membership functions are represented graphically and presented in Figs. 12(a)–(e). For the risk variable "Weather Condition," there are existing weather classification systems being used, such as the classification by McMurdo Weather Office (Mac Weather) (McCormick

Table V. Identified Risk Variables, Universe of Discourse, and Fuzzy Sets

Risk Variable	Universe of Discourse	Fuzzy Set
Distance of Mission	0–140 (km)	Short, average, long
Maximum Depth of Mission	0–5,000 (m)	Shallow, intermediate, deep
Time Duration Under Ice	0–24 (hours)	Short, medium, long
Weather Condition	0–10 (dimensionless)	Good, average, bad, severe
Average Experience of AUV Team with Under-Ice Missions	0–10 (years)	Short, average, long

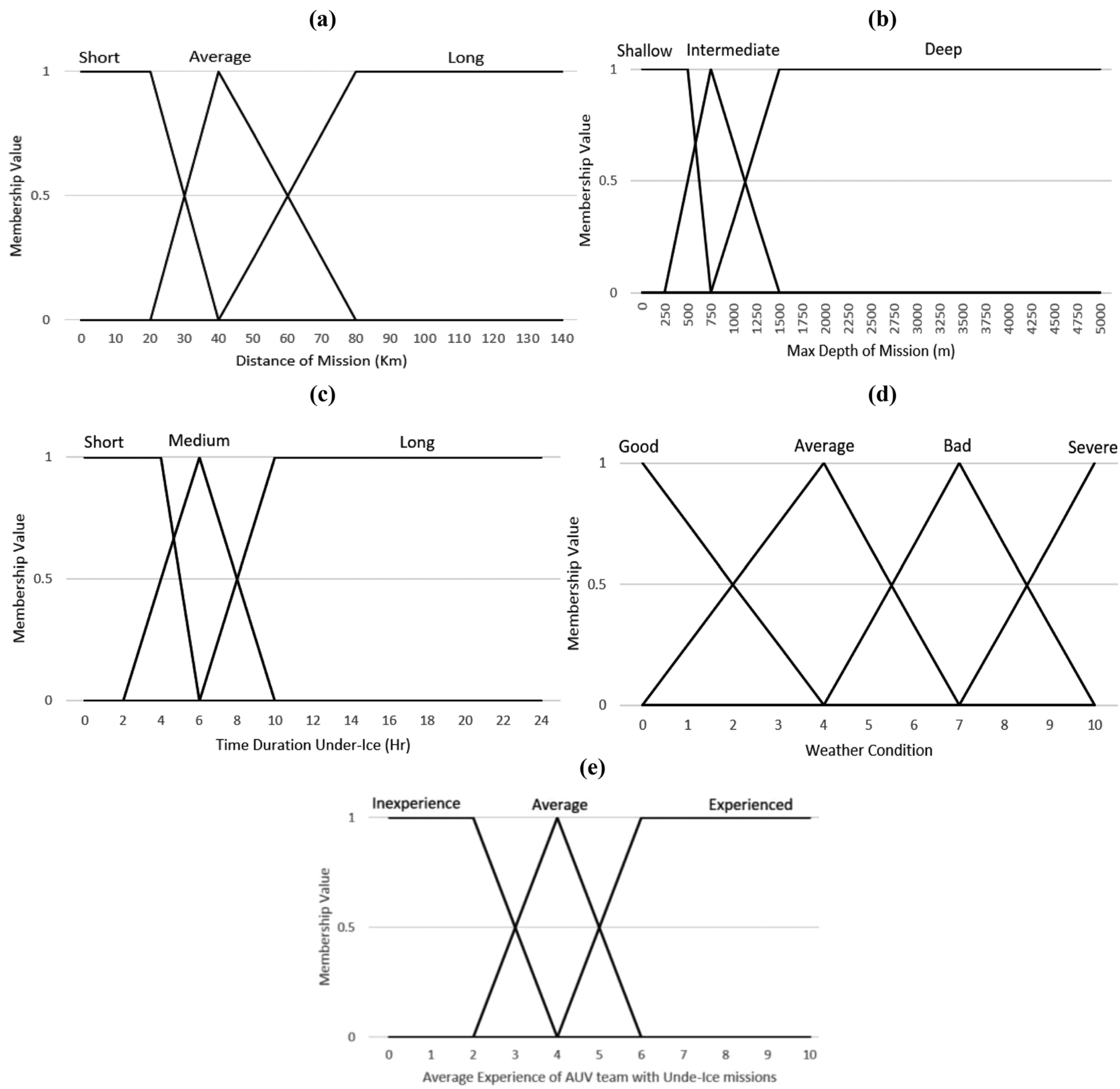

Fig. 12. Membership function for the identified risk variables. (a) "Distance of Mission." (b) "Maximum Depth of Mission." (c) "Time Duration Under Ice." (d) "Weather Condition." (e) "Average Experience of AUV Team with Under-Ice Missions."

