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HUMAN ERROR IN AUTONOMOUS UNDERWATER VEHICLE DEPLOYMENT: A SYSTEM DYNAMICS APPROACH.

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ABSTRACT

The use of Autonomous Underwater Vehicles (AUVs) for various applications have grown with maturing technology and improved accessibility. The deployment of AUVs for under-ice marine science research in the Antarctic is one such example. However, a higher risk of AUV loss is present during such endeavours due to the extremities in the Antarctic. A thorough analysis of risks is therefore crucial for formulating effective risk control policies and achieve a lower risk of loss. Existing risk analysis approaches focused predominantly on the technical aspects, as well as identifying static cause and effect relationships in chain of events leading to AUV loss. Comparatively, the complex interrelationships between risk variables and other aspects of risk such as human errors have received much lesser attention. In this paper, a systems-based risk analysis framework facilitated by system dynamics methodology is proposed to overcome existing shortfalls. To demonstrate usefulness of the framework, it is applied on an actual AUV program to examine the occurrence of human error during Antarctic deployment. Simulation of the resultant risk model showed an overall decline in human error incident rate with the increase in experience of the AUV team. Scenario analysis based on the example provided policy recommendations in areas of training, practice runs, recruitment policy and setting of risk tolerance level. The proposed risk analysis framework is pragmatically useful for risk analysis of future AUV programs to ensure the sustainability of operations, facilitating both better control and monitoring of risk.

Key Words: Systems-based; Risk of Loss; Human Error; AUV; Risk Analysis Framework

1. INTRODUCTION

1.1 Autonomous Underwater Vehicle

Autonomous Underwater Vehicles (AUVs) are self-powered robotic devices that are piloted and controlled by onboard computer systems. Its ability to navigate independently underwater and versatility with customizable payloads makes it an ideal tool for various scientific, commercial and military applications. As technology matures and accessibility improves, there is now a growing interest in the use of AUVs. In a more recent development, AUVs are now used for under-ice marine science research in the Antarctic (Cadena, 2011; Dowdeswell et al., 2008; Jenkins et al., 2010; Nicholls et al., 2006; G. Williams et al., 2014). However, the use of AUVs in the Antarctic's extreme environment pushes not only the technological limits of the AUV. It also challenges the on-site AUV team both physiologically and psychologically (Gunderson, 1967). Considerations are also needed to account for ice cover, inaccessibility and emergency abort procedures. It is, therefore, not surprising that the risk of AUV loss during Antarctic missions is higher as compared to open sea missions (Mario Paulo Brito, Griffiths, & Challenor, 2010).

There have been recorded incidents of AUV loss during deployment in the Antarctic. *Autosub2*, an AUV owned by the National Oceanography Centre, Southampton, United Kingdom was lost in 2005 during an Antarctic mission with unknown exact cause of loss (Gwyn Griffiths & Collins, 2006). SeaBED, an AUV owned by the Woods Hole Oceanographic Institution (WHOI) in Massachusetts got stuck under Antarctic ice during a mission and had to be recovered (Waters, n.d.). Seaglider SG522, an underwater glider owned by the University of East Anglia, United Kingdom was lost at the Weddell Sea in the Antarctic due to the erroneous parameters set by the operator (Mario P. Brito, Smeed, & Griffiths, 2014). The loss of an AUV in the Antarctic can impact the AUV community with higher insurance premiums. In addition, it can also delay research projects, damage the reputation of the AUV community, cause the loss of valuable research data and a possibility of harming the delicate Antarctic environment (Gwyn Griffiths & Collins, 2006). It is, therefore, imperative that the risk loss be analysed and managed effectively in an Antarctic AUV program.

1.2 Risk Analysis Approaches

The most widely accepted definition of risk by Lowrance (Lowrance, 1976) is that it is the probability and severity of harm. Therefore, risk is a measure, using either quantitative or qualitative means, of the combination of probability of occurrence and severity of the adverse event (Equation 1).

$$Risk = Probability \times Severity \qquad (1)$$

Behind this seemingly simplified definition lies the multidimensional, dynamic and sometimes fuzzy nature of risk (Haimes, 2009). The broad interpretation of risk also meant that there is 'no one size fits all' solution to analysing risk, resulting in a wide variety of risk analysis approaches. Consequently, different approaches have been adopted to examine different aspects of an AUV deployment, both spatially and temporally, in an attempt to manage the risk of loss. Most early risk analyses focused on improving the technical aspects of AUVs in areas such as; the mission management software, navigation system, collision avoidance system, emergency abort system, power system, homing system and communication system (Carreras, Palomeras, Ridao, & Ribas, 2007; Ganesan, Chitre, & Brekke, 2016; Lapierre, 2009; Marques et al., 2007; Oh & Oh, 2002; Paull, Saeedi, Seto, & Li, 2014; Pereira, Binney, A Hollinger, & S.Sukhatme, 2013; Reader, Potter, & Hawley, 2002). As AUV technology gradually matures, more proactive and systematic risk analysis approaches based primarily on historical performance data of the AUV (M Brito et al., 2012; Mario Paulo Brito et al., 2010; Gwyn Griffiths & Collins, 2006) emerges. In addition, there has also been a gradual shift in focus to other operating uncertainties and phases of deployment (Mario Brito & Griffiths, 2016; Mario P. Brito & Griffiths, 2018; G Griffiths & Brito, 2008).

Despite this development, there are still shortfalls to be addressed. First, existing risk analysis approaches often view AUV incidents as chains of events, attributing the loss to a root cause. Adopting such a view neglects the systemic complexity behind an incident and misdirect the focus on identifying a 'root cause' where there may not be one (Leveson, 2011). Second, much of existing risk analysis and risk control effort still lies on the technical dimension. Although undeniably important, a more comprehensive analysis requires an inclusive approach encompassing other aspects such as the role of human error. Lastly, many existing approaches are discrete-based. These do not effectively capture the time dependency of risk factors such as ageing of the AUV with time.

This paper aims to overcome the mentioned shortfalls for risk analysis of Antarctic AUV programs by proposing a systems-based risk analysis framework using system dynamics. To our best knowledge, a systems dynamics framework has never been proposed analysing risk of AUV loss. The approach is then demonstrated through an example to examine human errors with policy recommendations to improve risk control of Antarctic AUV operations. This paper is organised as follows: Section 2 introduces the proposed risk analysis framework based on system dynamics. Section 3 presents a well-developed example on its application. Finally, Section 4 concludes the paper with a discussion of the benefits, limitations and scope for future work.

2. METHODOLOGY

2.1 Overview

The use of a systems approach for analysing risk was first suggested by Reason (James Reason, 1995) when he found most accidents are the result of underlying system flaws. Since then, there has been a gradual shift in risk analysis focus, from static chain of event models to complex dynamic risk models which are more representative of real-world systems (Hollnagel, Pariès, Woods, & Wreathall, 2013)(Katsakiori, Sakellaropoulos, & Manatakis, 2009). The importance of adopting a systems approach for risk analysis was further recognised after investigations of several high-profile industrial accidents. For instances, the Three Mile Island accident (Herndl, C.G, Fennell, B.A., & Miller, 1991), Bhopal gas tragedy (Aini & Fakhrul-Razi, 2010) and the Chernobyl nuclear disaster (N. Pidgeon & O'Leary, 2000). All three accidents were attributed, at least partially, to human errors of operators who played a supervisory controller role with passive monitoring of the system state. However, these human errors were the long-term effect of other systemic issues such as production pressure, poor workforce planning, weak governance, lack of communication channels, poor resource planning or placing priority on productivity over safety (Leveson, 2011). An AUV operator plays a very similar supervisory controller role during an Antarctic deployment. The main difference between conventional systems and AUV systems is the level of autonomy, with the interactions between human operator and autonomous system being more complex to understand. This paper adopts valuable lessons from past industrial incidents to propose a systems-based risk analysis framework using system dynamics.

2.2 System Dynamics

The field of system dynamics was established by Jay Forrester (Jay W Forrester, 1958) for analysis of dynamic complex systems. Sterman (John D. Sterman, 2000) described system dynamics as a method to learn about dynamic complexity, understand the sources of policy resistance and design of more effective policies. System dynamics uses concepts from the field of feedback control to demonstrate how the structure of the system with its feedback loops are responsible for its dynamic behaviour.

Central to system dynamics are models representing feedback processes, expressed through reinforcing and balancing loops (Fig. 1), stock and flow structures (Fig. 2) and time delays (John D. Sterman, 2000). A reinforcing loop is one where an initial change influences more of the same change while a balancing loop seeks equilibrium by counteracting change. In the hypothetical example shown in Fig. 1, schedule pressure increases the occurrence of human error, which slows down mission completion rate and causes a higher incident rate. This adds further schedule pressure in a reinforcing loop (R). On the contrary, schedule pressure can also increase team productivity, which increases the mission completion rate and reduces schedule pressure in a balancing loop (B).

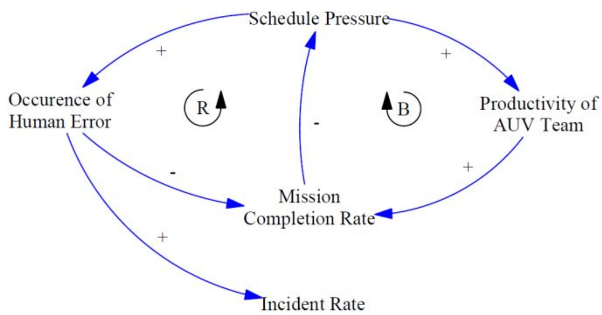


Fig 1. An example of a causal loop diagram showing both reinforcing feedback (R) and balancing feedback loop (B).