& Mastro, 2002) for Antarctica. However, an arbitrary scale of 0–10 was in this case used for simplicity, where 0 represents excellent weather and 10 represents extreme weather.

3.3. Analysis

To facilitate the construction of fuzzy rules, an incremental hierarchical fuzzy system, as shown in Fig. 13, was used. "Distance of Mission," "Maximum Depth of Mission," and "Time Duration Under Ice" were grouped under "Mission Profile Risk" while "Weather Condition" and "Average Experience of AUV Team with Under-Ice Missions" were separate input to "Risk of AUV Loss."

For elicitation of a fuzzy rules base, a 3D hypercube matrix consisting of three input risk variables and one risk-level output were used (Fig. 14). The

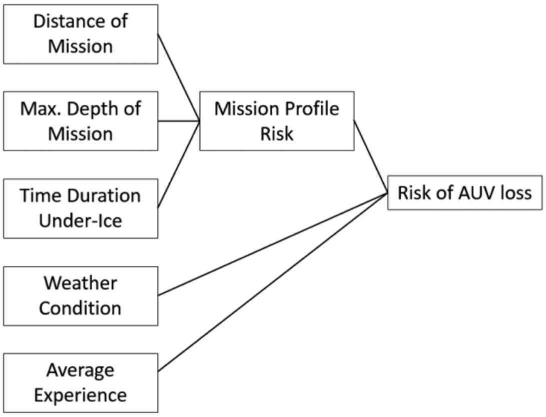

Fig. 13. The risk variables in an incremental hierarchical fuzzy system.

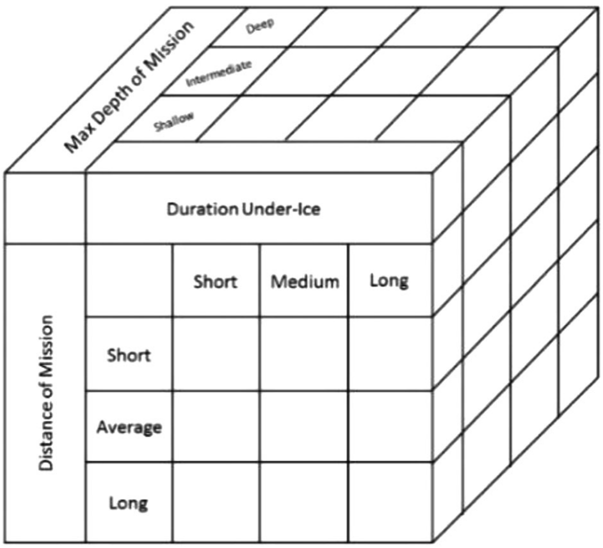

Fig. 14. A 3D hypercube matrix to elicit experts' opinion on the construction of fuzzy rules for "Mission Profile Risk."

cube was further sliced into separate tables as shown in Table VIA, where there were three slices, and Table VIB, where there were four slices. These tables represent a series of IF–THEN rules such as:

> IF Distance of Mission is Short AND Time Duration Under Ice is Short AND Max. Depth of Mission is Shallow THEN Mission Profile risk is Low.

For the next task of fuzzy inference, the Mamdani method was adopted as it is widely accepted for capturing experts' knowledge (Kaur & Kaur, 2012). Many methods exist for the composition of fuzzy relations for use in Mamdani inference. Examples include *min–max*, *max–max*, *min–min*, *max–min*, and *max–product*. Among these, the *max–min* and *max–product* inference are the most commonly used (Nasr, Rezaei, & Barmaki, 2013). In *max–min* inference, the inferred output of each rule is a fuzzy set chosen from the minimum firing strength, which is the degree to which the rule matches the input (Mamdani & Assilian, 1975). The resultant output set has its membership function cut off at the top, resulting in some information loss. In the *max–product* inference, the inferred output of each rule is a fuzzy set scaled down by its firing strength via an algebraic product (Mamdani & Assilian, 1975). This way, the original shape of the fuzzy set is preserved, resulting in less information loss as compared to *max–min* inference (Senthil Kumar, 2014; Zimmermann, 2001). Therefore, the *max–product* inference was adopted for this example. To apply the *max–product* inference, consider two rules with three risk variable (RV) inputs and one risk-level (RL) output of the following form:

> IF $RV1$ *is* L_A and $RV2$ *is* L_B and $RV3$ *is* L_C THEN $RL = P_D$,
>
> IF $RV1$ *is* L_W and $RV2$ *is* L_X and $RV2$ *is* L_Y THEN $RL = P_Z$.

Note that L and P are adjectives of the fuzzy set associated with the risk variables and risk level, respectively. The alphabetical subscripts differentiate different values of L and P. The aggregated output membership function $\mu_Q(RV,RL)$, which is a function of both the input risk variables and output risk levels, can then be calculated as:

$$\mathrm{Max}\left\{\begin{array}{c}\min(\mu\mathrm{LA}\ (RV1), \mu\mathrm{LB}\,(RV2), \\ \mu\mathrm{LC}\ (RV3))\mu\mathrm{PD}\ (RL), \\ \\ \min(\mu\mathrm{LW}\ (RV1), \mu\mathrm{LX}\,(RV2), \\ \mu\mathrm{LY}\ (RV3))\mu\mathrm{PZ}\ (RL)\end{array}\right\}.$$

To demonstrate the Mamdani *max–product* inference, two fuzzy rules were extracted from Table VIA of the following form:

> IF *Distance of Mission is* Long and *Maximum Depth of Mission is* Intermediate and *Time Duration Under Ice is* Medium, THEN *Mission Profile Risk* = High
> IF *Distance of Mission is* Long and *Maximum Depth of Mission is* Deep and *Time Duration Under Ice is* Medium, THEN *Mission Profile Risk* = Extreme.

Table VIA. Fuzzy Rule Table for "Mission Profile Risk"

		Time Duration Under Ice		
		Short	Medium	Long
Maximum Depth of Mission—shallow				
Distance of Mission	Short	Low	Low	Moderate
	Average	Low	Moderate	High
	Long	Moderate	High	Extreme
Maximum Depth of Mission—intermediate				
Distance of Mission	Short	Low	Moderate	High
	Average	Low	High	Extreme
	Long	Moderate	High	Extreme
Maximum Depth of Mission—deep				
Distance of Mission	Short	Moderate	High	High
	Average	High	High	Extreme
	Long	High	Extreme	Extreme

Table VIB. Fuzzy Rule Table for "Risk of AUV Loss"

		Average Experience of AUV Team		
		Experienced	Average	Inexperienced
Weather Condition—good				
Mission Profile Risk	Low	Low	Low	Moderate
	Moderate	Low	Low	Moderate
	High	Moderate	Moderate	High
	Extreme	High	High	Extreme
Weather Condition—average				
Mission Profile Risk	Low	Low	Low	Moderate
	Moderate	Moderate	Moderate	Moderate
	High	Moderate	High	High
	Extreme	High	High	Extreme
Weather Condition—bad				
Mission Profile Risk	Low	Moderate	Moderate	High
	Moderate	Moderate	High	High
	High	High	High	Extreme
	Extreme	Extreme	Extreme	Extreme
Weather Condition—severe				
Mission Profile Risk	Low	High	High	Extreme
	Moderate	High	Extreme	Extreme
	High	Extreme	Extreme	Extreme
	Extreme	Extreme	Extreme	Extreme

Using the *max–product* inference, the aggregated output membership function μ_Q can be calculated as:

$$\mathrm{Max}\left\{\begin{array}{c}\min(\mu\mathrm{Long}\ (\mathit{Dist}), \mu\mathrm{Int}\,(\mathit{Depth}), \\ \mu\mathrm{Med}\ (\mathit{Time}))\ \mu\mathrm{High}\ (\mathit{Risk}), \\ \\ \min(\mu\mathrm{Long}\ (\mathit{Dist}), \mu\mathrm{Deep}\,(\mathit{Depth}), \\ \mu\mathrm{Med}\ (\mathit{Time}))\ \mu\mathrm{Ext}\ (\mathit{Risk})\end{array}\right\}.$$

The graphical representation in Fig. 15 shows the aggregation of output membership functions for each rule to result in μ_Q. Essentially, μ_Q is comprised of the outer envelopes of the individual truncated membership forms for each rule.