Stocks are referred to as entities that accumulate or deplete over time while flows define the rate of change in a stock. Stocks characterise the system state by providing inertia and memory, which can also lead to time delays when a difference between inflow and outflow rate exist. As the example in Fig.2 shows, the number of AUV engineers in an organisation is a stock that is increased through hiring inflow and is reduced by attrition outflow. The clouds represent boundaries of the model environment.

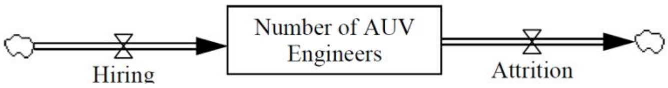


Fig 2. An example of a stock and flow diagram.

The widespread application of system dynamics modelling transcends disciplinary boundaries from politics to healthcare. Cooke (D. L. Cooke, 2003) modelled the systemic issues leading to the Westray mine disaster using system dynamics methodology. The models revealed that organisational factors such as putting a priority on productivity over safety accelerated incident rates at the mine. Bouloiz et al. (Bouloiz, Garbolino, Tkiouat, & Guarnieri, 2013) demonstrated the use of system dynamics models to formalise causal interdependencies between safety factors in the context of a chemical storage unit. The study also shows that integration of safety factors from technical, organisational and human dimensions allow for better risk analysis, leading to improved organisational decision making. The use of system dynamics in the AUV domain was first attempted by Brito and Griffiths (Mario P Brito & Griffiths, 2012). In their work, system dynamics models were used to analyse the impact of multiple AUVs deployments on risk mitigation efforts. Based on a generic "rework cycle" system archetype, the risk model focused on human resource management with suggestions made to investigate organisational, cultural and stress factors using the same approach. Their study represents a proof of concept for using system dynamics in risk analysis of AUV operations. However, there is no proposal of a structured framework and the study also lacks validation of the risk model.

2.3 Risk Analysis Framework

The generic risk analysis framework proposed in this paper and shown in Fig.3 consists of three main iterative steps with further description of each step presented in subsequent sections.

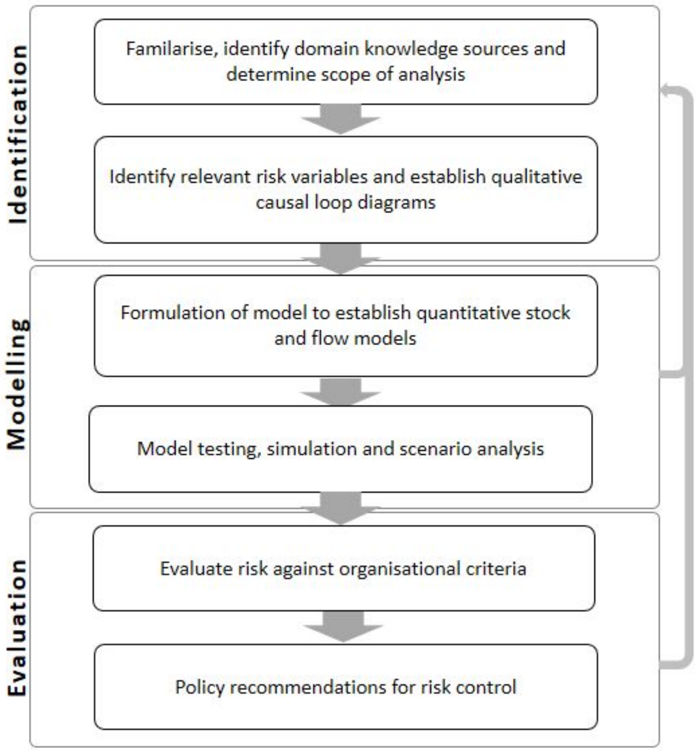


Fig 3. A broad overview of the proposed risk analysis framework based on system dynamics methodology.

2.3.1 Identification

The objectives of this step are to acquaint with the AUV program objectives, expected performance requirements, as well as finding and recognising causes that can lead to the loss of the AUV during Antarctic deployment. The first task is to establish available sources of knowledge about the AUV of interest. Experts' knowledge is often regarded as the best source of information (Kuhnert, Martin, & Griffiths, 2010), and this can come from AUV engineers, AUV program owner as well as manufacturer or contractors. Important considerations for experts' elicitation are the choice and number of experts necessary to capture both spatial and temporal risk variables of interest. While there is no formal procedure tailored specifically to risk assessment of AUV operations, guidance can be taken from the recommended selection criteria published by Pulkkinen and Simola (Pulkkinen & Simola, 2000) and Kotra et al. (Kotra, Lee, & Dewispelare, 1996). The number of experts to interview lies between 6 - 12 as recommended by Cooke and Probst (R. Cooke & Probst, 2006). In addition to experts' knowledge, information can also be sought from organisational documentation such as technical specifications of the AUV, safe work procedures, fault logs, risk assessment records, program schedule, budget plan, previous audit findings, organisation charts and previous incident reports. Future deployment plans and expected performance requirements also contain important information for the risk analysis.

The second task involves the investigation of context, systemic issues, existing risk controls and risk variables that can cause or culminate the loss of the AUV in the Antarctic. To address the shortfall of existing risk analysis approaches (Section 1.2) where focus very much lies on the technical dimension of an AUV, risk variables from other aspects should be considered. This includes human, organisational and external factors. To facilitate this, a generic risk structure with some of the most frequently cited grouping of factors adopted from (Schein, 2016) and (James Reason, 1990) is proposed (Fig.4). This risk structure, the first of its kind tailored for risk analysis of AUV operations, offers an indication of how the interactions between risk variables of different dimensions can influence the risk of AUV loss. It serves as a useful guide, supporting earlier established sources of knowledge. The output of this task is a list of risk variables, which may influence the risk of AUV loss.

The third task to be performed for this step is to scope the risk analysis, which includes the setting of a realistic time horizon for the risk models. A realistic scope ensures relevancy of the models and yet avoids overwhelming both model users and the analyst. To do so, considerations on the availability of resources, knowledge and time had to be made. The analysis time horizon should be sufficient enough to capture both the emergence of systemic issues leading to the risk of losing AUV and the delayed effects of potential policies. This may encompass the entire AUV program period, from design through construction and operational phase to decommissioning. The determination of scope should follow the general decision analysis principles of defining decision context (Clemen, 1996)(Nikolova, Makedonska, & Tenekedjiev, 2004).

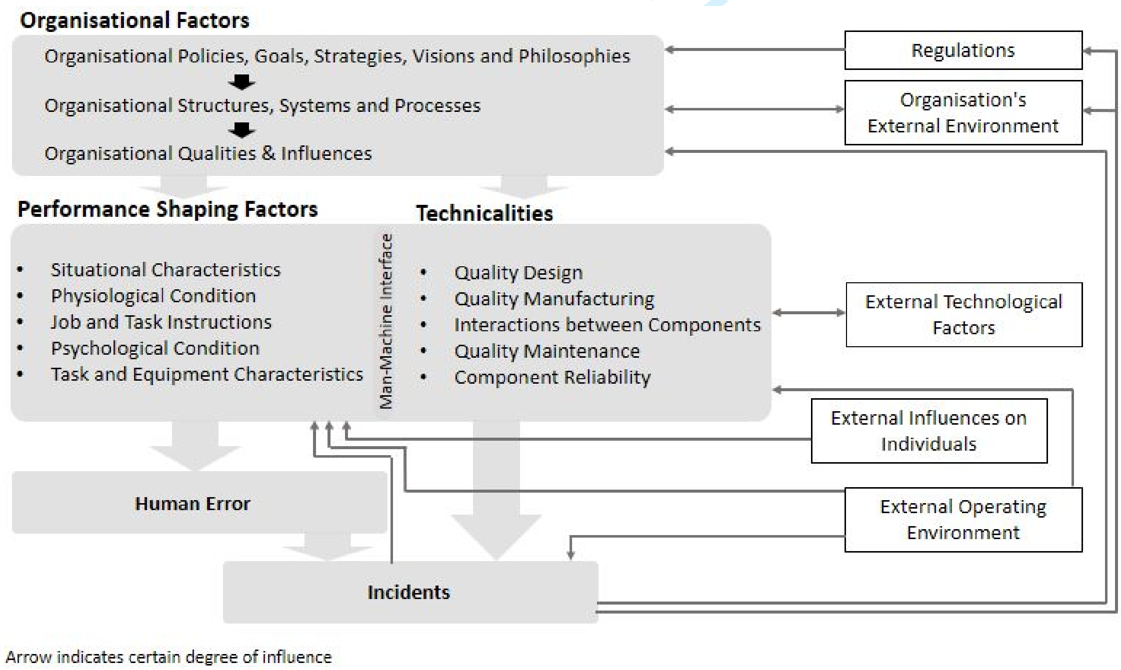


Fig 4. Generic risk structure influencing the risk of AUV loss with some taxonomies adapted from (Schein, 2016) and (James Reason, 1990).