For defuzzification, the commonly used centroid method was chosen for this example. It has the advantage of being well balanced, sensitive to the height and width of the fuzzy output, and provides consistent results (Negnevitsky, 2005). The centroid method defuzzifies by finding a point representing the center of gravity of the aggregated fuzzy set. For a fuzzy set A, the center

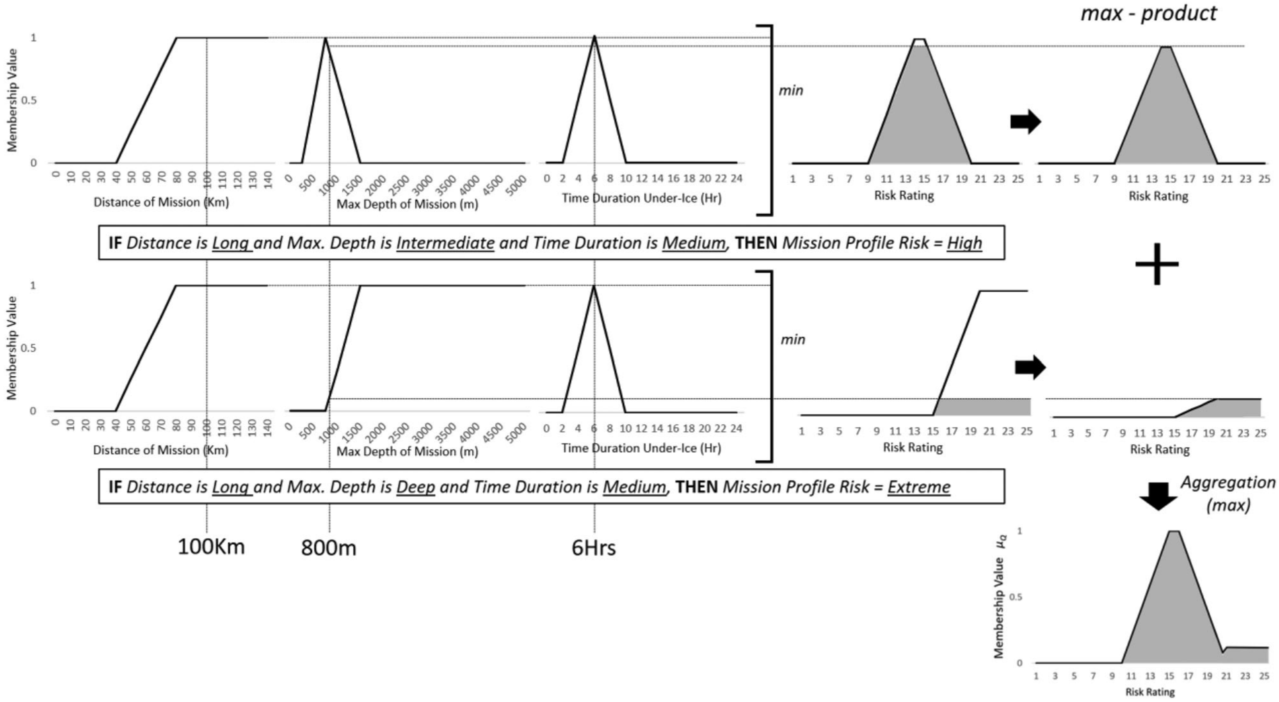

Fig. 15. The graphical representation of Mamdani max–product inference.

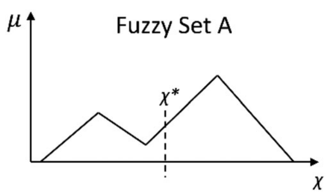

Fig. 16. The centroid method of defuzzification.

of gravity X^* can be expressed mathematically as (Fig. 16):

$$X^* = \frac{\int \mu_A(x)x\,dx}{\int \mu_A(x)dx}.$$

The fuzzy inference and defuzzification process were implemented using MATLAB® fuzzy logic toolbox 2017 (Fuzzy Logic Toolbox User's Guide, 2017). An example of the graphical interface is shown in Fig. 17. In the interface, membership functions from Figs. 12(a)–(c) and fuzzy rules from Table VIA were used as inputs to the model to assess "Mission Profile Risk." The fuzzy risk assessment matrix in Fig. 5 was used as the output. Using the above information, the proposed mission with a distance of 100 km, maximum depth of 800 m, and six hours under ice will have a mission profile risk rating of 14.97. Under the University of Tasmania's organization's risk assessment matrix, a risk rating of 14.97 falls into the "high risk" category.

In the next level of the hierarchical fuzzy system (Fig. 13), the risk of AUV loss was computed using "Mission Profile Risk," "Weather Condition," and "Average Experience of AUV Team with Under-Ice Missions" as inputs. The average experience of the team is approximately three years, information attained by speaking with the team. In the Antarctic, December to February is the summer season with generally lower precipitation and wind speeds as compared to the winter season. Sørsdal Glacier, which is near to Davis Station, has a relatively milder climate due to the surrounding Vestfold Hills (Australian Antarctic Division, 2015). Despite this, the weather conditions in Antarctica can be highly dynamic and unpredictable (Carrkre, 1990). Therefore, it can be assumed at this stage that the weather is "good" with a rating of 2 of 10, with 10 being the most extreme weather expected. Using Simulink® software to construct the hierarchical fuzzy system as presented in Fig. 18, it was now possible to estimate the risk of AUV loss.

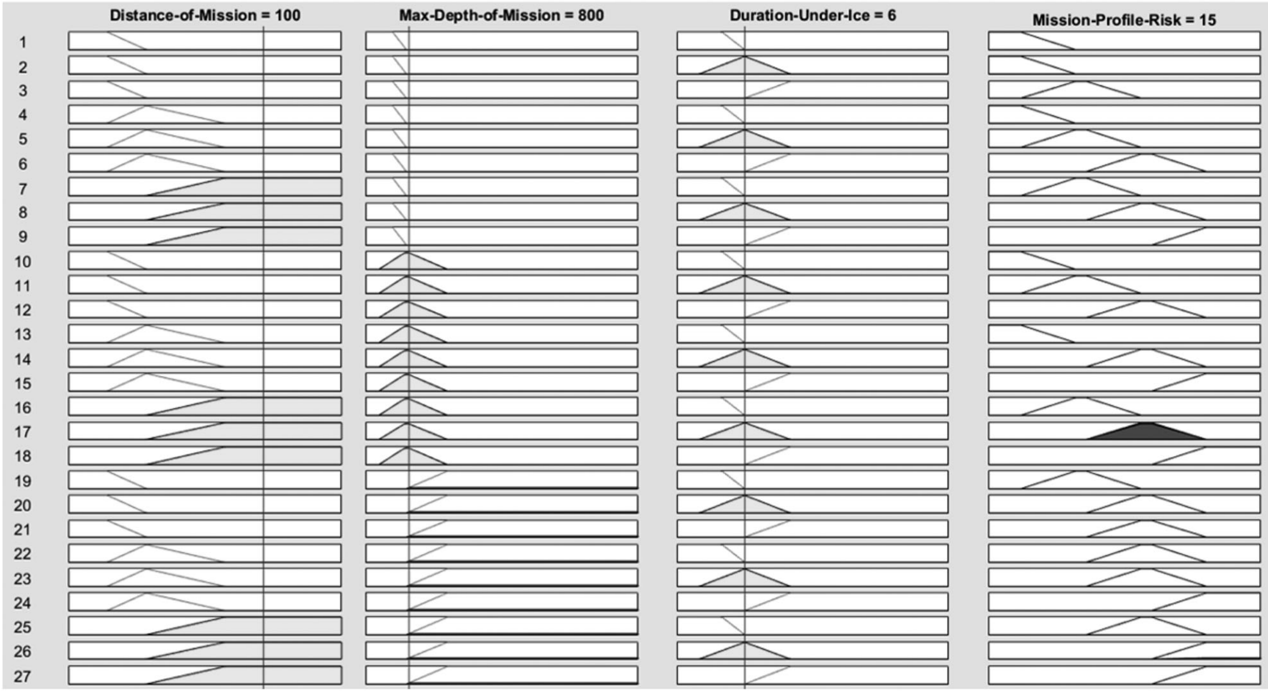

Fig. 17. The graphical interface of MATLAB Fuzzy Logic Toolbox showing "Mission Profile Risk."