The last task of this step is to establish causal relationships between the identified risk variables. Using the available sources of knowledge established earlier, this step involves multiple iterations between interviews, data collection, data comparisons and causal loop diagram modelling.

Although the concept of causation is ubiquitous in every branch of theoretical science (Salmon, 1997), one of the most commonly used criteria to determine causation was proposed by Sir Austin Bradford Hill (Hill, 1965). The same criteria can be adapted to establish causality in the context of AUV risk analysis. However, It is important to note that these criteria do not provide definitive causality conclusions and a certain level of judgement is still necessary.

Once causality has been established, it can be represented in a causal loop diagram. Causal loop diagram is a qualitative graphical tool that enables the visualisation of causal relationships, describes the causal mechanism and represent feedback structure of the system (J.D. Sterman, 2001). In a causal loop diagram, risk variables are connected by arrows with a polarity of either positive (+) or negative (-). The polarity is positive when the effect of the first variable will cause an effect in the same direction for the linked variable. The polarity is negative when the effect of the first variable will cause an effect in the opposite direction for the linked variable (John D. Sterman, 2000). Where the causal effects take time to manifest, the delay is represented by a double line (//) on the arrow. In the example shown in Fig. 5, quality of maintenance practices affects the occurrence of technical faults for the AUV, albeit a delay effect. As the number of technical faults increases, as does the risk of AUV loss, which reduces overall trust in the AUV systems. A lack of trust reduces complacency of the AUV team, which leads to an increase in the quality of maintenance practices to complete the balancing loop. These causal loop diagrams will be the foundation for further in-depth risk analysis in the next step.

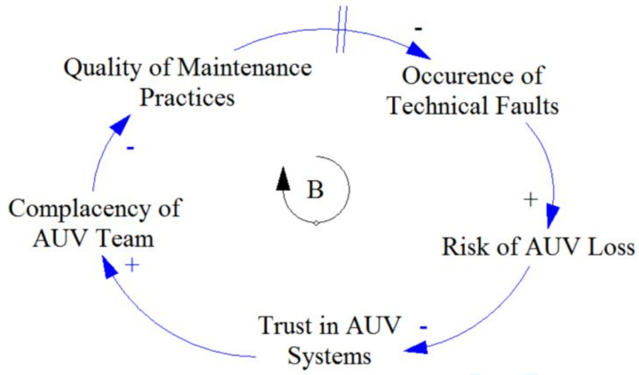


Fig 5. Example of positive, negative polarity, and delay effects in a causal loop diagram.

2.3.2 Modelling and Validation

Building on the causal loop diagrams, the objective of this step is to further specifications of the model structures, estimate parameters, formulate behavioural relationships, and establish initial conditions. This yields quantifiable stock and flow models which describes the system with integral or differential equations.

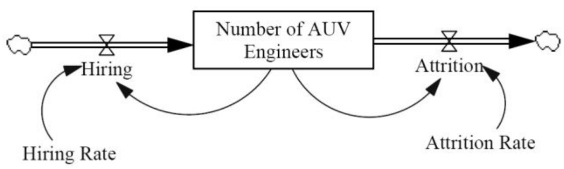


Fig 6. An example of stock and flow diagram, developed from fig 2.

For example, consider a stock and flow model as shown in Fig 6. The model consists of two flows determining the stock of '*Number of AUV engineers' (Engr)*. *'Hiring'* is the inflow and *'Attrition'* is the outflow, which are influenced by parameters *'Hiring Rate' (HR)* and *'Attrition Rate' (AR)* with the following equations (2) and (3):

$$Hiring = HR \times Engr \qquad (2)$$
$$Attrition = AR \times Engr \qquad (3)$$

To simulate the model, the rate of change of the stock and the level of stock at time *(t)* is required. This corresponds to the differential and integral equation of the model as:

$$\frac{d(Engr_t)}{dt} = (HR - AR) \times Engr_t \qquad (4)$$
$$Engr_t = Engr_0 + \int_0^t (HR - AR) \times Engr_t \times dt \qquad (5)$$

Where $Engr_t$ stands for equivalent full-time AUV engineers at time *t* and $Engr_0$ stands equivalent full-time AUV engineers at the start of the program.

The formulation of stock and flow models consist of multiple iterations between interviews, data collection, data comparison and fine-tuning of models. Other data sources such as publications, direct observations, organisational documents or additional interview sessions can be sought to fill information gaps. The conduct of interviews at this step focuses more on the validity and formulation of the stock and flow models. Any conflicting information provided by the interviewees should be reviewed and supported by other empirical sources of data as far as possible. The outcome of this step is a set of models demonstrating how risk of loss can culminate for an Antarctic AUV program.

To test the developed models, three main approaches were taken. First, local knowledge and available historical data were used to calibrate the model. Second, a series of tests were undertaken to uncover model errors and areas for improvement. Examples of key tests to be carried out are summarised in Table I, adapted from Sterman (John D. Sterman, 2000). The testing must be performed through discussion with stakeholders until the models converge sufficiently to be deemed reflective of the real-world system by those involved in the modelling. Last, simulations results from the model were discussed and compared with domain experts' opinion.

Table I. Key tests to be carried out on the developed models, adapted from (John D. Sterman, 2000).

Test	Purpose
a. Dimensional Consistency	Ensure that equations within the models are dimensionally consistent.
b. Extreme Conditions	Check whether models respond plausibly when subjected to extreme inputs.
c. Behavioural Reproduction	Ensure that the models should be a good representation of the behaviour of real-world systems.
d. Sensitivity Analysis	Check for numerical, behavioural and policy sensitivity when assumptions about parameters, boundary and aggregation are varied over a plausible range of uncertainty.

Once sufficient confidence is gained on the developed models, simulation of the models for scenario analysis can be undertaken. Scenarios to be analysed can be derived primarily from earlier interviews and should be performed in close discussion with decision makers in preparation for the final step of the risk analysis. The finality of this step is to establish a set of systemic behaviours based on various risk scenarios which influence the risk of AUV loss.

2.3.3 Evaluation

Simulation results from the analysis can then be evaluated against pre-determined organisational criteria with eventual risk control policy recommendations. For instance, this can be an acceptable risk rating level based on the semi-quantitative risk matrix of the organisation. Insights attained through analysis of the risk models can also be used for policy recommendations through the following:

a. Improving the mental models of decision makers, experts and stakeholders of the AUV program. According to Sterman (John D. Sterman, 2000) and Forrester (Jay W. Forrester, 1994)(Jay Wright Forrester, 2001), the performance of an organisation and its systems will improve when there is a better understanding of system behaviour;
b. Identifying leverage points to institute new management strategies or decision rules for risk controls; and ;
c. Identifying leading indicators which may suggest a potential migration of risk from low to high level. This involves recognising measurable and observable risk variables in the AUV program which influences the risk of AUV loss. The AUV team's average experience for Antarctic deployment, number of technical changes on the AUV per year or AUV engineer's turnover rate are examples of possible leading indicators.

Effectiveness of recommendations can only be achieved if they are adequately implemented by organisational leaders. It is therefore critical that this step is conducted in close consultation and consideration of feedbacks from decision-makers, experts and other key stakeholders in the AUV program. Although this is the last step of the proposed risk analysis framework (Fig. 3), the process is iterative in nature. Analysis of new information and filling of data gaps must be performed on a regular basis to ensure relevancy and more refined analysis of risks.

2.4 Modelling Software

A number of software packages facilitating system dynamics modelling and simulation is available. Three commonly used software are Stella®, Vensim® and PowerSim®. All three software promotes the development of system dynamics model with visual clarity. For this work, Vensim® is chosen due to its user-friendly interface, dimensional checks, the clear visual output of system behaviour and system status.

3. APPLICATION EXAMPLE

3.1 Overview

To demonstrate the application of the proposed framework, it is used to examine the occurrence of human error for an actual Antarctic AUV program. Although being able to operate autonomously, humans still play an important role in AUV deployments. They take control during an emergency, determine mission plans and perform the launch and recovery of the vehicle. Notably, during a four years deployment of the Autosub AUV from 1996 to 2000, Griffiths et al. (G Griffiths, Millard, McPhail, Stevenson, & Challenor, 2003) identified human error as the most common 'fault' instead of technological failures (Fig 7). These included the lack of attention, poor error checking, poor handling, distraction and wrong configuration setting. Thieme et al. (Thieme, Utne, & Schjølberg, 2015) presented the use of a qualitative BBN to assess the role of human factors in the monitoring of an AUV during missions. Trust, workload, fatigue and situation awareness were some of the factors mentioned to affect the performance of an AUV operator. Manley (Manley, 2007) highlighted the importance of managing human errors during AUV operations and suggested that the best strategy to mitigate operational risk is to have an experienced and well trained AUV team. Several other studies had also found human errors playing a significant role in contributing to the overall risk of AUV loss (Stokey et al., 1999)(Ho, Pavlovic, Arrabito, & Abdalla, 2011). The extremities of the Antarctic further amplifies the importance of managing human error not just during any mission, but also throughout the entire Antarctic AUV program. The proposed system approach is also aligned to Reason's (J. Reason, 2000) suggestion that human error originates from systemic factors and are consequences rather than causes of incident.