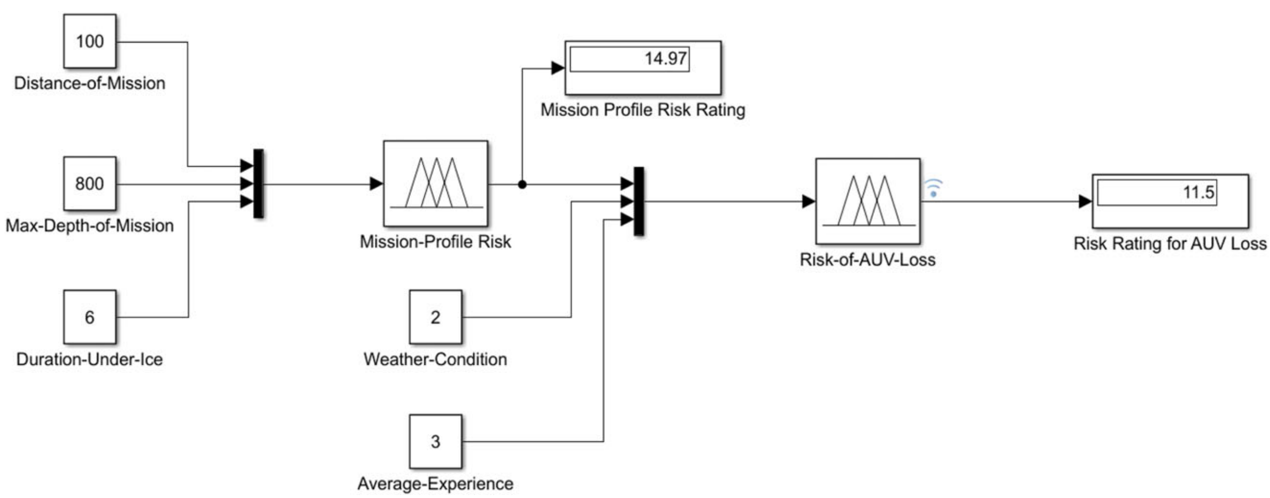

Fig. 18. The hierarchical fuzzy system constructed using Simulink® to assess "Risk of AUV Loss."

The resultant risk level for the risk of AUV loss has a rating of 11.5. Apart from achieving a numerical risk level, the behavior of the risk variables and the risk of AUV loss can also be studied using 3D plots. An example showing the influence of "Mission Profile Risk" and "Weather Condition" over "Risk of AUV loss" is shown in Fig. 19.

3.4. Evaluation

In the evaluation step, the significance of the result is used to support decision making. Referring to the University of Tasmania's "five-by-five" risk assessment matrix (Fig. 3), the risk rating of 11.5 falls between the "moderate" and "high" risk-level categories (Fig. 20).

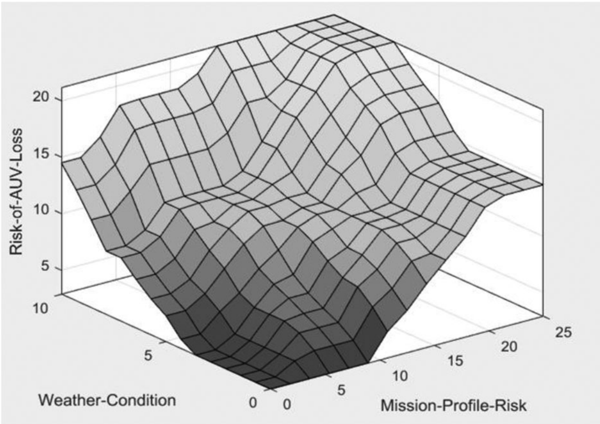

Fig. 19. A 3D plot showing the behaviour of model output with changes to model inputs.

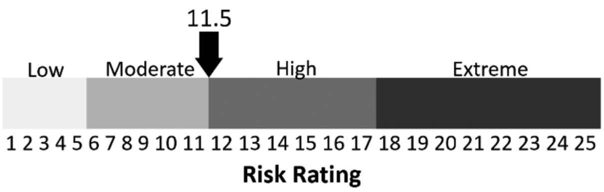

Fig. 20. Risk rating of 11.5 on the University of Tasmania's risk matrix.

Consequently, a set of actions can be determined using the Risk Management Standard from the University of Tasmania (Table VII) (Work Health and Safety Policy—University of Tasmania, 2013) as the evaluation criteria.

To err on the conservative side, the requirements for "high" risk level should be considered. Under the standard, a mission with "high" risk level requires approval from heads of school, budget centers, or staff on authorized job risk analysis. The audit and risk committee of the council and senior management team have to be kept informed of the mission and risk control measures reviewed annually. The risk of AUV loss is also to be included in strategic and capital planning and fiscal strategies.

3.5. Sensitivity Analysis

A sensitivity analysis was performed on the model to examine how changes to each risk variable input can affect the risk rating output. Using the established model in Fig. 20 as the base model, each input risk variable was then changed sequentially while the values of other risk variables remained constant. The universe of discourse for each risk variable was

Table VII. The University of Tasmania's Risk Management Policy

Risk Level	Authority to Accept Risk/Risk-Delegation Level	Notification/Communication Requirements	Formal Recording/Reporting Requirements	Inherent Risk Review and Control Requirements
Extreme	SMT	Audit and risk committee of council	Mandatory to faculty risk register, business cases, and project plans	Reviewed six monthly—controls implemented to reduce residual risk to high or below within 12 months
High	Heads of school/budget centers (or director level and above for a UTAS-wide corporate governance type risk) or all staff on authorized job risk analysis	Audit and risk committee of council and SMT	Mandatory to faculty risk register, business cases, and project plans	Reviewed 12 monthly—include consideration of this risk in strategic and capital planning and fiscal strategies
Moderate	Senior lecturer/senior researcher/manager level or all staff on authorized job risk analysis	SMT heads of school/budget centers (or director level and above for a UTAS-wide corporate governance type risk)	Mandatory to faculty risk register, business cases, and project plans	Controls to be identified and actions to reduce residual risk opportunistically pursued
Low	All staff	Heads of school/budget centers (or director level and above for a UTAS-wide corporate governance type risk)	Included in risk register	None

SMT = senior management team.

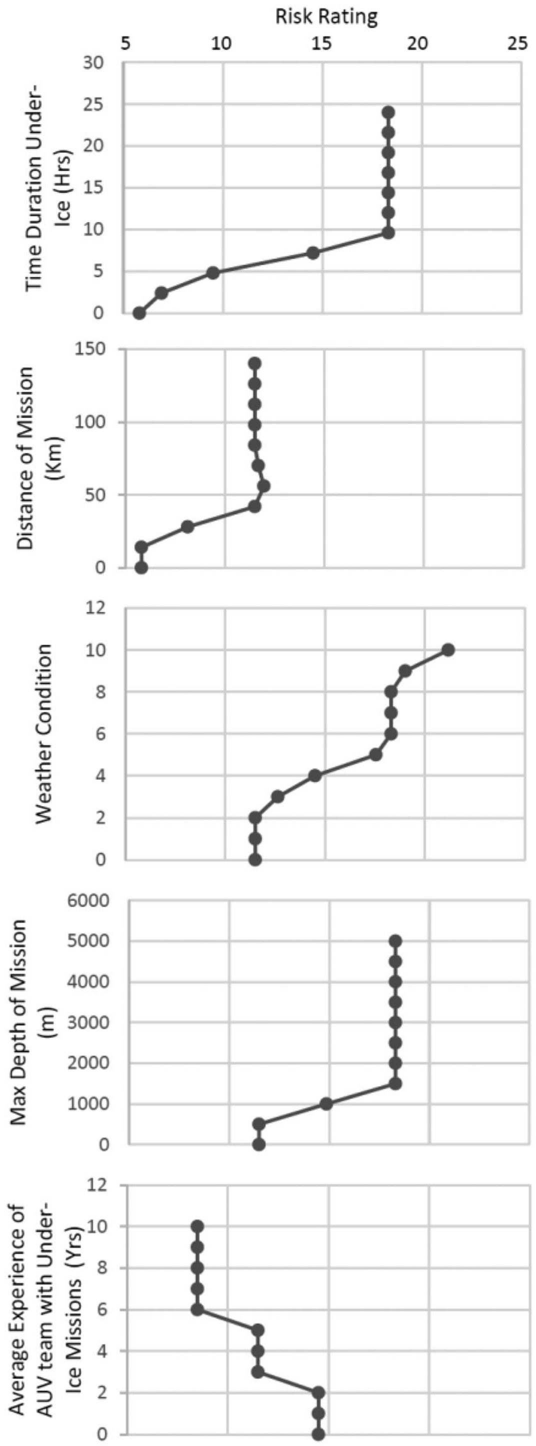

Fig. 21. Sensitivity analysis of how changes to each risk variable input affect the risk rating output.

divided into 10 equal incremental parts for the analysis, starting with minimum value. Graphical representation of the results is shown in Fig. 21.

The result of the analysis shows that the risk rating output is most sensitive to "Time Duration Under Ice," with an increase of 215% from a risk rating of 5.81–18.31 when time duration under ice increases from 0 to 9.6 hours. This is followed by risk variables "Distance of Mission," "Maximum Depth of Mission," "Average Experience of AUV Team with Under-Ice Missions," and, finally, "Weather Condition" toward which risk rating is least sensitive. The close similarity of sensitivity between "Time Duration Under Ice," "Distance of Mission," "Maximum Depth of Mission" to risk rating is expected due to some degree of proportionality. The result of the sensitivity analysis can also be used for identification of leverage points setting priorities for risk control. For instance, a reduction of "Time Duration Under Ice" from six hours to five hours reduces the eventual risk rating for AUV loss from 11.5 to 9.9.

It is difficult to validate the model at this stage without actual under-ice deployment and a lack of historical data record for the *nupiri muka* AUV. However, when results of the sensitivity analysis were compared to the risk and reliability analysis of *Autosub 6000* AUV (Brito, 2015), the findings were found to be quite similar. In the report on *Autosub 6000* AUV, mission distance and depth were analyzed against risk of AUV loss. The result shows the probability of loss increasing at a near constant rate before plateauing off at about 90 km. For depth of mission, the probability of loss remains nearly constant from 1,000 m to 2,500 m before a large increase in risk occurs at greater than 2,500 m depth. In the sensitivity analysis for *nupiri muka* AUV, risk-level plateaus off at 84 km for distance of mission and remains constant after 1,500 m of mission depth (Fig. 21).