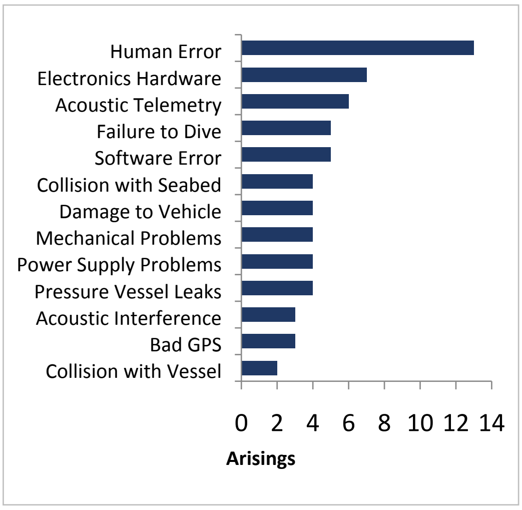


Fig 7. Pareto diagram of Autosub AUV failure modes during missions 1-240 by Griffiths et al. (G Griffiths et al., 2003).

The AUV program in this example is funded by the Antarctic Gateway Partnership initiative and managed by the University of Tasmania (UTAS) in Australia. It aims to acquire high-resolution data under sea ice and ice shelves in Antarctic regions for marine scientific research. Capable of exploring depths of up to 5,000 meters and a present cruising range of 140km, the Explorer-class AUV named *nupiri muka* is able to conduct long-range under-ice operations with its diverse scientific payload.

3.2 Identification

Delivered in May 2017 to UTAS, the *nupiri muka* AUV is relatively new at the time of writing and has very limited historical failure fault log data. The task of familiarisation was therefore performed using data from trial runs, information from manufacturer's operating manual, discussions with AUV engineers, direct observations and organisational documents such as standard operating procedures and risk assessments records. Literature on other AUVs also proved to be valuable references, such as those of *Autosub* AUV, developed and operated by the National Oceanography Centre, Southampton.

The primary AUV team in UTAS consists of four personnel; a facility coordinator, an engineer, a technician and a researcher. Out of the four, only two had previous Antarctic under-ice operating experience working on other AUVs. This lack of operating experience on the new AUV was therefore identified as one key risk factor. It can increase the likelihood of human error leading to higher incident rate and consequently, a higher risk of AUV loss (Wiegmann & Shappell, 2012)(G. Griffiths, Millard, McPhail, Stevenson, & Challenor, 2000). Presented with a high incident rate due to human error, the AUV owner may be reluctant to deploy the AUV to the Antarctic. Yet without actual deployment of the AUV, the team gains limited operational experience. Such a situation is analogous to the dilemma facing new job seekers where employers prefer to hire people with experience but new job seekers cannot gain that experience if nobody hires them. To mitigate the lack of experience, a series of trials were planned for and performed in a relatively benign environment (Tamar River, Tasmania) before actual deployment in the Antarctic.

Through semi-structured interviews with the AUV team which was guided by the generic risk structure shown in Fig 4, experience of the team, as well as other key risk variables relating to human error were identified below:

a. Human Resource (e.g Hiring and Attrition)
b. AUV Utilisation Rate
c. Management Risk Appetite
d. Average Experience of AUV Team
e. Experience Decay during Lull
f. On-the-Job Experience Gain

For this work, the scope of the analysis focuses on the incidence of human error. The time horizon for the analysis was set as 10 years, the expected operating life of the *nupiri muka* AUV.

To establish causal relationships between the identified risk variables, feedback was sought through interviews with the primary AUV team in UTAS, as well as taking reference from literature, risk assessment records and standard operating procedures. The resultant causal loop diagram is presented in Fig 8.

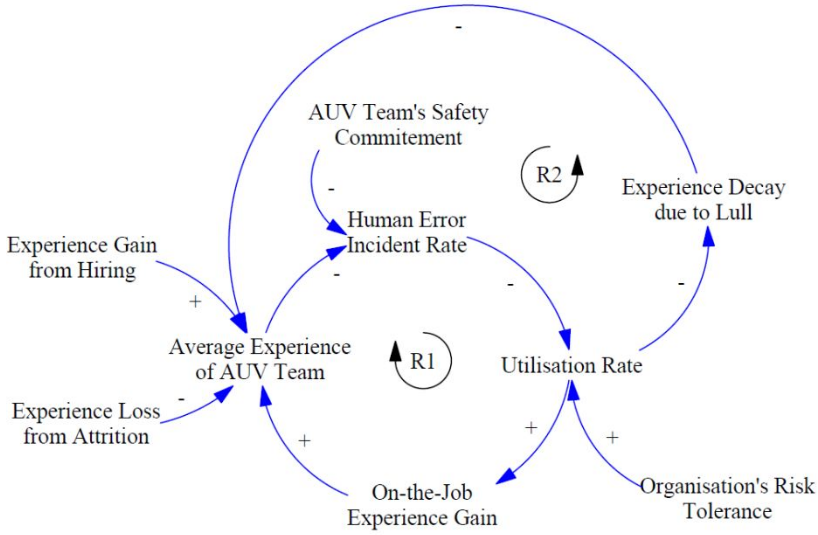


Fig 8. Causal loop diagram showing the influence of operating experience on human error incident rate.

The causal loop diagram shows two reinforcing loops R1 and R2. In both of them, the risk variable 'Average Experience of AUV Team' has a causal relationship to 'Human Error Incident Rate'. This causality was supported both by interviews and the literature (Wiegmann & Shappell, 2012)(James Reason, 1990). In addition, the 'AUV Team's Safety Commitment' level also influences the 'Human Error Incident Rate'. Depending on the level of risk tolerance by the organisation, 'Human Error Incident Rate' then affects the 'Utilisation Rate' of the AUV with a negative polarity. A decrease in utilisation of the AUV will result in less on-the-job experience gain which decreases the average experience of the AUV team, completing the R1 feedback loop. Conversely, a decrease in utilisation of the AUV will increase the amount of experience decay due to lull and decrease the average experience of the AUV team, completing the R2 feedback loop. This decay of experience is supported by several research on memory, which has shown that a significant amount of forgetting takes place naturally over time (Anderson, Fincham, & Douglass, 1999)(Arthur Jr., Bennett Jr., Stanush, & McNelly, 2006).

The two reinforcing loops seem to aggravate the problem of the lack of operating experience through utilisation rate of the AUV. Quantification of the model is carried out in the next step.

3.3 Modelling and Validation

To construct quantifiable stock and flow model, figures and equations used were elicited through multiple discussions with the primary AUV team, supported by other information sources as discussed previously. Interviews were carried out in semi-structured format and went through several iterations, with the risk model updated after each cycle. The derived stock and flow diagram consist of four stocks; 'Total Experience of AUV Team', 'Number of AUV Team Members', Human Error Incident Rate' and 'Utilisation Rate', as shown in Fig 9. Details of the formulation, definitions and initial conditions used are listed in Appendix A.

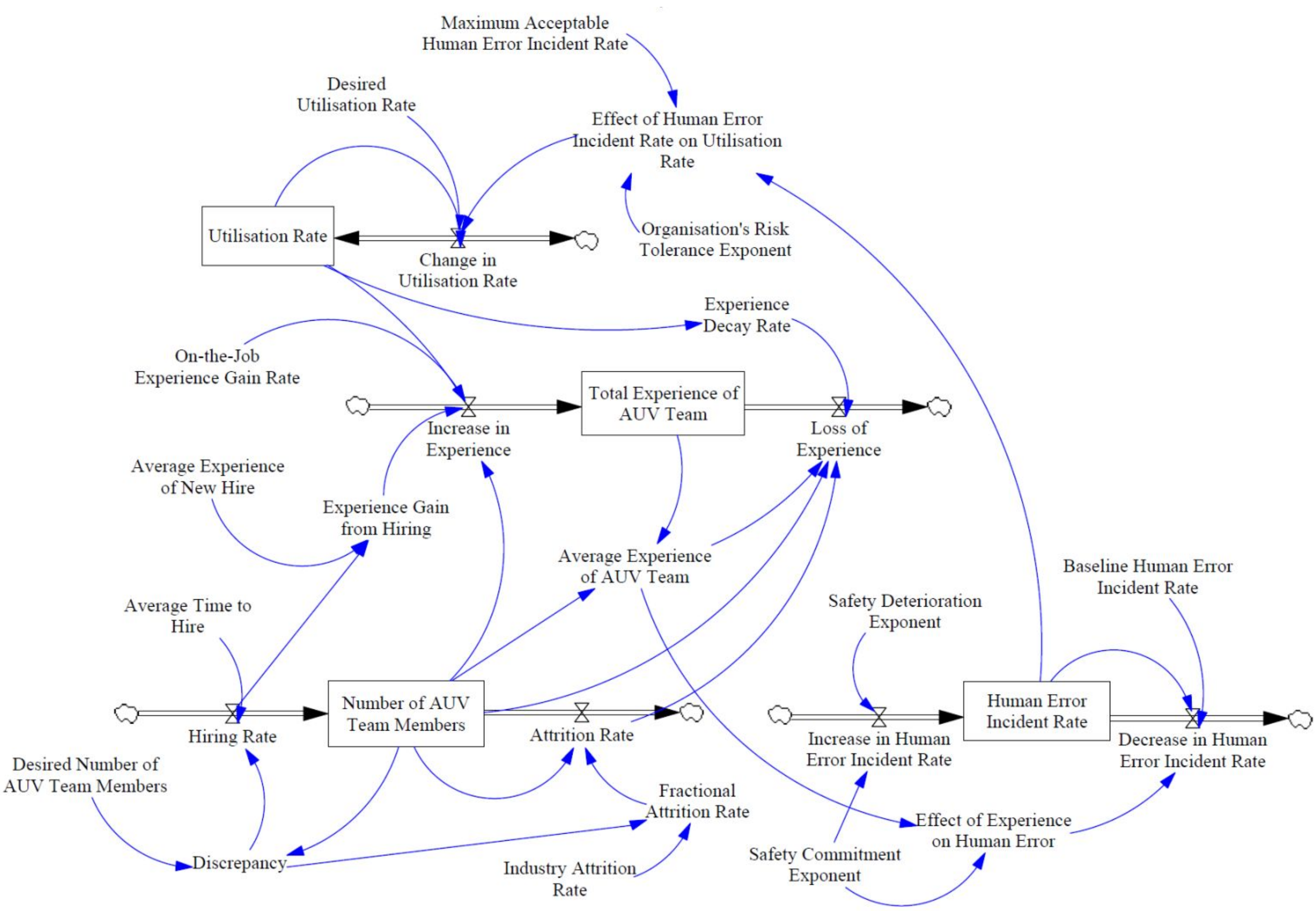


Fig 9. Stock and Flow diagram with four stocks.

The model was checked for violations of physical law. For instance, real quantities such as number of AUV team members, utilisation rate and human error incident rate do not go into a negative value. Similarly, outflows from these stocks have shown to be zero if the stock is zero. The model was also checked for dimensional consistency using inbuilt <Check Units> function within the software. Any inconsistencies with units of measure were reflected by the software when the equations were checked. Extreme condition tests were performed extensively to assess its robustness. By randomly changing variables to realistic maximum and minimum values while monitoring model behaviour, these tests ensure that the model behaves in a realistic manner even with extreme inputs. After performing these tests, simulation of the model was carried out with the result shown in Fig 10.

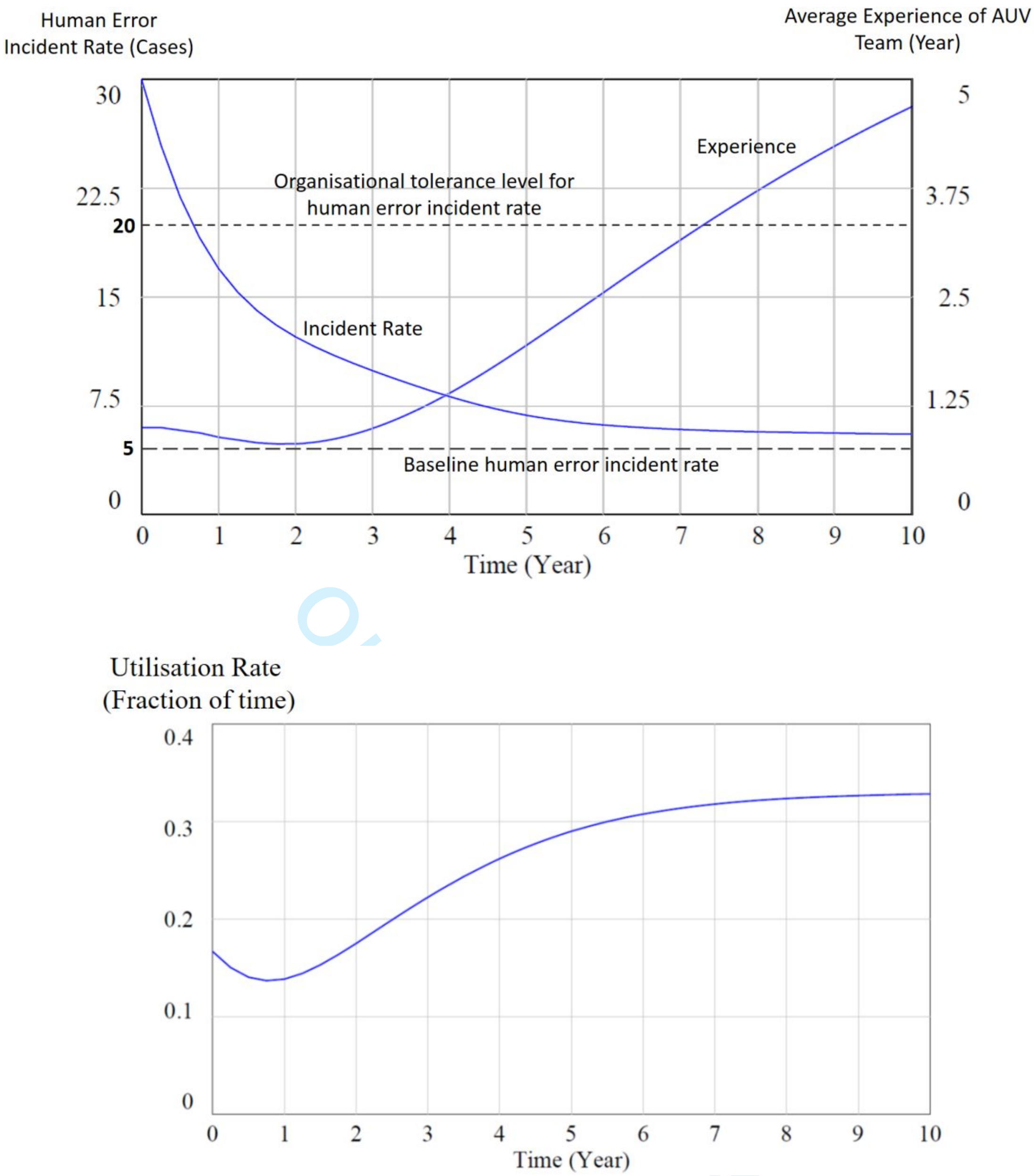


Fig 10. Simulation results showing the trend of human error incident rate, average experience of AUV team (Top) and utilisation rate (Bottom).

The simulation result showed that in the first 7 months of operation, the lack of Antarctic operating experience resulted in an incident rate which was above the organisation's tolerance level of 20 cases. As a result, deployment of the AUV was reduced which caused some loss of experience due to decay up to second year of the program. However, as the team gradually gain more experience through practice runs and training, the incident rate continues to decline towards the baseline level of 5 cases. This resulted in an increase in the utilisation rate. Overall, the simulation shows an overall declining human error incident rate with the increase in experience of the primary AUV team. With coherent results obtained thus far from the base model, three scenarios were simulated next to facilitate policy recommendations.

In the first scenario, the effect of having regular training and practice runs during lull periods was examined. Based on best estimate elicited from the AUV team, 'Experience Decay Rate' was reduced by half to represent having such practices during lull period to mitigate the effect of lack of actual Antarctic deployment. The assumption here is that both training and practice runs remain consistently and equally effective throughout the span of the program for each person in the AUV team. Despite this simplification, many studies across industries have shown that effective training and practice runs do reduces the occurrence of human error (Helmreich, 1997)(Morrow, North, & Wickens, 2005). Consequently, the simulation results show that there was no initial loss of experience as compared to the base scenario (Fig 11). In addition, there is also an apparent reduction of human error incident rate as compared to the base scenario, especially in the second and third year of operation (Fig 11).