4. DISCUSSION AND LIMITATIONS

cation of fuzzy-based risk assessment has its disadvantages. In this section, we will discuss the approach proposed, focusing on its limitations. Subject matter experts can sometimes have incomplete and episodic knowledge, especially when there is a lack of data. This can result in incorrect or incomplete fuzzy rule bases for the inference system, which lowers the model performance. Therefore, it is imperative that a suitable judgment elicitation process is adopted to enable reproducibility of the results.

In addition, redundant, inconsistent, or conflicting rules may be encountered during elicitation of fuzzy rules. Consequently, a significant amount of time is required to overcome this and fine-tune the model. Therefore, similar to formal judgment elicitation methods, the proposed method must be applied iteratively. The inability to self-learn means the model requires consistent regular review of rules and membership functions to ensure relevancy.

To overcome some of these drawbacks and present a better risk assessment approach for the AUV community, further research can follow three tracks. (1) Expand on the list of risk variables as input into the fuzzy-based risk model. This includes having a more robust method for identifying risk variables and the use of both crisp and fuzzy risk variables in the model. (2) Develop and explore risk aggregation methods for the fuzzy-based risk models to establish a risk level for an entire AUV deployment. This usually includes a number of open-water missions and under-ice missions during the deployment. Other aspects of the deployment such as launch and recovery as well as transportation of the AUV should also be considered. (3) Identify and quantify potential causal relationships between risk variables to better understand systemic behaviour. This can be performed with fuzzy cognitive maps or synthesising fuzzy logic with system dynamics or structural equation models.

There are different types of AUVs. Many faster vehicles (1 m/sec and more) have an endurance of days while slower buoyancy-driven vehicles (such as underwater gliders) or propeller-driven vehicles (speed less than 1 m/sec) tend to have an endurance of months. AUVs also vary in terms of operating depth and the required human effort for operation. Different AUV characteristics imply different membership functions and different risk variables influencing its risk of loss. When using the proposed method one must be aware of this and update the membership functions and, potentially, the fuzzy rules according to the vehicle characteristics. As a result, the risk profiles for different AUVs also differ.

5. CONCLUSION

In this article, a fuzzy-based risk assessment framework for under-ice AUV missions in the Antarctic is presented. The use of a fuzzy-based approach is especially well suited for an AUV program in its early phases due to the lack of historical fault log data for precise quantification of risks. It also takes into account the vagueness and ambiguity of many risk variables that are difficult to quantify and are usually described in natural language. The framework facilitates the capturing of knowledge and experience from subject matter experts to derive a quantifiable risk-level output. This output can then be evaluated against a set of risk criteria to aid decision making or to be used relatively to compare risks of different missions. Additionally, the framework can also be applied directly in the field during a deployment to assess risk in response to changes in situation. These benefits are the reasons the proposed fuzzy-based risk assessment framework is pragmatically useful for future under-ice AUV deployments.

Sensitivity analysis enables the user to tune the model for particular risk scenarios. Our sensitivity analysis has considered five risk variables, but more variables could have been included in this analysis. We could have included other environmental and operational variables such as the distance between the AUV and the seabed, the presence of icebergs, and others. We could also have included more detailed characteristics of the launch and recovery systems. The variables considered in this analysis were those deemed more important for the forthcoming deployment under the Sørsdal Glacier in the Antarctic.

Advancement of this work can potentially further its application outside the AUV domain. For complex new technology, there is often an absence of hard data and of expertise. This uncertainty is present in risk matrices used by organizations that are now adopting AUVs. We have proposed a method to homogenize the risk assessment used by organizations with those used for quantifying AUV risk. In doing so, a new methodology for AUV under-ice mission risk calculation is proposed. The fuzzy risk assessment framework can be adopted for other complex technologies such as other unmanned marine surface vessels or unmanned aerial vehicles (Marconato et al., 2016; Porathe, 2013), where there is an apparent lack of data. The difference between the AUV applications and others is in the variables considered and their dependencies. For example, with respect to an AUV mission under ice, the mission profile risk must be calculated based on the Distance of Mission, Max Depth of Mission, and Duration Under Ice. If we apply this methodology to other technology, for example, to an unmanned ship, the mission profile risk would have to consider other variables.

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