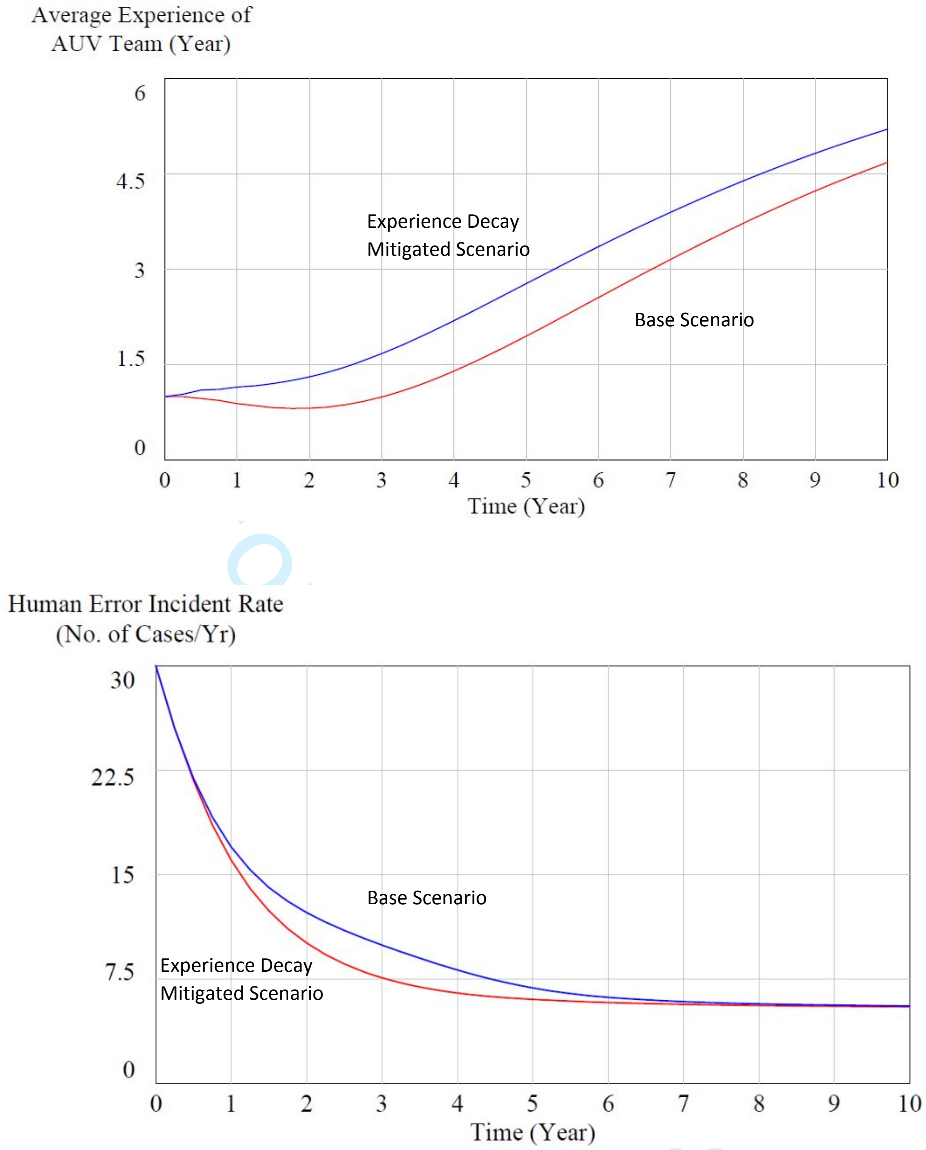


Fig 11. Simulation results showing the trend of average experience of AUV team (Top) and human error incident rate (Bottom) in an experience decay mitigated scenario.

The second scenario examines the impact of hiring and attrition on human error incident rate by varying the 'Average Experience of New Hire' (Fig 12). When recruitment policy requires new hires to the primary AUV team to have two years of relevant experience, an apparent reduction of human error incident rate as compared to the base scenario is observed. On the contrary, when there is no such requirement, the simulation shows a gradual decline in the average experience of the AUV team. This decline eventually leads to an increase in human error incident rate after the second year of the AUV program due to delays in the system. Faced with an increasing incident rate, the organisation reduces the utilisation rate of the AUV, further exacerbating the situation with even lesser opportunity for the team to gain experience. As a result, the rate of decay exceeds the rate of gain, with average experience of the team reduced to zero by the third year. Without the consideration of other factors, this may be an oversimplification of human cognitive function. However, the lack of utilisation has an undeniable negative impact on experience of the AUV team, which eventually leads to a premature end to the AUV program.

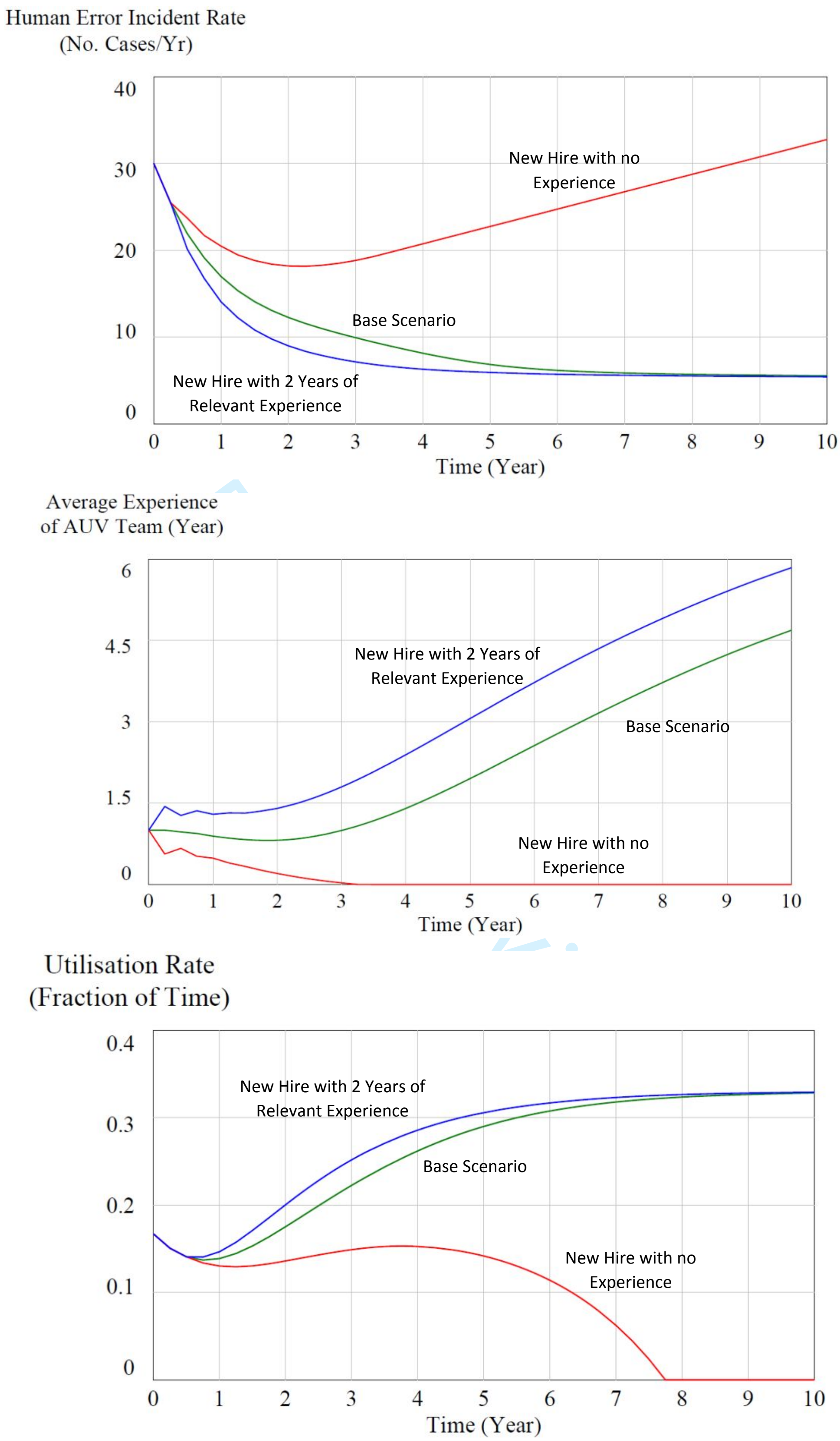
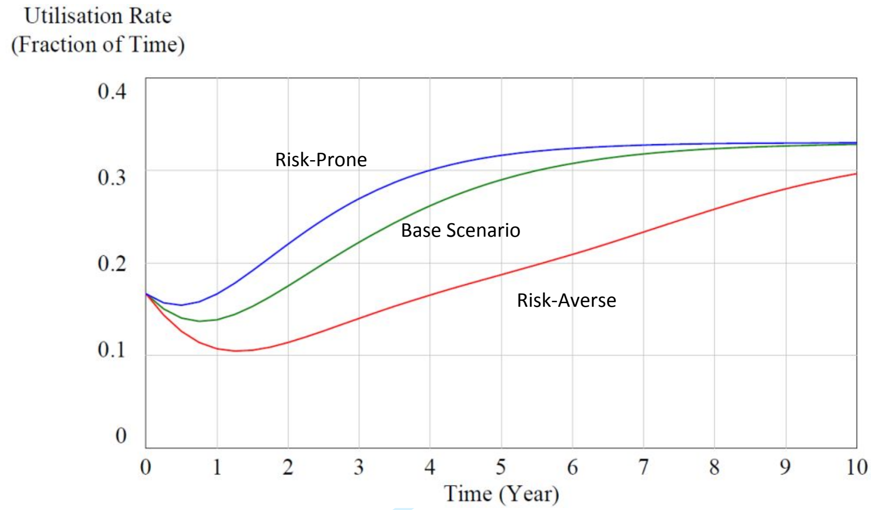
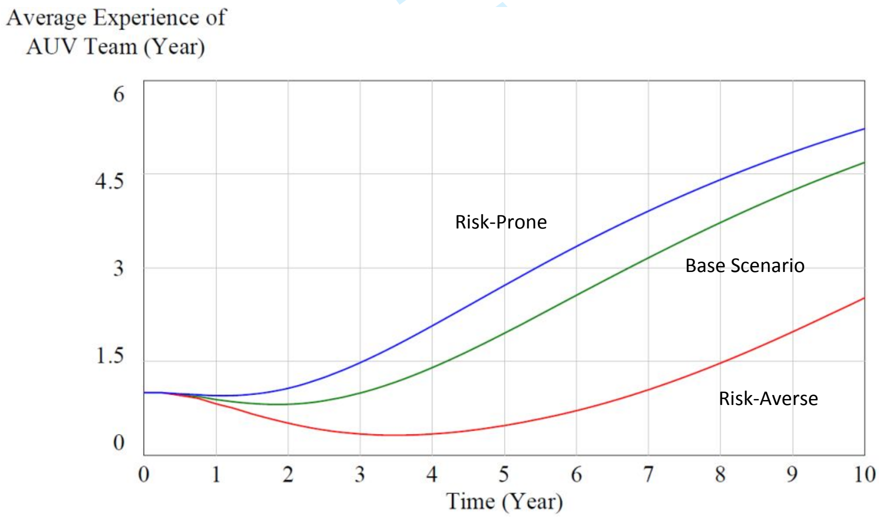


Fig 12. Simulation results showing the trend of human error incident rate (Top), average experience of AUV team (Middle) and utilisation rate (Bottom) in different recruitment policy.

In the third scenario, the impact of the organisation's risk appetite on human error incident rate was examined (Fig 13). Maximum acceptable human error incident rate, which represents either a risk-averse or risk-prone culture within the organisation was varied by ±20% for the analysis. This figure was elicited from the AUV team based on the best highest and lowest estimate of future changes in organisational risk appetite. In the risk-prone scenario, utilisation rate of the AUV was higher than the base scenario. This allows the primary AUV team to gain valuable experience which translates to lower human error incident rate after first year of the program. In the risk-averse scenario, maximum acceptable human error incident rate was decreased by 20%. With the organisation being less likely to take risks, utilisation rate of the AUV was lower than the base scenario. Consequently, the primary AUV team gains little experience if not losing experience to decay throughout the operating lifetime of the AUV. This eventually leads to a higher human error incident rate as compared to the base scenario. Although the simulation results seem to suggest that a risk-prone culture is desirable for reducing risk of loss, it is clearly not a rational recommendation without considering other factors. Instead, the simulation demonstrates the importance of establishing an optimal risk tolerance level from the beginning of the AUV program.





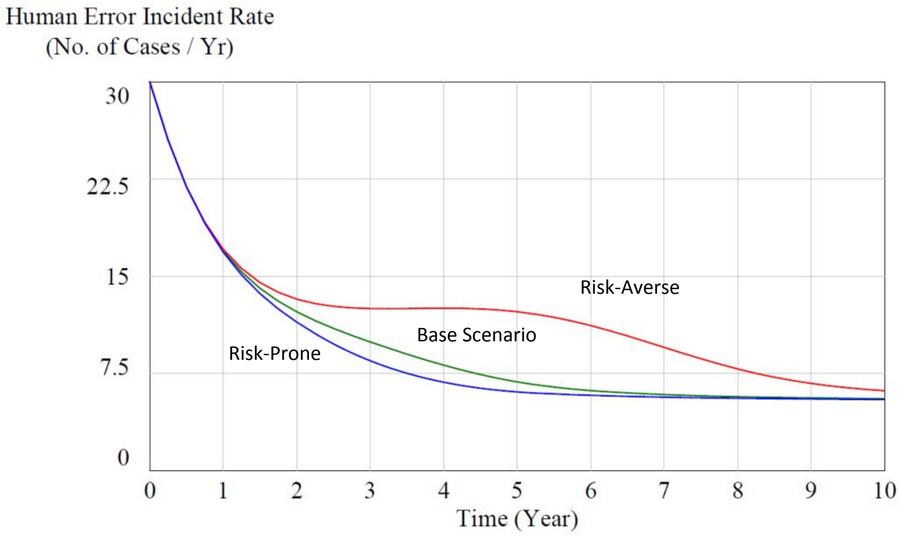


Fig 13. Simulation results showing the trend of utilisation rate (Top), average experience of AUV team (Middle) and human error incident rate (Bottom) in different risk culture.

The last scenario analysis consisted of having different input combinations of the above three scenarios to reflect possible real-life situations. These combinations are presented in Table II with the corresponding graph presented in Fig 14.

Table II. Different input combinations of earlier presented scenarios, with corresponding graph number indicated in Fig 14.

Graph Number	1	2	3	4	5	6	7	8	9	10	11	12	13	**14 (Base)**	15	16	17	18
Training and Practice during lull Y:Yes N:No	Y	Y	Y	Y	Y	Y	Y	Y	Y	N	N	N	N	N	N	N	N	N
Average Experience of new hire (Yrs)	0	0	O	1	1	1	2	2	2	0	0	0	1	1	1	2	2	2
Organisation's risk appetite RP: Risk Prone, RN: Risk Neutral, RA: Risk Averse	RP	RN	RA	RP	RN	RA	RP	RN	RA	RP	RN	RA	RP	RN	RA	RP	RN	RA

The results showed that the lowest level of human error incident rate occurs when the organisation provides training and practice runs during lull, requires new hires to the primary AUV team to have two years of relevant experience and is generally risk-prone (Graph 7). On the contrary, a risk-averse environment with no training or practice runs and a team without experience will incur the highest human incident rate (Graph 12). Notably, while training and a risk-prone culture do mitigate some effect from a lack of experience in new hires (See Graph 2 and Graph 10), the human error incident rate remains higher than the base scenario (Graph 14). However, the provision of training and the requirement for new hires to have 2 years of experience in a risk-averse culture reduces human error incident rate below the base scenario (see Graph 6 and Graph 18). More importantly, the simulation shows that the order of effectiveness in reducing human error incident rate is: having 2 years of experience for new hire (Graph 17), availability of training (Graph 5) and a risk-prone culture (Graph 13).

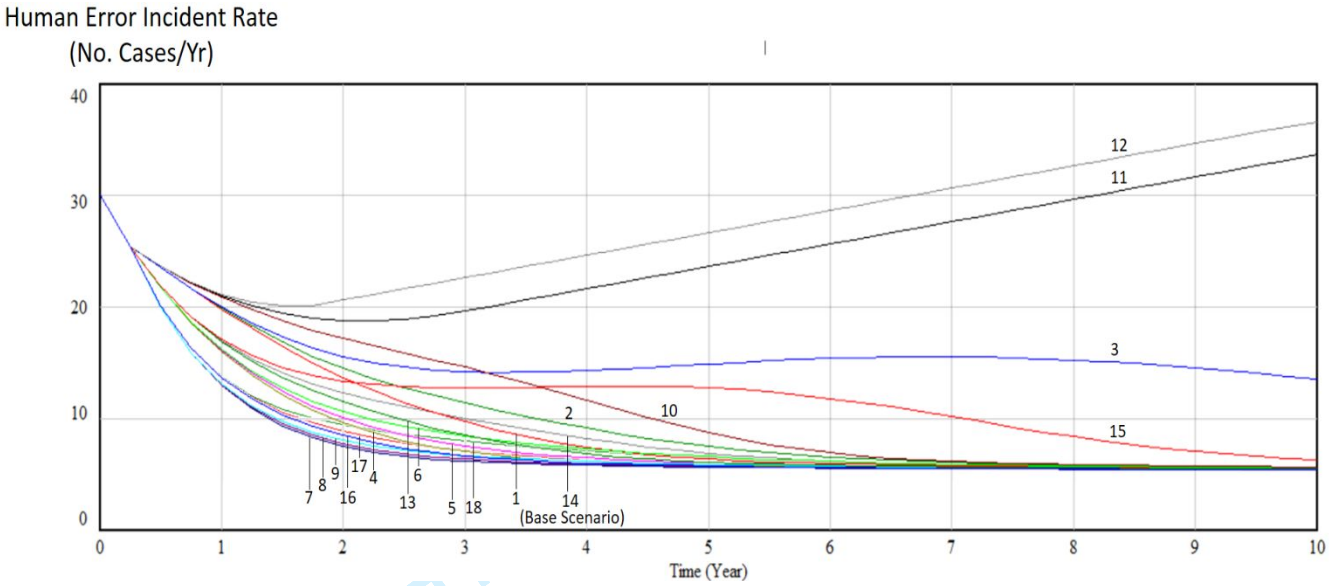


Fig 14. Simulation result showing human error incident rate for various combinations of scenarios.

3.4 Evaluation

Although simulation results from the analysis can be used to evaluate against a pre-determined evaluation criterion, an exact set of evaluation criterion has yet to be established as the program is still relatively new. Despite so, results from the scenario analysis can still be used to facilitate the formulation of risk control policies.

Simulation results from the first scenario analysis emphasise the importance of implementing a regular training regime and practice runs during lull periods which are similar to actual Antarctic deployment. This mitigates experience decay of the AUV team and consequently, reduces the risk of AUV loss during actual deployment (O' Hara, 1990). It is, therefore, also logical that utilisation rate of the AUV, amount of practice run and relevant training are monitored as leading indicators to risk of AUV loss. The second scenario analysis demonstrated the impact of new hire's relevant experience on human error incident rate. Optimising the recruitment criteria on the amount of required relevant experience can, therefore, be an ideal leverage point for reduction of risk of AUV loss. Conversely, the impact of staff turnover or attrition on the risk of loss can also be analysed with the model. While it is tempting to recommend recruiting as many experienced AUV engineers as possible, considerations have to be made on the effects of team dynamics and the amount of available resources (Helmreich, 1997). The third scenario analysis demonstrated that an excessively risk-averse culture may, ironically exacerbate the risk of AUV loss. This occurs when the primary AUV team loses experience through decay during lull period. While it is also illogical to ignore risks in Antarctic AUV deployment, the key to further risk reduction is to establish an optimal risk tolerance level. Finally, the combined scenario analysis shows 2 years' experience for new hire, training and a risk-prone culture are ranked in order of effectiveness in mitigating risk of AUV loss.

4. DISCUSSIONS AND LIMITATIONS

Despite the advantages of applying system dynamics for risk analysis of AUV operations, it also has its drawbacks. The multidimensional, dynamic and sometimes fuzzy nature of risk (Haimes, 2009) can make the modelling process a challenging and time-consuming task. Trying to model all identified issues faced by an Antarctic AUV program often result in models which are too complex for any practical analysis. As shown in the example, in the consideration of just a few risk variables relating to human error can result in a relatively complex risk model. Yet, the reduction of complexity meant working with assumptions which may be subjected to differing interpretations by different people. In addition, these assumptions may deteriorate relevance of the model to actual real-world situation. Other issues encountered are the poor availability of data as well as incomplete and episodic knowledge of domain experts. Lastly, the structural view of system dynamics models is often viewed as being too deterministic in nature (Nick Pidgeon, 1998). However, the origin of risk stems from uncertainties (Leveson, 2011), which may not be explicitly taken into account by deterministic system dynamic models. This problem becomes especially evident when the number of uncertainties in the causal relationships between risk variables becomes very large (Coyle, 2000).

To these drawbacks and improve the analysis of risk, further research can follow two tracks. First, further research can explore complimenting system dynamics with fuzzy set theory to develop a hybrid risk analysis approach. The main advantage of doing so is to account for the stochastic uncertainties in the system. This would overcome the constraint that system dynamics models are too 'deterministic' and result in a more robust risk analysis methodology. Additional research can explore means of effective data aggregation, especially for disparate information acquired during the risk analysis process. This can facilitate and expedite the identification of relevant risk variables, improve the clarity of assumptions and aid quantification of the risk models.

The proposed generic framework (Fig.3) and novel risk structure (Fig.4) can be adopted by any organisations that operates AUV. However, there are different types of AUV, operated by different organisations for different purposes. This implies that the issues and risk variables influencing the risk of AUV loss also varied widely. For instance, the parameters used in the application example were elicited from the AUV team and would be different for another team from a different organisation. It is important then, to tailor the system dynamics models according to the problem and intent of the organisation when applying the proposed framework. As a result, the risk profile may also differ significantly from this work.

5. CONCLUSION

This work presents a systems-based risk analysis approach for an Antarctic AUV program. Presented as a framework, the use of system dynamics enables a comprehensive analysis of risks for more effective policy recommendations. It overcomes drawbacks of existing risk analysis approaches, which are generally based on a chain-of-events paradigm with focus inclined towards the technical aspects of an AUV. Application of the proposed framework facilitates modelling of the complex, interrelated and dynamic systems behind an Antarctic AUV program, which may lead to increased risk of AUV loss. An example based on an actual Antarctic AUV program is presented, examining the occurrence of human error in the program.

Traditional human error analysis techniques such as Human Error Assessment and Reduction Technique (HEART) (J. C. Williams, 1985), Technique for Human Error Rate Prediction (THERP) (Swain & Guttmann, 1983) and others (Bell & Holroyd, 2009) have proven useful for estimating human error generation rate for well-defined and constrained tasks. Such techniques can also be applied to estimate human error incident rate for particular phases of the AUV deployment and operation, for example piloting. However, these techniques would not allow estimating the risk of AUV loss due to human error as a function of organisational factors. Application of the proposed framework showed an overall declining human error incident rate with the increase in experience of the primary AUV team. Three scenarios were then simulated with the following findings: First, implementing a regular training regime and practice runs similar to actual operation during lull periods mitigates the effect of lack of actual Antarctic AUV deployment. Second, the amount of new hire's relevant experience is an important leverage point for reducing human error incident rate. Last, an optimal risk tolerance level must be established by the organisation as being excessively risk-averse may ironically exacerbate the risk of AUV loss. Despite the seemingly intuitive policy recommendations, this example demonstrates how the proposed framework could be pragmatically useful for analysing more complex issues in future AUV programs.

Further advancement of this work to enhance the risk analysis framework can focus on two areas. First, to incorporate secondary methodologies such as fuzzy logic to overcome the 'deterministic' nature of system dynamics. Secondly, to work on means of effective data aggregation, especially for disparate information. The generic nature of the proposed risk analysis framework allows for application in other areas apart from risk of loss in an Antarctic AUV program. It can be relevant to different organisational needs, AUV types and usage purposes. In addition, it may also be useful for analyzing risk of other complex technological systems, such as the budding field of autonomous cars, unmanned aerial vehicles and unmanned vessels.

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Appendix I

Table III. Details of the formulation, definitions and initial conditions used in the stock and flow model.

Risk variable	Definition	Equation	Remarks
Total Experience of AUV Team	The total experience of the primary AUV team in Antarctic under-ice deployment.	INTEG (Increase in Experience-Loss of Experience); Initial value = 4 Years	INTEG: Numerical Integration
Increase in Experience	The amount of experience gained on-the-job and from hiring.	("On-the-Job Experience Gain Rate"*Utilisation Rate*Number of AUV Team Members)+Experience Gain from Hiring	
Loss of Experience	The amount of experience loss through decay during lull and attrition.	(Experience Decay Rate*Number of AUV Team Members)+(Attrition Rate*Average Experience of AUV Team)	
Experience Gain from Hiring	The amount of experience gained from hiring.	Average Experience of New Hire*Hiring Rate	
On-the-Job Experience Gain Rate	The amount of experience gained on-the-job. Set at 3 times the utilisation rate to account for preparation and planning of deployment.	3	A constant value subject to change by model user
Average Experience of New Hire	The amount of relevant experience of new hire.	1 Year	A constant value subjected to change by model user
Experience Decay Rate	Amount of experience decay during lull. Assumed that time will be spent on non-AUV related activities during lull.	1-Utilisation Rate*3	
Average Experience of AUV Team	Average experience of the primary AUV team in Antarctic under-ice AUV deployment.	MAX (0,Total Experience of AUV Team/Number of AUV Team Members)	MAX: Maximum of two alternatives
Number of AUV Team Members	The total number of personnel in the primary AUV team.	INTEG (Hiring Rate-Attrition Rate) Initial value = 4 Personnel	
Hiring Rate	Rate at which new AUV team members are hired when there is a shortfall.	MAX (0, Discrepancy/Average Time to Hire)	
Discrepancy	Difference between desired number of AUV team members and current number.	Desired Number of AUV Team Members-Number of AUV Team Members	
Desired Number of AUV Team Members	Target number of personnel in the primary AUV team.	6	A constant value subject to change by model user
Attrition Rate	Rate at which AUV team member leaves the organisation.	Number of AUV Team Members*Fractional Attrition Rate	

Industry Attrition Rate	Reported annual attrition rate by industry and region.	0.15	A constant value subject to change by model user
Fractional Attrition Rate	The expected percentage of AUV team member leaving the organisation annually. Each excess in manpower increases attrition rate by 0.05 on top of industry attrition rate.	IF THEN ELSE(Discrepancy<0 , 0.05*Discrepancy+Industry Attrition Rate, Industry Attrition Rate)	
Average Time to Hire	Average time needed to fill a position in the AUV team.	2 Months	A constant value subject to change by model user
Human Error Incident Rate	Number of recorded human error related incidents.	INTEG (Increase in Human Error Incident Rate-Decrease in Human Error Incident Rate) Initial value = 30 Cases	
Increase in Human Error Incident Rate	Rate at which new human error incidents are reported.	(1-Safety Commitment Exponent)*Safety Deterioration Exponent	
Decrease in Human Error Incident Rate	Rate at which human error incidents reduces.	(Human Error Incident Rate-Baseline Human Error Incident Rate)*Effect of Experience on Human Error	
Effect of Experience on Human Error	The degree of influence that average experience of the primary AUV team had over human error incident rate.	Average Experience of AUV Team*Safety Commitment Exponent	
Safety Commitment Exponent	Safety commitment level of the primary AUV team. Represents strength of the relationship between average experience and human error incident rate. Ranges from 0 to 1.0 with higher value indicates higher commitment level.	0.8	A constant value obtained through average values of interview inputs
Safety Deterioration Exponent	Baseline deterioration of safety commitment by the primary AUV Team due to lack of safety initiatives. Higher value indicates more deterioration.	10 Cases/Year	A constant value subject to change by model user
Baseline Human Error Incident Rate	Baseline human error incidents attributed to other reasons other than experience of the team.	5 Cases	A constant value subject to change by model user
Effect of Human Error Incident Rate on Utilisation Rate	The degree of influence that human error incident rate had over utilisation rate.	(Maximum Acceptable Human Error Incident Rate-Human Error Incident Rate)*Organisation's Risk Tolerance Exponent	
Maximum Acceptable Human Error Incident Rate	The number of recorded human error related incidents before the organisation begins to reduce utilisation of the AUV.	20 Cases	A constant value subject to change by model user
Organisation's Risk	Risk tolerance level of the organisation. Represents strength	0.4	A constant value obtained through

Tolerance Exponent	of the relationship between human error incident rate and utilisation rate. Ranges from 0 to 1.0 with higher value indicates risk aversion.		average values of interview inputs
Desired Utilisation Rate	Target percentage of time the AUV spends at the Antarctic in a year.	0.33	A constant value subject to change by model user
Change in Utilisation Rate	The amount of change in utilisation rate of the AUV.	(Desired Utilisation Rate-Utilisation Rate)*Effect of Human Error Incident Rate on Utilisation Rate	
Utilisation Rate	The percentage of time the AUV spends at the Antarctic in a year.	IF THEN ELSE ((Utilisation Rate<=0, 0, INTEG (Change in Utilisation Rate)) Initial value = 2 Months	IF THEN ELSE: Alternative formulations based on condition

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